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

Online Appendix

This document provides additional information regarding our data and sample construction. We also present and discuss the results of supplementary analyses referred to in the main paper.

A. Data Appendix

A.1 CFTC Positions Data and Summary Statistics

This appendix supplements the description of CFTC positions data in Section III.A of the paper. We use publicly available data from the Commodity Futures Trading Commission (CFTC) to study the positions that the MM (Managed Money, or Money Managers, as the CFTC uses these two terms interchangeably) category take in U.S. commodity futures markets.[1] To form our signal measures, we use the CFTC Disaggregated Commitments of Traders (DCOT) reports, which aggregate the holdings for five categories of market participants in the U.S. futures markets (each defined in Table A.1) from Wednesday to Tuesday close, and release the weekly positions data as of Tuesdays on Fridays.

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), whereas Producer/Merchant/Processor/User (PM) and Nonreporting (NR) positions are simply divided into long or short.[2] 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 expression above each brace represents the contribution of open interest accountable to each of the trader categories:

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

It should be noted that, according to the CFTC, 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; failure to answer the form

[1] 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 DCOT reports in the disaggregated format on September 4, 2009 and provided historical data back to June 2006 on October 20, 2009. The DCOT reports, required per CFTC regulations and collected under the Commodity Exchange Act, provide a breakdown of open interest for markets in which 20 or more traders hold positions at or above the reporting levels established by the CFTC.

[2] Spreading measures the extent to which a trader holds equal long and short futures positions. For example, if a money manager 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. 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.

TABLE A.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. The category thus groups together positions of both producers and buyers of the commodity who manifestly have opposite hedging demands.
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. Swap dealers take both long *and* short positions, which is consistent with their business as intermediaries who facilitate the on-average net long positioning desired by speculative traders, most of whom are passive commodity index investors, and the on-average net short position desired by commercial hedgers.
Managed Money (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. As opposed to industry parlance which generally views CTAs/CPOs as simple trend followers, the CFTC definition of CTAs/CPOs within MM is solely based on legal registration status under the Commodity Exchange Act and encompasses most hedge funds (especially the sizable ones) with nontrivial positions in commodity futures, including many funds that are more sophisticated than simple trend followers. The category captures also the futures-based positions of commodity ETFs, that are essentially passive in nature, although they constitute only a small portion of MM's total open interest (in dollars), even under generous assumptions.
Other Reporting (OR)	Other reportable traders who are not placed into one of the above three categories.
Nonreporting (NR)	Smaller traders who are not obliged to report their positions.

truthfully is a violation of the Commodity Exchange Act (CEA) 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 DCOT reports for different commodities. However, due to legal restraints (CEA Section 8, data and confidential business practices), the CFTC does not publish information on how individual traders are classified in the DCOT reports.

Figure A.I shows the average market share held by each of the five trader categories over the sample period and across all ten commodities under study. On average, 23.5% of the market share goes to MM, 30.9% to PM, 17.8% to SW, 18.5% to OR, and 9.3% to NR.

FIGURE A.I Breakdown of Total Open Interest (TOI) by Trader Category

This figure shows the average market share, for the ten commodities considered in our analysis, held by each of the five trader categories in the commodity futures market over the whole sample period from January 2007 to March 2020. The trader categories are defined in Table A.1.

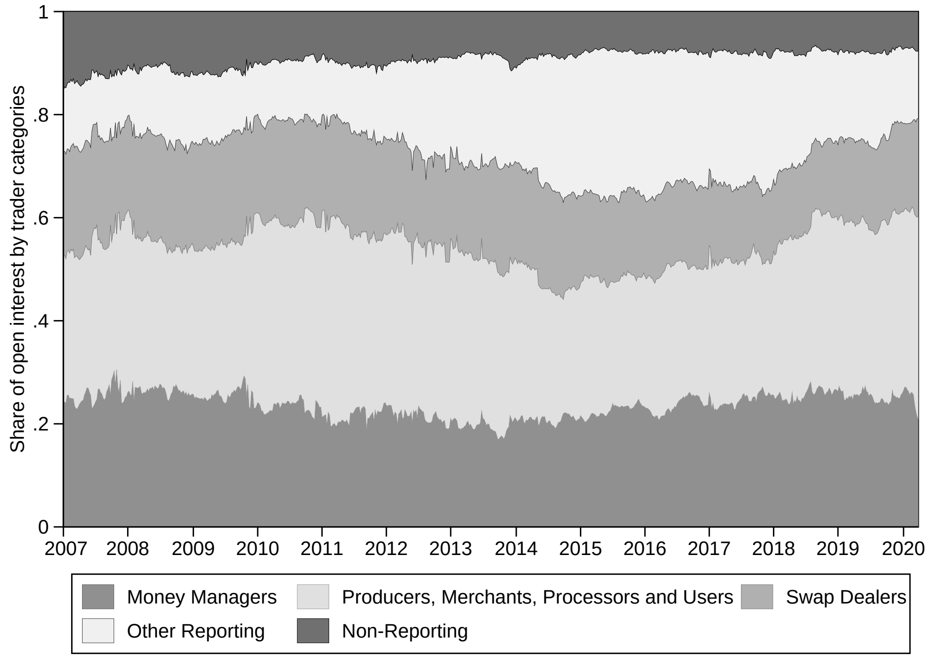


Table A.2 provides a summary of the net positions for the different DCOT trader categories in our sample of 10 commodities. For each commodity, we report the position by each trader category as measured by the average weekly net (long) position (i.e., long minus short, and then scaled as a percentage of the open interest of that trader category), its standard deviation, the percentage of the weeks in which the position is long, and the first-order autocorrelation coefficient of the net 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 to the extent producers are represented within the PM category, the producers generally act as hedgers for the most part (with the caveat that the PM category groups together the positions of both producers and buyers of the commodity who manifestly have opposite hedging demands). In contrast, SW and OR positions are less clear cut on average. Money managers can both long and short different commodities in a given week, and their average net long position across commodities is 23%. Also, 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 around 25% per week. While money managers are almost equally likely to be long or short in copper, steel, and lumber, their positions are more likely to be long in other commodities (except for coal). Finally, unsurprisingly for weekly positions, all traders' positions across all commodities exhibit a high degree of persistence, although we note that the signal measures we construct in the paper are more concerned about the changes in positions.

A.2 Detailed Procedure to Identify Commodity Producers' Stocks

This appendix supplements the description of the procedure to identify our sample of commodity producers' stocks in Section III.B of the paper. To identify and match commodity-producing firms with the commodities for which the CFTC is collecting the DCOT information, we follow a procedure similar to the industry code matching algorithm proposed by Gorton and Rouwenhorst (2006).

First, for each commodity that can be appropriately identified with a four-digit U.S. SIC code, we associate all publicly traded companies with that same code.[3]

Second, to expand our sample size of commodity-producing firms and to address quality issues related to the SIC code information provided by CRSP (Gandhi and Lustig, 2015), we also utilize Bloomberg's BICS code.[4] BICS code information, whenever available, is used to identify the commodity producers, as it is more detailed, delineated, and accurate compared to SIC. If a firm is identified by the BICS code as a commodity producer, but not by the header SIC code, we add it to our sample. Furthermore, Bloomberg also contains data on firms' breakdown of revenues according to the BICS classification of business activities, which is especially useful for our purpose, as some commodity-producing firms are not necessarily only involved in the production and processing of a commodity but can also be involved in a number of sideline businesses, or the business activities related to commodity production are not their primary focus. To address this issue, we thus exclude from our sample, whenever available, any firm for which the primarily source of revenue (BICSRevLvlAsgn) assigned to our target BICS industry code for our concerned commodity is less than 50%.

[3]We use header SIC Code (HSICCD) instead of historical SIC code (SICCD) from CRSP because the former has better accuracy. In addition, historical SIC code suffers from quality issues over time such as the "SIC code drift" phenomenon discovered by Gandhi and Lustig (2015).

[4]The BICS hierarchical industry classification scheme has ten sectors that represent the broadest classification, and each sector is further refined with a granularity of up to seven hierarchical levels with progressively narrower and more precisely classified business activities. For comparison, the four-digit SIC code has 1,005 unique industries, whereas the BICS classification code, which has a maximum of 16 digits, has a total of 2,288 unique industries.

TABLE A.2 Summary of Positions Held by the DCOT's Traders Categories, January 2007–March 2020

The table summarizes the positions of traders in the commodity futures markets according to the classification employed in the DCOT reports. For each category of traders, as described in Table A.1, positions are measured as Net Long (long minus short and scaled by the open interest of that trader category). The columns show 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 March 2020 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 a Percentage of Open Interest																			
	Managed Money				**Producers Merchants Processors & Users**				**Swap Dealers**				**Other Reporting**				**Nonreporting**			
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 (2007m1)	4.2	27.1	52.6	0.96	−44.7	23.3	1.6	0.97	59	13.6	100	0.97	−13.1	18.6	24.6	0.95	−4.5	13.6	41.2	0.93
Steel (2012m12)	6.6	60.2	54.4	0.98	−5.3	45.9	38.1	0.99	83.6	29.5	96.6	0.97	−4.7	33.3	26.1	0.99	49.3	50.1	85.8	0.83
Gold (2007m1)	44.7	25.7	94.2	0.96	−54.6	19	1.3	0.96	−23.5	15.7	8.4	0.96	26.9	13	96.5	0.94	30.3	18.1	93.9	0.95
Silver (2007m1)	29.1	22	88.6	0.95	−59.8	14.7	0	0.96	−3.1	20.4	42.5	0.97	24.2	14.8	98.6	0.94	36.4	12.3	100	0.91
Misc. Metals (2007m1)	54.8	27.1	95.1	0.98	−72.8	13.5	0	0.97	−32	19.5	7.1	0.94	45.8	14.9	98.8	0.89	41.6	15.8	99.9	0.93
Biofuel (2009m11)	56.2	32.8	94.4	0.9	−17.1	21.9	18.1	0.96	−12.6	42.6	37.5	0.91	10.9	29.6	62.4	0.93	21.8	19.4	87.9	0.79
Oil & Gas (2007m1)	9.7	9.5	85.3	0.98	−16.3	12	9.8	0.99	−6.4	20	44.8	1	2.7	10.5	64.5	0.98	12.9	6.7	99	0.87
Gasoline (2007m1)	39.4	18.4	97.7	0.96	−35.6	6.2	0	0.88	46.9	14.8	100	0.97	15.8	15.7	81.2	0.95	15.1	12.4	87.9	0.89
Coal (2007m6)	−14.4	52.5	34.9	0.97	−10.1	30.7	33.9	0.99	−15.2	52.7	37	0.98	29.7	44.3	67.9	1	−0.2	25.4	45.4	0.91
Lumber (2007m1)	4.4	44.6	51.4	0.97	−39.7	39.3	17.2	0.96	96.4	11.5	100	0.78	−1.3	18	44.9	0.92	5.4	11.8	67.3	0.89

Finally, there are some exceptions to the general rule for three commodities, as SIC or BICS codes lead to imprecise identification of producers. As Gorton and Rouwenhorst (2006) notice, for the case of the precious metal palladium, identification by SIC or BICS codes may be inadequate, as the SIC codes 1099 and 1090 (i.e., "metal ores, not elsewhere classified" and "miscellaneous metal ores", respectively) include not only companies mining palladium but also firms mining metals such as platinum, thus necessitating the creation of the miscellaneous metals commodity consisting of palladium and platinum; in our case, we simply handpick the few firms within this category. In addition, the authors note that silver producers are often involved in the mining of several other metals, and silver may not be their first line of revenue. For the case of lumber, neither SIC nor BICS codes could precisely identify lumber producers because the users of the commodity—for example, "paper mills" and "wood building materials"—are generally grouped together with the producers of the commodity under the same industry code (which has the risk of capturing the opposite lead-lag effect in our analysis, as opposed to commodity producers). Thus, from the few firms that could potentially be identified as silver, miscellaneous metals, and lumber producers by the closest SIC and BICS codes we could find, we double-check our selection against the firms' annual reports and exclude those that are either users (instead of producers) of the commodity or when the concerned commodity is not their primary line of revenue.

Ultimately, ten commodities[5] are considered: two industrial metals—copper and steel; three precious metals—gold, silver and miscellaneous metals (palladium and platinum); four energy commodities—biofuel, crude oil and natural gas, gasoline (refining), and coal; and one soft commodity—lumber. The SIC and BICS codes utilized for identification in seven out of the ten commodities, as well the PERMNO of the handpicked firms (listed in parentheses), are provided in Table A.3, which also contains details on the futures contracts selected. Overall, our sample of commodity producers' stocks from January 2007 to March 2020 contains 341 firms in total, with 192 firms on average per week.[6]

[5] Given that crude oil and natural gas are grouped together as one composite commodity in our setting and similarly for the case of miscellaneous metals (palladium and platinum), we in fact utilize CFTC positions information on twelve individual commodities.

[6] Compared to Gorton and Rouwenhorst (2006), the number of producers' stocks reported in Table A.3 is not directly comparable to the one shown in their paper in the table "Summary of Matches of Companies to Commodities." The period covered in their analysis ends in December 2003, while ours starts in January 2007. Our sample covers a shorter and different time period; in addition, we focus on ordinary common stocks (SHRCD= 10 or 11) and Canadian stocks traded in the United States, among other sample filters.

TABLE A.3 Sample of Commodity Producers

The number of companies, together with the SIC and BICS codes (plus, whenever we handpick a firm in addition to industry code matching, its five-digit PERMNO in parentheses) are reported in the table. We restrict our attention to U.S.-listed North American commodity producers with ordinary common shares that have CRSP share codes 10 and 11 and Canadian firms that are also traded at a U.S. exchange. Section A.2 provides a full description of the sample construction process. *These include all child industry codes with hierarchies below the described BICS code. **Three commodities, silver, miscellaneous metals, and lumber are handpicked only due to the lack of appropriate SIC or BICS codes.

The futures contracts used are shown in the first column in brackets. [1]Biofuel uses futures contract [25601] up to July 2018 and contract [25651] afterwards. [2]Crude oil and natural gas comprises crude oil [067651] and natural gas [23651], weighted yearly by the lagged U.S. oil and gas industry's total revenue (with data retrieved from the U.S. Energy Information Administration). [3]Coal aggregates contracts [24658] and [24651] up to December 2017 and uses contract [24656] afterward. [4]Misc. metals combine, with the same weight, palladium [075651] and platinum [076651] contracts.

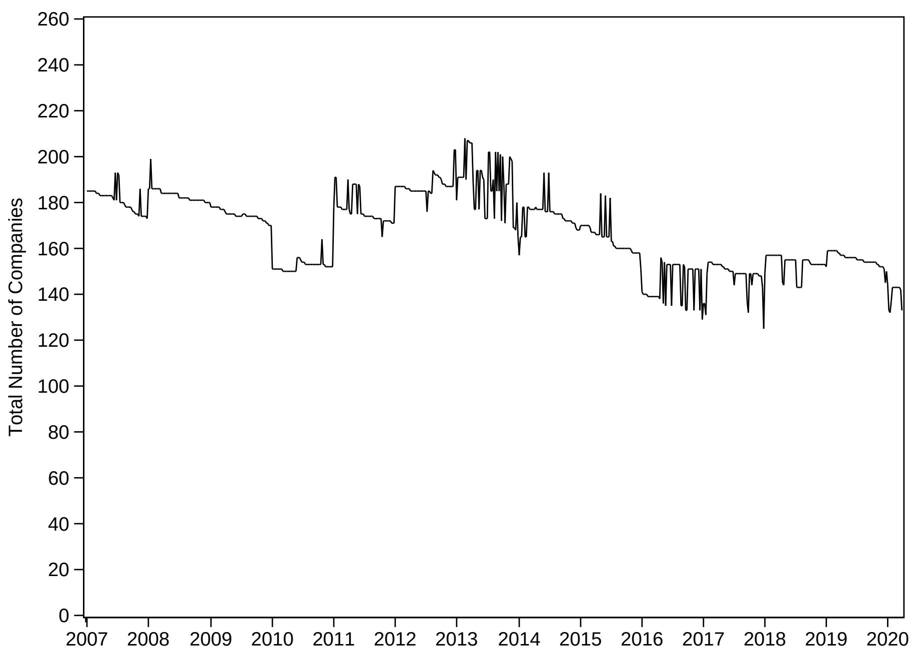
Commodity [Contract Code]	Industry Codes (and PERMNO)	Industry Code Descriptions	Total # of Stocks
Copper [85692]	SIC: 1020; 1021; 3331 BICS: 17151012; 1715101210* (91418)	SIC: Copper ores; Primary copper BICS: Copper; Copper mining	10
Steel [192651]	SIC: 3310; 3312 BICS: 1714* (80375)	SIC: Steel works, blast furnaces, and rolling mills BICS: Iron and steel	18
Gold [88691]	SIC: 1041; 1040 BICS: 17151110	SIC: Gold ores; Gold and silver ores BICS: Gold mining	64
Biofuel[1]	SIC: 2860; 2869 BICS: 131110*	SIC: Industrial organic chemicals BICS: Biofuels	15
Crude Oil and Natural Gas[2]	SIC:1310; 1311 BICS: 131011*	SIC: Crude petroleum and natural gas extraction BICS: Exploration and production	183
Gasoline (Refining)	SIC: 2910; 2911 BICS: 131014*	SIC: Petroleum refining extraction BICS: Refining and marketing	17
Coal[3]	SIC: 1220; 1221; 1222 BICS: 131016*	SIC: Bituminous coal and lignite mining BICS: Coal operations	20
Silver** [84691]	(12447; 78236; 90796; 91689; 92262)	N/A	5
Misc. Metals**[4]	(11999; 79853; 81173; 83601; 90069)	N/A	5
Lumber** [58643]	(13766; 56143; 56223; 76123)	N/A	4
Sample period: January 2007–March 2020		Total =	341

Crude oil and natural gas are grouped together, as firms engaged in crude oil production often also engage in natural gas extraction, and therefore the SIC and BICS codes often classify them together under the same code. For these firms, the signals in the commodity futures market are weighted yearly by the lagged U.S. oil segment and gas segment's total revenue (with data retrieved from the U.S. Energy Information Administration). Furthermore, miscellaneous metals comprise both platinum and palladium as firms engaged in platinum production often also engage in palladium production, and as mentioned before, the two commodities appear in the SIC code category ''miscellaneous metal ore.''

Reasons for not selecting more commodities are twofold. First, based on their SIC codes, too few publicly traded U.S. producers can be matched to a unique commodity for the cases of coffee, sugar, cattle, cocoa, cotton, and so forth. Second, most of the listed producers in the soft category are highly diversified firms exposed to several agricultural goods simultaneously, thus preventing matches to a unique commodity.

FIGURE A.II Total Number of Stocks Traded Each Week

This figure shows the total number of stocks traded in each week from January 2007 to March 2020, summed over all matched commodities that are reporting non–missing CFTC positions data.

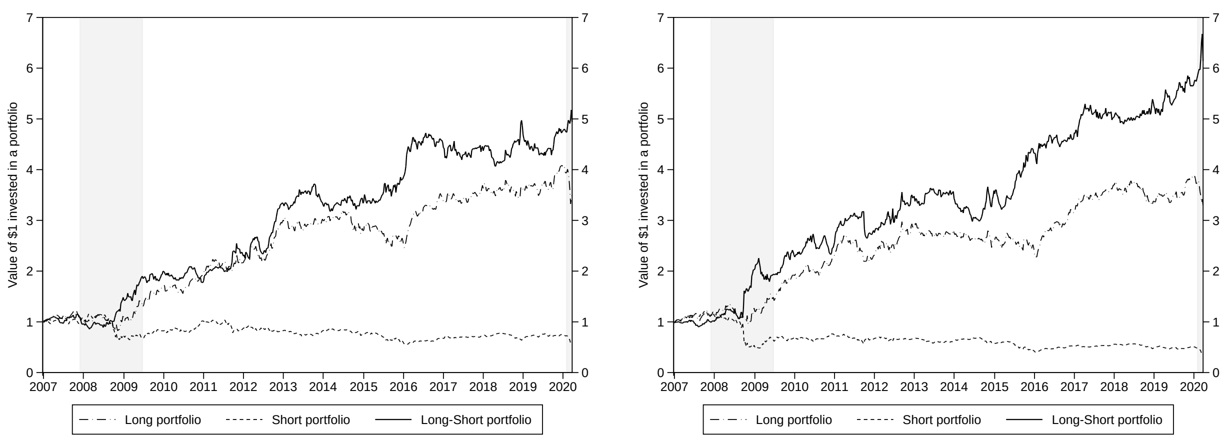


A.3 Long-Run Performance of the Long-Short Portfolios

Figure A.III presents the value-weighted long-short portfolios' long-run performance signaled by the 2-week and 12-week backward moving average of MM Long Proportion Growth. There is a marked difference between the long and short portfolios' performance. For the $J = 2$ case in the left panel, an investment of \$1 in the long portfolio in January 2007 at the beginning of our sample period would have grown to \$3.50 by March 2020, whereas a \$1 investment in the short portfolio would have declined to \$0.62 over the same period. A dollar invested in the long-short portfolio at start would have grown to \$4.94 by March 2020, representing an annualized mean excess return of 12.29%. Likewise, for the $J = 12$ case in the right panel, a dollar invested in the long-short portfolio would have grown to \$6.14 by March 2020, representing an annualized mean excess return of 14.33%. The long-short returns in both panels reveal a clear upward trend over the entire sample period.[7]

FIGURE A.III Cumulative Gains from Investments, Signaled by J-Week-Lagged Managed Money Long Proportion Growth (Value-Weight)

$J = 2$ $J = 12$



Shaded areas correspond to NBER recession periods, i.e., from January 2008 to June 2009, and from February 2020 to sample end (March, 2020).

[7]There is heightened volatility during the 2015–2016 period, which can be partly attributed to financial turmoil in China, including a stock market crash and subsequent economic stimulus beginning in 2015, which spilled over to the commodity market, as well as uncertainties about the future prospect of China's demand for commodities. In unreported figures, we further disaggregate the weekly return of the long and short portfolios into the return contribution of each individual commodity-equity portfolio. We confirm that the large increase in the cumulative return of the long-short portfolio beginning in 2015, which was steadily growing even before this period, cannot be entirely attributed to any one commodity in particular.

A.4 Commodity Futures Returns and Commodity Price Factors

This appendix reviews the construction of commodity futures returns and commodity price factors used in the paper. We select relevant factors that are established in the existing literature in the study of the behavior of commodity returns.[8] Specifically, we construct a number of commodity price factors, namely, i) the past 12 months' futures momentum, ii) the futures basis (which captures inventory effects, that is, "backwardation," in commodities markets), iii) a benchmark commodity market index, and iv) the futures basis-momentum, which is the difference between momentum in first- and second-nearby futures contracts; v) furthermore, we also test the principal components of commodity futures returns.

Commodity Futures Returns

We collect daily data from Bloomberg on the prices of exchange-traded, liquid commodity futures contracts with different maturities for each of the commodities that have been matched to our sample of commodity producers over the period between January 2007 and March 2020.[9] The number of distinct contracts that mature within any given year generally varies across commodities.[10] We construct rolling commodity futures excess returns at a weekly frequency for commodity c as follows:[11]

$$FR_{c,t}^{T_1} = \frac{F_{c,t}^{T_1}}{F_{c,t-1}^{T_1}} - 1, \tag{1}$$

where $F_{c,t}^{T_1}$ is the end-of-week t closing price (the end-of-week day is usually a Tuesday, unless it is a federal holiday) of the first-nearby futures contract for commodity c with expiration at T_1, and $F_{c,t-1}^{T_1}$ is the price of the *same* contract at the end-of-week $t-1$. Regarding the choice of the contract, following Szymanowska et al. (2014) and Boons and Prado (2019), for

[8]See, for example, Gorton and Rouwenhorst (2006), Erb and Harvey (2006), Miffre and Rallis (2007), Gorton et al. (2013), Szymanowska et al. (2014), Bakshi et al. (2019), Boons and Prado (2019), and Christoffersen et al. (2019).

[9]The Henry Hub natural gas, light sweet crude oil, RBOB gasoline, hot-rolled coil steel, palladium, and platinum data are from the New York Mercantile Exchange; gold, silver, and copper data are from the Commodity Exchange, Inc.; denatured fuel ethanol data is from the Chicago Board of Trade; and random length lumber and coal (API 2) data are from the Chicago Mercantile Exchange. The data are retrieved through the Bloomberg terminal.

[10]As before, we use ten commodity sets. Given that crude oil and natural gas are grouped together, similarly for the case of miscellaneous metals, we utilize information on 12 individual commodities, and 11 of them have 12 distinct contracts within any given year, while lumber has only 6 per year.

[11]As is standard in the literature, we assume that investment is made on a fully collateralized basis.

any given week t, we utilize the first-nearby futures contract that will expire at least 60 days from the current week t,[12] and accordingly, this approach avoids holding contracts close to expiration when unusual price and volume behavior sometimes occurs.

The Commodity Momentum Factor

Commodity price momentum has been documented by Erb and Harvey (2006), Gorton and Rouwenhorst (2006), Miffre and Rallis (2007), Gorton et al. (2013), among others. The futures return momentum in week t is calculated for each commodity futures c as the return over the previous 12 months (52 weeks):

$$M_{c,t} = \prod_{s=t-51}^{t} \left(1 + FR_{c,s}^{T_1}\right) - 1, \tag{2}$$

where $FR_{c,s}^{T_1}$ is the week s return of the nearest-to-maturity futures contract (as referenced in Eq. 1). The commodity momentum factor is constructed as follows: at the end of each week t, we rank all commodities on their 12-month commodity futures returns momentum $M_{c,t-1}$ (as of week $t-1$), and we accordingly assign the ranked commodities to the high- (low-) momentum portfolio. Since our analysis centers on the *equity space*, as it focuses on the predictability of equity returns of commodity producers, we populate the high- and low-momentum portfolios with the commodity producers' stock returns in week t associated with the respective commodities using the procedure as described in Appendix A.2. Both portfolios are equally weighted, that is we use the same weight for each stock.[13] For robustness, we also construct a commodity momentum factor in the *futures space*. In this case, we are not restricted to only the commodities matched to our sample of commodity producers stocks, and we thus include additional commodities.[14] The returns of this portfolio in week t are computed as the difference in returns of the commodity futures in the top and bottom half ranked by their 12-month commodity futures returns momentum M_{t-1}^{c}, equally weighting each commodity within each of the two commodity-futures portfolios.[15]

[12] It additionally follows this is also a sufficient condition to ensure that the same contract (for the calculation of $F_{c,t}^{T_1}$ and $F_{c,t-1}^{T_1}$) is utilized in the calculation of futures excess return in a given week.

[13] Alternatively, our results are robust to the weighting scheme in which the stocks within each commodity-equity portfolio are value-weighted by their lagged market capitalization.

[14] The additional commodities are soybean oil, corn, cocoa, wheat, cotton, cattle, heating oil, aluminum, lead, nickel, tin, and zinc. Results remain unchanged if we only consider our baseline ten commodity sets.

[15] In addition to the cross-sectional momentum factor, we construct a time series momentum factor,

The Commodity Basis Factor

Practitioners often refer to futures basis as the "roll yield" (Gorton et al., 2013). Per Bessembinder (2018), the roll yield is not an actual cash gain or loss to a futures investor, whose cash gains are determined solely by changes in the prices of individual contracts while positions are held. Thus, Bessembinder describes the roll yield as a "misnomer"; nevertheless, it still captures important information about the commodity futures market. We construct the basis factor to capture the term structure of futures prices by utilizing the annualized slope of the futures curve between the contracts with maturities T_1 and T_2. The basis in week t is calculated for each commodity futures c as:

$$B_{c,t} = \left(\frac{F_{c,t}^{T_1}}{F_{c,t}^{T_2}} - 1\right)\left(\frac{365}{D_2 - D_1}\right), \tag{3}$$

where $F_{c,t}^{T_1}$ is the end-of-week (usually a Tuesday) price of the nearest-to-maturity futures contract (as referenced in Eq. 1) and $F_{c,t}^{T_2}$ is the end-of-week price of the further-out-to-maturity futures contract. D_1 and D_2 are the number of days until the last trading date of the respective contracts. As a baseline and following Gorton et al. (2013), the futures basis is computed as the slope between the two nearest contracts in the curve. For robustness, we also compute the basis as the slope between the first nearby contract F^{T_1} and its next-year counterpart $F^{T_2 b}$, which helps to reduce volatility and the impact of seasonality in futures prices; using contracts with a fixed one-year distance between them also gives us a measure that is more homogeneous across the different commodities (Arnott et al., 2014). At the end of each week t, we construct the high- and low-futures basis portfolios by ranking all commodities on their previous-week basis $B_{c,t-1}$. The procedures to construct the long-short basis factor mirror the ones for the commodity momentum factor and are not repeated for brevity.

The Commodity Basis-Momentum Factor

Following Boons and Prado (2019), we consider the commodity basis-momentum factor, defined as the difference between the past 12-month momentum in first- and second-nearby

following the procedures in Moskowitz et al. (2012), wherein commodities are sorted into high- and low-momentum portfolios based on the *sign* of their respective past 12-month futures returns M_{t-1}^{c}.

futures contracts. Formally,

$$BM_{c,t} = \prod_{s=t-51}^{t} \left(1 + FR_{c,s}^{T_1}\right) - \prod_{s=t-51}^{t} \left(1 + FR_{c,s}^{T_2}\right), \tag{4}$$

where $FR_{c,s}^{T_1}$ is the week s return of the nearest-to-maturity futures contract (as referenced in Eq. 1) and $FR_{c,s}^{T_2}$ is the week s return of the further-out-to-maturity futures contract. The basis-momentum factor cannot be explained by the classical commodity futures pricing theories (theories of storage, backwardation, and hedging pressure), but rather represents compensation for commodity volatility and liquidity risks that affect the market-clearing ability of speculators and financial intermediaries (Boons and Prado, 2019). At the end of each week t, we construct the high- and low-futures basis-momentum portfolios by ranking all commodities on their previous-week $BM_{c,t-1}$. Our construction of the commodity basis-momentum factor then follows the same procedures as the commodity momentum factor.

The Commodity Market Factor

As a benchmark, for the commodity market factor defined on the *equity space*, we utilize the weekly total returns of the MSCI USA Commodity Producers Index, which tracks the equity performance of globally listed large- and mid-cap commodity producers across the energy, metal, and agricultural sectors. With regard to the benchmark commodity market index defined on the *futures space*, we follow Bhardwaj et al. (2014) and use the Mount Lucas Index of Commodity Sector (Bloomberg Ticker ''MLMCCOD Index''), which takes both long and short positions in different commodity futures contracts based on the 200-day moving average. We obtain similar results with the Standard and Poor's GSCI future-based index or using a long-only equally weighted portfolio of commodity futures, as in Gorton and Rouwenhorst (2006).

Principal Components

Finally, we also identity common factors in the cross-section of commodity futures returns by means of principal component analysis, following Christoffersen et al. (2019). We select the first five orthogonal principal components that explain 34.5%, 8.9%, 8.2%, 6.9%, and 5%, respectively, for a total of 63.5% of the cross-sectional variation in a sample of 21 commodity futures returns during 2007–2020.

A.5 Contribution of ETFs within the MM Category

This appendix provides the details underlying the estimation of ETFs' contribution to the open interest of the Managed Money category in the DCOT reports. Below, we show quantitatively that commodity futures-based ETFs[16] are not major players within the MM category for the sample of commodities analyzed in the paper (in terms of their maximal possible contribution to MM's open interest within the DCOT reports under generous assumptions), and are thereby unlikely to have much influence on our MM predictability results.[17] While CFTC is unable to give us fund-level data for privacy and legal reasons (from which we could perform a direct calculation), we nevertheless gather a comprehensive list of ETFs and concentrate in the following analysis on commodity-focused futures-based ETFs, whose futures positions would fall under the MM category in the CFTC DCOT reports.

To maximize data coverage, we collect data on commodity-oriented ETFs from both Bloomberg and CRSP with the following procedure. We obtain the list of ETFs from Bloomberg with "Fund Asset Class Focus" (i.e., the broad asset sector that the fund invests in, as stated in the prospectus) flagged as commodities. Similarly, we obtain the ETFs listed in the CRSP Survivor-Bias-Free Mutual Fund database by identifying the *et_flag*= F or N, as well as using Lipper Objective Name and Lipper Asset Class Focus to identify commodity ETFs.[18] The ETF lists are then combined from both sources. We also include descriptive ETF data from CRSP and Bloomberg on whether these ETFs are mainly physically based, derivatives-based, or equity-based, and whether they are short-oriented inverse funds and complement missing ETF characteristics based on prospectuses' descriptions.

From this raw list of commodity ETFs, we read through each ETF name and prospectus description and hand-match each fund to a specific commodity among the ten commodities in our analysis. We thus disregard funds that seek to replicate the performance of baskets

[16]We use the term "ETF" to encompass both exchange-traded funds (ETFs), and exchange-traded notes (ETNs) which are structured as debt obligations; per Fevurly (2013), "an exchange-traded note (ETN) is so similar to an ETF that commonly they are lumped together."

[17]This is independent to the additional argument that passively managed commodity ETFs are unlikely to have large changes in positions at 100% of assets under management (AUM) in every week, reducing their potential contribution to the weekly MM position changes even further.

[18]We restrict our sample to the following Lipper Objective Name: "Commodities Funds," "Precious Metals Funds," "Gold Oriented funds," or "Natural Resources Funds." We also include the following Lipper Asset Class Focus: AU—Precious Metals Equity Funds, CMD—Commodities Funds, CME—Commodities Energy Funds, CMG—Commodities General Funds, CMM—Commodities Base Metals Funds, CMP—Commodities Precious Metals Funds, CMS—Commodities Specialty Funds, or NR—Natural Resources Funds.

of commodities and those focusing on commodities not in our analysis. Among the ETFs that invest in commodity derivatives, some obtain price exposure by entering directly into positions in futures contracts, whereas others do so through swap instruments. Similar to index funds that track multiple commodities,[19] broad-market commodity basket ETFs also generally enter into over-the-counter (OTC) contracts with swap dealers to gain the desired exposure to commodities, and as such, their investment would be aggregated into the reported futures positions of Swap Dealers (SW) in the DCOT reports (provided that swap dealers, after internal netting, hedge this price risk in the regulated futures markets), not under the MM category. Hence, we include in our analysis single-commodity ETFs whose positions (assumed conservatively to be directly invested in futures with 100% AUM despite the fact that they are often known to also hold swap and other instruments to gain indirect exposure, as sometimes attested by their websites)[20] would have been counted under the MM category.

As opposed to ETFs that utilize derivative-based replication (including futures), we do not consider the physically backed commodity ETFs that hold physical commodities in their possession to achieve exposure, and physically backed ETFs actually represent the bulk of the total commodity ETF universe in the United States.[21] We remove as well for this exercise equity-based commodity ETFs that achieve exposure and replication by the stocks of commodity producers. Regarding leveraged ETFs, whereas some studies (e.g., Cheng and Madhavan, 2009) argue that most rely on the usage of swaps to achieve their synthetic leverage, we notice in our sample that the majority of them make direct investment in futures,

[19] Cheng et al. (2015) analyze the positions of commodity index traders (CITs) and "identify CITs based on the CIT classification of the CFTC's Supplemental COT report and two additional criteria motivated by the trading patterns of broad-based portfolio investors in commodity indexes: namely 1) they should be invested in many commodities (greater than eight in our sample); and 2) they should be mostly net long in those commodities over the previous year (more than 70% net long in our sample)." The authors additionally state that "at a practical level, CITs often establish commodity index positions by acquiring index swap contracts from swap dealers, rather than taking long positions in individual commodity futures."

[20] Per Bessembinder et al. (2016), "ETFs can also obtain exposure to oil prices using swaps or other derivatives sold by commodity dealers." For example, "the United States Oil Fund is a popular exchange-traded security with retail investors known for its 'USO' ticker" (CNBC), and its website reads, "USO invests primarily in listed crude oil futures contracts and other oil-related contracts, and may invest in forwards and swap contracts."

[21] The majority of commodity ETFs are physically backed ETFs that track precious metals, and, apparently, "investors...struggle with futures-based products" (John Hyland, 2021); furthermore, as of June 2021, "the 33 precious metals ETFs, almost all of which are physically based, hold $123 billion in assets ... the other 77 ETFs split the remaining $23 billion; you could argue that investors like commodities just fine if they are physically based." The largest of which, SPDR Gold Shares, under the Ticker GLD, states on its website, "[it] will not hold or trade in commodity futures contracts."

thus we prudently exclude only the leveraged ETFs that gain exposure through swaps while keeping futures-based leveraged ETFs.

For each week t and commodity c, we calculate the (maximally possible, assuming 100% AUM) proportion ($p_{c,t}$) of commodity-focused futures-based ETFs in the total open interest of MM published in the CFTC DCOT reports, as follows:[22] $p_{c,t} = \frac{\sum_{j=1}^{N_c} L_{c,j} AUM_{c,j,t}}{OI_{c,t}^{MM} F_{c,t}}$, where the numerator is the dollar size of all ETFs (indexed by j from 1 to N_c) in the commodity market c, with $AUM_{c,j,t}$ denoting the assets under management and $L_{c,j}$ its leverage (thus, the AUM of a "2× leveraged" ETF would be multiplied by 2). The denominator is computed as MM's open interest in week t ($OI_{c,t}^{MM}$, i.e., the number of outstanding contracts held by MM) multiplied by the corresponding commodity future price ($F_{c,t}$).[23]

The total dollar amount committed by the MM category as reported by the CFTC on an average week is much larger compared to the combined size (AUM) of commodity futures-based ETFs. Overall, we find that commodity-focused and futures-based ETFs could constitute only a tiny fraction of the MM category in terms of the open interest (in dollars) published in the CFTC DCOT reports. As a whole, they would represent on average (over time) only 3.17% of the MM's open interest, as we examine the distribution of this proportion across all weeks and commodities under our analysis. They are even less important as constituents of the MM category for certain commodities, such as gold (0.85%), copper (1.27%), and coal (0.36%). Accordingly, commodity-focused and futures-based ETFs are unlikely to have much influence on our predictability results from MM position changes based signals—notwithstanding the additional argument that passively managed commodity ETFs are unlikely to have large changes in positions at 100% of AUM in every week and thus even more unlikely to make a large contribution to affect the weekly MM position change measures we have constructed in the paper.

[22]We compute the share as a net ETF fraction (long ETFs minus inverse ETFs), which nonetheless has little impact on our estimates.

[23]Our estimates are based on the open interests not limited to the near-term (or nearest) futures contracts but summed up across all contract expirations as dictated by the CFTC's aggregation method in the DCOT reports. For instance, as of August 2021, the share of total open interest for the two front contracts relative to all maturities represents 27.8% in oil, 30.5% in natural gas, and 7.7% in gold.

B. Additional Empirical Results

B.1 Supplementary Results to Section IV

TABLE B.1 Calendar-Time Regression Results Relative to the Carhart Four-Factor Model (%, per Week), After Removing Small-Cap Stocks

This table presents the Carhart four-factor alphas from weekly calendar-time regressions of the portfolio returns of U.S.-listed North American commodity-producing firms sorted with respect to each of the three MM signal measures. The signals are constructed as a 1-week lag or as a J-week backward moving average. We remove the small-cap stocks, i.e., those in the bottom 45% of market capitalization using annually updated cutoffs calculated from the CRSP universe. After equal-weighting (EW) or value-weighting (VW) the stock returns belonging to the same commodity, the commodity-equity portfolios are averaged weekly into two portfolio bins by buying the stocks with positive signals and selling short the stocks with negative signals, as described in Section III.C. The weekly α's, multiplied by 100 so they can be interpreted as percentages, are reported with their t-statistics in parentheses (based on White standard errors).$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Money Managers' Signal Measure:	**Net Change**		**Long Proportion Growth**		**Short Proportion Growth**	
Weight / ***J***	EW	VW	EW	VW	EW	VW
J = 1	0.272*** (3.12)	0.261*** (3.14)	0.299*** (3.33)	0.299*** (3.56)	−0.247*** (−2.79)	−0.243*** (−2.91)
J = 2	0.258*** (3)	0.254*** (3.17)	0.269*** (3.07)	0.264*** (3.24)	−0.242*** (−2.73)	−0.232*** (−2.84)
J = 6	0.179** (1.99)	0.108 (1.32)	0.249*** (2.87)	0.165** (2.09)	−0.184** (−2.03)	−0.102 (−1.24)
J = 9	0.339*** (3.05)	0.286*** (2.81)	0.242*** (2.67)	0.178** (2.01)	−0.311*** (−2.77)	−0.254** (−2.46)
J = 12	0.406*** (3.48)	0.331*** (3.12)	0.431*** (3.85)	0.321*** (3.12)	−0.407*** (−3.51)	−0.324*** (−3.06)

TABLE B.2 Alpha Results Relative to the Stambaugh and Yuan Mispricing Factor Model (%, per Week), January 2007–December 2016

This table presents the alphas relative to the Stambaugh and Yuan mispricing factor model (SY4 α) of the weekly returns for portfolios of U.S.-listed North American commodity-producing firms sorted with respect to each of the three MM signal measures. The signals are constructed as a 1-week lag or as a J-week backward moving average. Panel A presents the results from calendar-time portfolio return regressions (along the lines of Table 2 in the paper), wherein after equal-weighting (EW) or value-weighting (VW) the stock returns belonging to the same commodity, the commodity-equity portfolios are grouped into two portfolio bins each week based on the sign of the associated signal; specifically we long (short) the stocks associated with a positive (negative) signal as measured by changes in the corresponding MM positions. Panel B presents the results from the single-sort procedure (along the lines of Table 3 in the paper), wherein the commodity-equity portfolios are sorted weekly, in this case, into three portfolio bins based on the MM signal's value, and averaged within each tercile with equal-weight. The long-short portfolios' returns are then derived by going long on the highest tercile and going short on the lowest tercile. Section III.C provides further details on these two procedures. The weekly α's, multiplied by 100 so they can be interpreted as percentages, are reported with their t-statistics in parentheses (based on White standard errors). All our results pertaining to the SY4 model are based on a shorter sample period ending in December 2016, due to factor data availability. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Panel A: Calendar-Time Regression with Positive vs. Negative Signal Bins

Money Managers' Signal Measure:	**Net Change**		**Long Proportion Growth**		**Short Proportion Growth**	
J \ **Weight**	EW	VW	EW	VW	EW	VW
J = 1	0.304***	0.285***	0.334***	0.326***	−0.267**	−0.257**
	(2.85)	(2.78)	(3.03)	(3.11)	(−2.46)	(−2.51)
J = 2	0.378***	0.286***	0.404***	0.315***	−0.338***	−0.239**
	(3.47)	(2.91)	(3.62)	(3.15)	(−3.05)	(−2.39)
J = 6	0.192*	0.096	0.271**	0.151	−0.179	−0.066
	(1.66)	(0.92)	(2.52)	(1.59)	(−1.57)	(−0.63)
J = 9	0.264*	0.243**	0.199*	0.147	−0.221	−0.186
	(1.92)	(2.03)	(1.72)	(1.35)	(−1.54)	(−1.53)
J = 12	0.322**	0.315**	0.386***	0.324***	−0.310**	−0.281**
	(2.23)	(2.41)	(2.98)	(2.69)	(−2.10)	(−2.16)

Panel B: Single-Sort Results with Three Ranked Signal Bins

Money Managers' Signal Measure:	**Net Change**		**Long Proportion Growth**		**Short Proportion Growth**	
J \ **Weight**	EW	VW	EW	VW	EW	VW
J = 1	0.317***	0.307***	0.303***	0.299***	−0.275***	−0.275***
	(3.35)	(3.24)	(3.31)	(3.25)	(−2.86)	(−2.98)
J = 2	0.279***	0.211**	0.377***	0.306***	−0.307***	−0.249***
	(2.90)	(2.40)	(3.55)	(3.20)	(−3.25)	(−2.86)
J = 6	0.291***	0.177*	0.324***	0.181*	−0.281***	−0.16*
	(2.96)	(1.94)	(3.22)	(1.96)	(−2.93)	(−1.79)
J = 9	0.277***	0.229**	0.269**	0.218**	−0.172*	−0.123
	(2.89)	(2.50)	(2.52)	(2.26)	(−1.74)	(−1.35)
J = 12	0.249***	0.243***	0.363***	0.318***	−0.258***	−0.245***
	(2.61)	(2.89)	(3.41)	(3.41)	(−2.67)	(−2.86)

TABLE B.3 Calendar-Time Regression Results Relative to the Carhart Four-Factor Model (%, per Week): Signals Based on Total Open Interest Growth

This table presents the Carhart four-factor alphas from weekly calendar-time regressions of the portfolio returns of U.S.-listed North American commodity-producing firms sorted by the total open interest growth signal, which is based on the aggregate positions of all five trader categories in the commodity futures market. The signal is constructed as a 1-week lag or as a J-week backward moving average. After equal-weighting (EW) or value-weighting (VW) the stock returns belonging to the same commodity, we construct the long-short portfolio returns by averaging the commodity-equity portfolios weekly into two portfolio bins wherein we buy the stocks with positive signals and sell short the stocks with negative signals, as described in Section III.C. The left-hand side presents the baseline results for the total open interest growth signal, while the right-hand side shows results where stocks in the bottom 45% of market capitalization are removed. The weekly α's, multiplied by 100 so they can be interpreted as percentages, are reported with their t-statistics in parentheses (based on White standard errors). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Signal: **Total Open Interest Growth (Across All Five Trader Categories)**				
	Baseline Results		**After Removing Small-Cap Stocks**	
J \ **Weight**	EW	VW	EW	VW
J = 1	−0.003 (−0.05)	0.034 (0.49)	−0.014 (−0.19)	0.033 (0.49)
J = 2	−0.079 (−0.9)	−0.038 (−0.46)	−0.075 (−0.88)	−0.038 (−0.46)
J = 6	−0.026 (−0.3)	−0.091 (−1.15)	−0.046 (−0.55)	−0.092 (−1.17)
J = 9	−0.054 (−0.59)	−0.059 (−0.72)	−0.055 (−0.6)	−0.059 (−0.72)
J = 12	0.06 (0.57)	0.013 (0.14)	0.04 (0.37)	0.012 (0.12)

TABLE B.4 Calendar-Time Regression Results (%, per Week): Signals Based on "Producers, Merchants, Processors, and Users" Category

This table presents the average returns and alphas from weekly calendar-time regressions of the portfolio returns of U.S.-listed North American commodity-producing firms sorted with respect to each of the three signal measures based on the positions of "Producers, Merchants, Processors, and Users" (PM) traders in the commodity futures market. The signals are constructed as a 1-week lag or as a J-week backward moving average. After equal-weighting (Panel A) or value-weighting (Panel B) the stock returns belonging to the same commodity, the commodity-equity portfolios are averaged weekly into two portfolio bins by buying the stocks with positive signal ("Pos") and selling short the stocks with negative signal ("Neg"), as described in Section III.C. From the long-short portfolio returns ("Pos−Neg"), we then calculate the abnormal return (α) relative to the Carhart four-factor model (C4 α) and to the Fama and French five-factor model (FF5 α). The average weekly portfolio returns and alphas, multiplied by 100 so they can be interpreted as percentages, are reported together with their t-statistics in parentheses (based on White standard errors). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

PM's Long Proportion Growth

Portfolio Rank	Panel A: Equal-Weight					Panel B: Value-Weight				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
Neg	0.057	0.105	0.099	0.220	0.140	0.057	0.089	0.076	0.217	0.168
Pos	0.069	0.014	0.088	−0.114	−0.069	0.049	0.029	0.085	−0.081	−0.047
(Pos−Neg)	0.011	−0.090	−0.011	−0.335***	−0.208*	−0.007	−0.060	0.008	−0.298***	−0.214**
	(0.13)	(−1.04)	(−0.12)	(−3.18)	(−1.90)	(−0.09)	(−0.71)	(0.10)	(−3.07)	(−2.12)
C4 α	0.009	−0.094	−0.023	−0.362***	−0.245**	−0.013	−0.073	−0.009	−0.325***	−0.240**
	(0.11)	(−1.04)	(−0.23)	(−3.11)	(−2.19)	(−0.16)	(−0.85)	(−0.10)	(−3.08)	(−2.37)
FF5 α	−0.006	−0.092	−0.017	−0.358***	−0.213*	−0.026	−0.068	−0.006	−0.320***	−0.215**
	(−0.06)	(−1.02)	(−0.17)	(−3.01)	(−1.91)	(−0.31)	(−0.79)	(−0.07)	(−3.04)	(−2.12)

PM's Net Change

Portfolio Rank	Panel A: Equal-Weight					Panel B: Value-Weight				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
Neg	0.061	0.117	0.099	0.221	0.142	0.052	0.101	0.078	0.203	0.149
Pos	0.050	0.002	0.072	−0.104	−0.062	0.040	0.019	0.079	−0.069	−0.034
(Pos−Neg)	−0.011	−0.115	−0.027	−0.325***	−0.204*	−0.012	−0.082	0.001	−0.272***	−0.184*
	(−0.12)	(−1.37)	(−0.29)	(−3.00)	(−1.69)	(−0.15)	(−1.00)	(0.02)	(−2.75)	(−1.67)
C4 α	−0.012	−0.115	−0.037	−0.353***	−0.258**	−0.018	−0.093	−0.018	−0.301***	−0.227*
	(−0.14)	(−1.33)	(−0.39)	(−2.94)	(−2.00)	(−0.22)	(−1.12)	(−0.21)	(−2.77)	(−1.96)
FF5 α	−0.025	−0.112	−0.028	−0.346***	−0.216*	−0.028	−0.087	−0.012	−0.292***	−0.195*
	(−0.29)	(−1.29)	(−0.28)	(−2.83)	(−1.68)	(−0.34)	(−1.05)	(−0.13)	(−2.69)	(−1.68)

PM's Short Proportion Growth

Portfolio Rank	Panel A: Equal-Weight					Panel B: Value-Weight				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
Neg	0.018	−0.042	0.033	−0.064	−0.098	0.022	−0.014	0.034	−0.022	−0.061
Pos	0.071	0.120	0.121	0.180	0.163	0.044	0.098	0.076	0.153	0.164
(Pos−Neg)	0.053	0.162**	0.088	0.244**	0.262**	0.022	0.112	0.042	0.175**	0.225**
	(0.64)	(1.98)	(1.07)	(2.49)	(2.31)	(0.29)	(1.44)	(0.56)	(1.97)	(2.26)
C4 α	0.048	0.148*	0.102	0.247**	0.303**	0.022	0.113	0.061	0.180*	0.259**
	(0.58)	(1.75)	(1.20)	(2.33)	(2.45)	(0.29)	(1.43)	(0.79)	(1.89)	(2.38)
FF5 α	0.058	0.137	0.101	0.237**	0.282**	0.030	0.105	0.058	0.170*	0.240**
	(0.71)	(1.58)	(1.20)	(2.18)	(2.30)	(0.39)	(1.31)	(0.76)	(1.78)	(2.24)

TABLE B.5 Calendar-Time Regression Results (%, per Week): Signals Based on ‘‘Swap Dealers’’ Category

This table presents the average returns and alphas from weekly calendar-time regressions of the portfolio returns of U.S.-listed North American commodity-producing firms sorted with respect to each of the three signal measures based on the positions of ‘‘Swap Dealers’’ (SW) traders in the commodity futures market. The signals are constructed as a 1-week lag or as a J-week backward moving average. After equal-weighting (Panel A) or value-weighting (Panel B) the stock returns belonging to the same commodity, the commodity-equity portfolios are averaged weekly into two portfolio bins by buying the stocks with positive signals (‘‘Pos’’) and selling short the stocks with negative signals (‘‘Neg’’), as described in Section III.C. From the long-short portfolio returns (‘‘Pos−Neg’’), we then calculate the abnormal return (α) relative to the Carhart four-factor model (C4 α) and to the Fama and French five-factor model (FF5 α). The average weekly portfolio returns and alphas, multiplied by 100 so they can be interpreted as percentages, are reported together with their t-statistics in parentheses (based on White standard errors). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Swap Dealers’ Long Proportion Growth

Portfolio Rank	Panel A: Equal-Weight					Panel B: Value-Weight				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
Neg	0.103	0.116	0.032	0.072	0.111	0.134	0.093	0.006	0.059	0.058
Pos	−0.036	−0.001	0.116	0.129	0.049	−0.081	0.003	0.130	0.121	0.078
(Pos−Neg)	−0.139	−0.117	0.085	0.057	−0.062	−0.215**	−0.089	0.124	0.062	0.020
	(−1.45)	(−1.43)	(0.80)	(0.52)	(−0.64)	(−2.47)	(−1.19)	(1.32)	(0.66)	(0.22)
C4 α	−0.163	−0.133	0.066	0.044	−0.080	−0.238***	−0.101	0.115	0.054	0.000
	(−1.59)	(−1.52)	(0.63)	(0.41)	(−0.76)	(−2.62)	(−1.29)	(1.26)	(0.59)	(0.00)
FF5 α	−0.175*	−0.144	0.072	0.046	−0.077	−0.238***	−0.103	0.125	0.051	−0.006
	(−1.67)	(−1.63)	(0.69)	(0.43)	(−0.74)	(−2.60)	(−1.31)	(1.39)	(0.57)	(−0.06)

Swap Dealers’ Net Change

Portfolio Rank	Panel A: Equal-Weight					Panel B: Value-Weight				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
Neg	0.158	0.174	0.091	0.112	0.080	0.179	0.138	0.050	0.087	0.056
Pos	−0.008	−0.044	0.097	0.050	0.068	−0.034	−0.015	0.115	0.078	0.099
(Pos−Neg)	−0.166*	−0.218**	0.006	−0.062	−0.011	−0.213**	−0.152**	0.065	−0.009	0.042
	(−1.66)	(−2.56)	(0.06)	(−0.73)	(−0.12)	(−2.30)	(−1.98)	(0.74)	(−0.12)	(0.50)
C4 α	−0.182*	−0.233***	−0.015	−0.068	−0.026	−0.227**	−0.163**	0.052	−0.014	0.027
	(−1.70)	(−2.59)	(−0.16)	(−0.77)	(−0.27)	(−2.36)	(−2.04)	(0.61)	(−0.18)	(0.30)
FF5 α	−0.188*	−0.238***	−0.017	−0.065	−0.021	−0.222**	−0.159**	0.056	−0.013	0.030
	(−1.70)	(−2.63)	(−0.18)	(−0.73)	(−0.22)	(−2.28)	(−2.01)	(0.66)	(−0.17)	(0.35)

Swap Dealers’ Short Proportion Growth

Portfolio Rank	Panel A: Equal-Weight					Panel B: Value-Weight				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
Neg	−0.010	−0.036	0.030	−0.004	0.068	−0.028	0.000	0.051	0.047	0.087
Pos	0.188	0.218	0.173	0.151	0.131	0.200	0.171	0.109	0.123	0.095
(Pos−Neg)	0.199**	0.253***	0.142*	0.156*	0.063	0.228**	0.171**	0.058	0.076	0.008
	(1.99)	(2.85)	(1.76)	(1.87)	(0.73)	(2.47)	(2.19)	(0.79)	(1.00)	(0.11)
C4 α	0.212**	0.267***	0.152*	0.162*	0.075	0.240**	0.181**	0.064	0.083	0.021
	(2.00)	(2.86)	(1.83)	(1.90)	(0.86)	(2.50)	(2.25)	(0.85)	(1.08)	(0.27)
FF5 α	0.217**	0.273***	0.155*	0.156*	0.069	0.234**	0.178**	0.060	0.077	0.016
	(1.99)	(2.91)	(1.89)	(1.83)	(0.80)	(2.42)	(2.23)	(0.80)	(1.02)	(0.21)

TABLE B.6 Durbin-Watson Statistics for the Calendar-Time Regression Results

This table presents the Durbin-Watson (DW) statistics for the residuals from the calendar-time portfolio return regressions as in Table 2 in the paper and Table B.2 (Panel A) which presented the abnormal returns (α) relative to the Carhart four-factor model (C4), the Fama and French five-factor model (FF5), and the Stambaugh and Yuan mispricing factor model (SY4). All the cases presented in the calendar-time regressions are considered here, namely, the signals from the futures market are constructed as a 1-week lag or as a J-week backward moving average, for both the equal-weight (Panel A) and the value-weight (Panel B) schemes, and for all three MM signal measures. The null hypothesis is that there is no autocorrelation and critical values for α=5% level of significance are utilized (Durbin and Watson, 1950; Savin and White, 1977). The DW statistics would have been highlighted in bold if there is statistical evidence that the error terms are either positively autocorrelated or negatively autocorrelated. The value of the DW statistic would have been highlighted by italicizing (underlining) it when the Durbin-Watson test is inconclusive against the alternative hypothesis that there is positive (negative) autocorrelation.

Money Managers' Long Proportion Growth

	Panel A: Equal-Weight					**Panel B: Value-Weight**				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
C4 DW	1.97	1.91	1.99	1.97	1.87	1.88	1.94	2.00	2.04	1.96
FF5 DW	1.95	1.89	1.99	1.97	1.86	1.87	1.92	2.01	2.04	1.94
SY4 DW	1.93	1.87	1.94	1.97	1.83	1.85	1.92	1.99	2.07	1.95

Money Managers' Net Change

	Panel A: Equal-Weight					**Panel B: Value-Weight**				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
C4 DW	1.91	1.87	2.01	2.05	2.13	1.87	1.92	2.06	2.09	2.16
FF5 DW	1.90	1.85	2.01	2.04	2.13	1.86	1.90	2.06	2.08	2.15
SY4 DW	1.86	1.82	1.97	2.00	2.03	1.83	1.88	2.04	2.06	2.08

Money Managers' Short Proportion Growth

	Panel A: Equal-Weight					**Panel B: Value-Weight**				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
C4 DW	1.93	1.94	2.06	2.04	$\underline{2.20}$	1.90	1.97	2.10	2.10	$\underline{2.20}$
FF5 DW	1.92	1.92	2.06	2.01	$\underline{2.18}$	1.89	1.94	2.10	2.09	$\underline{2.18}$
SY4 DW	1.88	1.89	2.01	1.95	2.11	1.86	1.94	2.06	2.04	2.11

TABLE B.7 Durbin-Watson Statistics for the Single-Sort Results

This table presents the Durbin-Watson (DW) statistics for the residuals from the single-sort analysis as in Table 3 in the paper and Table B.2 (Panel B) which presented the abnormal returns (α) relative to the Carhart four-factor model (C4), the Fama and French five-factor model (FF5), and the Stambaugh and Yuan mispricing factor model (SY4). All the cases presented in the single-sort analysis are considered here, namely, the signals from the futures market are constructed as a 1-week lag or as a J-week backward moving average, for both the equal-weight (Panel A) and the value-weight (Panel B) schemes, and for all three MM signal measures. The null hypothesis is that there is no autocorrelation and critical values for α=5% level of significance are utilized (Durbin and Watson, 1950; Savin and White, 1977). The DW statistics would have been highlighted in bold if there is statistical evidence that the error terms are either positively autocorrelated or negatively autocorrelated. The value of the DW statistic would have been highlighted by italicizing (underlining) it when the Durbin-Watson test is inconclusive against the alternative hypothesis that there is positive (negative) autocorrelation.

Money Managers' Long Proportion Growth

	Panel A: Equal-Weight					**Panel B: Value-Weight**				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
C4 DW	1.97	1.96	2.01	1.97	1.95	1.90	1.90	1.97	1.97	2.03
FF5 DW	1.97	1.95	2.01	1.98	1.96	1.89	1.89	1.96	1.97	2.02
SY4 DW	1.90	1.91	2.01	1.96	1.94	1.84	1.84	1.97	1.98	2.04

Money Managers' Net Change

	Panel A: Equal-Weight					**Panel B: Value-Weight**				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
C4 DW	1.86	1.92	1.88	2.00	2.03	1.88	1.86	2.02	2.01	2.06
FF5 DW	1.85	1.92	1.89	2.00	2.03	1.86	1.86	2.03	2.02	2.05
SY4 DW	*1.78*	1.87	1.86	2.01	2.03	1.82	*1.81*	2.01	2.03	2.05

Money Managers' Short Proportion Growth

	Panel A: Equal-Weight					**Panel B: Value-Weight**				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
C4 DW	1.87	1.96	1.96	1.99	2.01	1.83	1.94	2.14	2.06	2.05
FF5 DW	1.86	1.96	1.98	2.00	2.01	1.82	1.94	2.15	2.07	2.05
SY4 DW	1.83	1.91	1.95	1.98	2.01	*1.79*	1.90	2.15	2.08	2.07

TABLE B.8 Alpha Results (%, per Week), After Applying Newey-West Standard Errors or the Cochrane-Orcutt Transformation

This table presents the Carhart four-factor (C4) and the Fama and French five-factor (FF5) alphas of the weekly returns for long-short portfolios of U.S.-listed North American commodity producers sorted with respect to the MM Long Proportion Growth signal measure, constructed as a 1-week lag or as a J-week backward moving average. Panel A shows the results from calendar-time portfolio return regressions, wherein after equal-weighting or value-weighting the stock returns belonging to the same commodity, the commodity-equity portfolios are grouped into two portfolio bins each week based on the sign of the associated signal; specifically, we long (short) the stocks associated with a positive (negative) signal. Panel B shows the results from the single-sort procedure, wherein the commodity-equity portfolios are sorted weekly into three portfolio bins based on the signal's value, and averaged within each tercile with equal-weight. The long-short portfolios' returns are then derived by going long on the highest tercile and going short on the lowest tercile. As opposed to Tables 2 and 3 in the paper, this table reports the results in which the t-statistics in parentheses are derived based on heteroscedastic- and autocorrelation-consistent standard errors using the Newey-West procedure with a lag length of 5 (based on Greene's (2000) rule-of-thumb lag length of $T^{1/4}$). Moreover, the table presents the results wherein the iterative Cochrane and Orcutt (1949) procedure is applied to correct for first-order serial dependence in the regression residuals, together with t-statistics based on White standard errors and the Durbin-Watson (DW) statistics obtained after the transformation. The weekly α's are multiplied by 100. ***p<0.01, **p<0.05, *p<0.1.

Panel A: Calendar-Time Regression with Positive vs. Negative Signal Bins

	Equal-Weight					Value-Weight				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
Alpha's and t-statistics with Newey-West Standard Errors:										
C4 α	0.299***	0.316***	0.252***	0.217**	0.371***	0.299***	0.267***	0.166**	0.178**	0.321***
	(3.20)	(3.05)	(2.81)	(2.34)	(3.00)	(3.31)	(3.04)	(2.17)	(1.99)	(3.04)
FF5 α	0.296***	0.309***	0.246***	0.210**	0.351***	0.289***	0.257***	0.158**	0.163*	0.301***
	(3.13)	(2.93)	(2.73)	(2.26)	(2.94)	(3.16)	(2.88)	(2.03)	(1.83)	(2.97)
Alphas, t-statistics, and Durbin-Watson statistics for the Cochrane-Orcutt Transformed Series:										
C4 α	0.297***	0.314***	0.255***	0.219**	0.371***	0.297***	0.266***	0.169**	0.182**	0.324***
	(3.28)	(3.29)	(2.89)	(2.34)	(3.22)	(3.35)	(3.19)	(2.16)	(2.11)	(3.12)
FF5 α	0.294***	0.307***	0.249***	0.213**	0.352***	0.287***	0.255***	0.160**	0.167*	0.304***
	(3.25)	(3.20)	(2.82)	(2.22)	(3.08)	(3.21)	(3.04)	(2.05)	(1.94)	(2.96)
C4 DW	2.000	2.001	1.997	1.991	1.991	2.000	1.994	1.991	1.984	1.984
FF5 DW	2.000	2.001	1.996	1.992	1.991	1.998	1.993	1.990	1.984	1.982

Panel B: Single-Sort Results with Three Ranked Signal Bins

	Equal-Weight					Value-Weight				
	J=1	J=2	J=6	J=9	J=12	J=1	J=2	J=6	J=9	J=12
Alphas and t-statistics corrected with Newey West:										
C4 α	0.248***	0.285***	0.284***	0.242***	0.330***	0.276***	0.245***	0.175**	0.210***	0.304***
	(3.35)	(2.81)	(3.34)	(2.88)	(3.49)	(3.67)	(2.76)	(2.40)	(2.73)	(3.96)
FF5 α	0.247***	0.282***	0.277***	0.230***	0.312***	0.263***	0.235***	0.164**	0.196***	0.290***
	(3.35)	(2.78)	(3.33)	(2.81)	(3.37)	(3.55)	(2.67)	(2.27)	(2.61)	(3.83)
Alphas, t-statistics, and Durbin-Watson statistics for the Cochrane-Orcutt Transformed Series:										
C4 α	0.246***	0.285***	0.289***	0.243***	0.333***	0.275***	0.244***	0.179**	0.212***	0.309***
	(3.20)	(3.27)	(3.49)	(2.76)	(3.80)	(3.53)	(2.99)	(2.31)	(2.66)	(4.15)
FF5 α	0.245***	0.282***	0.281***	0.232***	0.316***	0.262***	0.235***	0.168**	0.198**	0.294***
	(3.19)	(3.22)	(3.41)	(2.64)	(3.63)	(3.38)	(2.88)	(2.15)	(2.50)	(3.97)
C4 DW	1.999	1.999	1.994	1.994	1.990	1.992	1.996	1.991	1.993	1.984
FF5 DW	1.998	1.999	1.994	1.994	1.988	1.990	1.995	1.991	1.993	1.982

TABLE B.9 Fama-MacBeth Regressions, Managed Money Net Change

This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and t-statistics based on White standard errors in parentheses) of firms' subsequent weekly return (subtracted by the risk-free rate) on lagged signal and other lagged controls for expected returns. The weekly 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 public holidays) following the newest DCOT report. We run the Fama-MacBeth regression at a weekly frequency. The signals from the futures market are constructed as a 1-week lag or as a J-week backward moving average. 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, $ln(ME)$ is the log of the market value of equity at the end of the previous calendar year, and $ln(BE/ME)$ is the log of the book-to-market value of equity, where the book value is measured at the end of the previous fiscal year. $FR_{c,t-1}$ is the relative change in commodity price over the previous week. The row labeled Adj. R^2 displays 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 weeks utilized in the regression. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	J=1		J=2		J=3	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money Net Change	0.014*	0.021***	0.029***	0.026***	0.025**	0.026**
	(1.950)	(2.630)	(3.390)	(3.220)	(2.510)	(2.530)
$ln(BE/ME)$	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.400)	(−0.240)	(−0.290)	(−0.240)	(−0.330)	(−0.380)
$ln(ME)$	0.000	0.000	0.000	0.000	0.000	0.000
	(0.280)	(0.570)	(0.390)	(0.600)	(0.440)	(0.610)
ret_{-1}	−0.001	−0.003	−0.001	−0.002	−0.001	−0.003
	(−0.270)	(−0.770)	(−0.140)	(−0.570)	(−0.190)	(−0.630)
$ret_{-2,-12}$	0.001	0.001	0.001	0.001	0.001	0.001
	(0.640)	(0.650)	(0.630)	(0.610)	(0.420)	(0.430)
$FR_{c,t-1}$		0.052		0.073**		0.089***
		(1.300)		(2.140)		(2.650)
N–Observations	691	691	691	691	691	691
N–Companies	328	328	328	328	328	328
Adj. R^2	0.107	0.129	0.109	0.129	0.109	0.129
	J=6		J=9		J=12	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money Net Change	0.049***	0.052***	0.048***	0.040**	0.048**	0.042*
	(3.140)	(3.580)	(2.630)	(2.130)	(2.150)	(1.780)
$ln(BE/ME)$	0.000	0.000	0.000	0.000	0.000	0.000
	(−0.250)	(−0.220)	(0.000)	(−0.040)	(0.030)	(−0.040)
$ln(ME)$	0.000	0.000	0.000	0.000	0.000	0.000
	(0.440)	(0.560)	(0.440)	(0.620)	(0.440)	(0.590)
ret_{-1}	−0.001	−0.004	−0.002	−0.003	−0.002	−0.004
	(−0.350)	(−0.850)	(−0.390)	(−0.800)	(−0.450)	(−1.010)
$ret_{-2,-12}$	0.001	0.001	0.001	0.001	0.001	0.001
	(0.520)	(0.400)	(0.390)	(0.330)	(0.540)	(0.360)
$FR_{c,t-1}$		0.085**		0.080**		0.102***
		(2.360)		(2.290)		(2.920)
N–Observations	691	691	691	691	691	691
N–Companies	328	328	328	328	328	328
Adj. R^2	0.107	0.129	0.107	0.129	0.108	0.13

TABLE B.10 Fama-MacBeth Regressions, Managed Money Short Proportion Growth

This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and t-statistics based on White standard errors in parentheses) of firms' subsequent weekly return (subtracted by the risk-free rate) on lagged signal and other lagged controls for expected returns. The weekly 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 public holidays) following the newest DCOT report. We run the Fama-MacBeth regression at a weekly frequency. The signals from the futures market are constructed as a 1-week lag or as a J-week backward moving average. 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, $ln(ME)$ is the log of the market value of equity at the end of the previous calendar year, and $ln(BE/ME)$ is the log of the book-to-market value of equity, where the book value is measured at the end of the previous fiscal year. $FR_{c,t-1}$ is the relative change in commodity price over the previous week. The row labeled Adj. R^2 displays 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 weeks utilized in the regression. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

	J=1		J=2		J=3	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money Short Proportion Growth	−0.013 (−1.090)	−0.025** (−2.180)	−0.043*** (−3.290)	−0.036*** (−2.850)	−0.034** (−2.200)	−0.036** (−2.040)
$ln(BE/ME)$	0.000 (−0.380)	0.000 (−0.190)	0.000 (−0.200)	0.000 (−0.180)	0.000 (−0.300)	0.000 (−0.340)
$ln(ME)$	0.000 (0.380)	0.000 (0.630)	0.000 (0.390)	0.000 (0.570)	0.000 (0.420)	0.000 (0.560)
ret_{-1}	−0.001 (−0.320)	−0.003 (−0.820)	−0.001 (−0.170)	−0.002 (−0.590)	−0.001 (−0.210)	−0.003 (−0.620)
$ret_{-2,-12}$	0.001 (0.660)	0.001 (0.700)	0.001 (0.600)	0.001 (0.580)	0.001 (0.310)	0.001 (0.400)
$FR_{c,t-1}$		0.061 (1.570)		0.082** (2.420)		0.089*** (2.640)
N–Observations	691	691	691	691	691	691
N–Companies	328	328	328	328	328	328
Adj. R^2	0.107	0.129	0.11	0.129	0.109	0.129

	J=6		J=9		J=12	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money Short Proportion Growth	−0.065*** (−2.750)	−0.074*** (−3.400)	−0.055** (−2.030)	−0.057* (−1.940)	−0.057* (−1.870)	−0.042 (−1.300)
$ln(BE/ME)$	0.000 (−0.320)	0.000 (−0.300)	0.000 (−0.150)	0.000 (−0.150)	0.000 (−0.150)	0.000 (−0.180)
$ln(ME)$	0.000 (0.510)	0.000 (0.610)	0.000 (0.500)	0.000 (0.650)	0.000 (0.480)	0.000 (0.640)
ret_{-1}	−0.001 (−0.260)	−0.003 (−0.800)	−0.001 (−0.280)	−0.003 (−0.670)	−0.001 (−0.290)	−0.003 (−0.840)
$ret_{-2,-12}$	0.001 (0.460)	0.001 (0.400)	0.001 (0.370)	0.001 (0.380)	0.001 (0.540)	0.001 (0.400)
$FR_{c,t-1}$		0.081** (2.310)		0.078** (2.180)		0.101*** (2.840)
N–Observations	691	691	691	691	691	691
N–Companies	328	328	328	328	328	328
Adj. R^2	0.108	0.129	0.107	0.129	0.107	0.129

TABLE B.11 Fama-MacBeth Regressions at Daily Frequency, MM Long Proportion Growth

This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and Newey-West adjusted t-statistics with five lags in parentheses) of firms' subsequent daily return (subtracted by the risk-free rate) 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 one day due to public holidays) following the newest DCOT report. We run the Fama-MacBeth regression at a daily frequency. The signals from the futures market are constructed as a 1-week lag or as a J-week backward moving average. 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, $ln(ME)$ is the log of the market value of equity at the end of the previous calendar year, and $ln(BE/ME)$ is the log of the book-to-market value of equity, where the book value is measured at the end of the previous fiscal year. $FR_{c,t-1}$ is the relative change in commodity price over the previous week. The row labeled Adj. R^2 displays 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 days utilized in the regression. ***p<0.01, **p<0.05, *p<0.1.

	J=1		J=2		J=3	
	(1)	(2)	(3)	(4)	(5)	(6)
Managed Money Long Proportion Growth	0.015***	0.017***	0.018***	0.014***	0.015**	0.011*
	(3.100)	(3.150)	(3.500)	(2.660)	(2.360)	(1.780)
$ln(BE/ME)$	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.600)	(-0.410)	(-0.390)	(-0.350)	(-0.430)	(-0.390)
$ln(ME)$	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.080)	(0.130)	(0.030)	(0.170)	(0.050)	(0.240)
ret_{-1}	0.000	-0.001	0.000	-0.001	0.000	-0.001
	(-0.320)	(-0.710)	(-0.200)	(-0.670)	(-0.270)	(-0.700)
$ret_{-2,-12}$	0.000	0.000	0.000	0.000	0.000	0.000
	(0.830)	(0.810)	(0.840)	(0.780)	(0.820)	(0.700)
$FR_{c,t-1}$		0.008		0.019***		0.023***
		(1.080)		(2.690)		(3.250)
N–Observations	3333	3333	3333	3333	3333	3333
N–Companies	328	328	328	328	328	328
Adj. R^2	0.095	0.115	0.095	0.115	0.094	0.114

	J=6		J=9		J=12	
	(7)	(8)	(9)	(10)	(11)	(12)
Managed Money Long Proportion Growth	0.031***	0.031***	0.045***	0.042***	0.034**	0.040***
	(3.120)	(3.190)	(3.620)	(3.470)	(2.520)	(2.780)
$ln(BE/ME)$	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.340)	(-0.310)	(-0.140)	(-0.170)	(-0.210)	(-0.310)
$ln(ME)$	0.000	0.000	0.000	0.000	0.000	0.000
	(-0.010)	(0.070)	(-0.080)	(0.100)	(-0.020)	(0.090)
ret_{-1}	0.000	-0.001	0.000	-0.001	0.000	-0.001
	(-0.450)	(-0.930)	(-0.550)	(-0.960)	(-0.510)	(-1.120)
$ret_{-2,-12}$	0.000	0.000	0.000	0.000	0.000	0.000
	(0.890)	(0.770)	(0.880)	(0.730)	(0.880)	(0.700)
$FR_{c,t-1}$		0.023***		0.020***		0.021***
		(3.250)		(2.910)		(3.090)
N–Observations	3333	3333	3333	3333	3333	3333
N–Companies	328	328	328	328	328	328
Adj. R^2	0.094	0.115	0.094	0.115	0.094	0.115

B.2 Investigation of Potential Announcement Effects

The CFTC reports are compiled based on the positions as of Tuesdays, and are then released on Fridays. In this appendix, we further disentangle the information environment and investigate whether the predictability arises simply as a result of a self-fulfilling prophecy in which the market participants are just following MM positions after announcements of the DCOT reports on Fridays.[24] The analysis is conducted from two angles.

As a first step, we repeat our single-sort exercise by decomposing our Wednesday-to-Tuesday weekly interval (Wed–Tue) into two new intervals—namely, Wednesday-to-Friday (Wed–Fri) and Monday-and-Tuesday (Mon–Tue)—in order to treat separately the time span before and after the release of DCOT reports on Friday. Table B.12 presents the results for our three MM signal measures that are constructed either as a 1-week lag or as a 2-week backward moving average (i.e., $J = 1$ or 2). We observe for the Wed–Fri rows that the abnormal returns are generally statistically significant, and stronger than the Mon–Tue rows.[25] This is consistent with the notion that the predictability results are already present prior to the publication of the DCOT reports on Fridays.

Second, we use the high-frequency Trade and Quote (TAQ) database to further dispel the concern that our predictability results arise mainly because equity investors trade commodity producers' stocks in the same direction as MM futures market positions immediately after the release of the DCOT reports at 3:30 p.m. on Fridays. Following Schwarz (2012), we run the following cross-sectional regression in each week t:

$$R_{i,t}^{3:30pm-4pm} = \alpha_t + \beta_t^a Signal_{c,t-J} + \gamma_t' W_{i,t-1} + \epsilon_{i,t}, \qquad i = 1, 2, ..., N, \tag{5}$$

where $R_{i,t}^{3:30pm-4pm}$ is the stock return of firm i belonging to commodity c on a Friday from the time interval 3:30 p.m. to 4 p.m.,[26] following a new generation of signals (compiled as of

[24] We thank Brian Henderson (discussant at the AFA 2019 Annual Meeting) for this suggestion.

[25] Incidentally, we have also explored whether the time lag for incorporating information contained in MM positions into producers' equity prices is longer than what is captured by our baseline weekly interval from Wednesday to the next Tuesday (which is the next compilation date), using instead an interval consistent with the actual release schedule of the DCOT reports. In this approach, the report release date, which is usually a Friday, is considered the signal-generation date for signals that would determine the portfolio formation on the following Monday, and the portfolio is held until the next release date. Although this weekly interval forgoes the three days (Wednesday, Thursday, and Friday) immediately following the compilation of the DCOT reports on a Tuesday, in unreported results we still find significant return predictability, albeit smaller as we are getting further away in time and are mainly present in harder-to-analyze equities with higher information asymmetry.

[26] We use our baseline sample but with the condition that there are actual trades registered in the

the Tuesday of the same week), which are just released on Friday at 3:30 p.m.[27] Table B.13 reveals that the coefficients on the MM signals ($\hat{\beta}^a = \frac{1}{T}\sum_{t=1}^{T}\hat{\beta}_t^a$) are insignificant, indicating that producers' equity prices do not respond immediately to the newest DCOT release of MM positions. Hence, we confirm that our predictability results are already present prior to the release of MM positions and are not attributed to the announcement effects of the DCOT reports.

TABLE B.12 Decomposing the Wednesday-to-Tuesday Interval, Single-Sort Results

After equal-weighting (Panel A) or value-weighting (Panel B) the producers' stock returns belonging to the same commodity, the commodity-equity portfolios are sorted weekly into three portfolio bins based on the MM signals and averaged within each tercile with equal-weight, following Section III.C. The signals are constructed as a 1-week lag ($J = 1$) or as a 2-week backward moving average ($J = 2$). From the return difference of the highest over the lowest tercile (3−1), we calculate the abnormal return (α) relative to the Carhart four-factor model (C4), the Fama and French five-factor model (FF5), and the Stambaugh and Yuan mispricing factor model (SY4). The table splits the Wednesday-to-Tuesday (Wed–Tue) timing interval into two sub-intervals, from Wednesday-to-Friday (Wed–Fri), and from Monday-to-Tuesday (Mon–Tue). The average weekly portfolio returns and α's, multiplied by 100 so they can be interpreted as percentages, are reported together with their t-statistics in parentheses (based on White standard errors). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Money Managers' Long Proportion Growth

		Panel A: Equal-Weight				**Panel B: Value-Weight**			
Interval	J	(3−1)	C4 α	FF5 α	SY4 α	(3−1)	C4 α	FF5 α	SY4 α
Wed–Tue	1	0.245***	0.249***	0.247***	0.303***	0.272***	0.277***	0.263***	0.299***
		(3.30)	(3.27)	(3.27)	(3.31)	(3.76)	(3.72)	(3.58)	(3.25)
	2	0.294***	0.285***	0.282***	0.377***	0.245***	0.245***	0.235***	0.306***
		(3.48)	(3.34)	(3.30)	(3.55)	(3.21)	(3.16)	(3.05)	(3.20)
Wed–Fri	1	0.15**	0.148**	0.155**	0.232***	0.158***	0.154***	0.161***	0.206***
		(2.46)	(2.42)	(2.50)	(3.18)	(2.77)	(2.67)	(2.75)	(2.91)
	2	0.2***	0.191***	0.199***	0.279***	0.163***	0.155***	0.165***	0.215***
		(3.11)	(3.00)	(3.07)	(3.63)	(2.75)	(2.62)	(2.71)	(3.01)
Mon–Tue	1	0.105**	0.11**	0.105**	0.07	0.121***	0.12***	0.104**	0.085
		(2.28)	(2.32)	(2.23)	(1.27)	(2.80)	(2.69)	(2.34)	(1.60)
	2	0.099**	0.095*	0.081*	0.082	0.085*	0.081*	0.061	0.066
		(2.06)	(1.96)	(1.67)	(1.37)	(1.92)	(1.81)	(1.36)	(1.19)

TAQ database in the intervals between 3:30 p.m. and 3:35 p.m., and between 3:55 p.m. and 4:00 p.m. $R_{i,t}^{3:30pm-4pm}$ is calculated as the return or price change based on the average prices in those two time intervals. Appropriate adjustments are made for the few instances when the Friday happens to be a public holiday and the release date is moved to the next trading day. Since all DCOT reports prior to September 4, 2009 are released retroactively on that date, rather than rolling on a weekly basis, we thus remove the observations prior to that date.

[27]The MM signals are constructed either as a 1-week ($J = 1$) lag (i.e., compiled using positions data as of the same week's Tuesday) or as a 2-week backward moving average ($J = 2$). Control variables in $W_{i,t-1}$ include the stock return in the previous trading day, over the previous month, and over the 11 months preceding the previous month (ret_{-1day}, ret_{-1}, and $ret_{-2,-12}$, respectively); the log of the book-to-market value of equity ($ln(BE/ME)$); and the log of the market value of equity ($lnME$).

TABLE B.12 Decomposing the Wednesday-to-Tuesday Interval, Single-Sort Results (Continued)

Money Managers' Net Change

		Panel A: Equal-Weight				Panel B: Value-Weight			
Interval	J	(3−1)	C4 α	FF5 α	SY4 α	(3−1)	C4 α	FF5 α	SY4 α
Wed–Tue	1	0.266***	0.276***	0.267***	0.317***	0.271***	0.281***	0.265***	0.307***
		(3.53)	(3.58)	(3.44)	(3.35)	(3.67)	(3.72)	(3.51)	(3.24)
	2	0.229***	0.232***	0.231***	0.279***	0.189***	0.193***	0.187**	0.211**
		(2.98)	(2.96)	(2.92)	(2.90)	(2.66)	(2.66)	(2.56)	(2.40)
Wed–Fri	1	0.209***	0.209***	0.218***	0.29***	0.189***	0.185***	0.195***	0.235***
		(3.39)	(3.38)	(3.50)	(3.89)	(3.19)	(3.12)	(3.24)	(3.21)
	2	0.161***	0.156**	0.165***	0.222***	0.113**	0.106*	0.116**	0.141**
		(2.66)	(2.57)	(2.68)	(3.03)	(2.01)	(1.89)	(2.02)	(2.07)
Mon–Tue	1	0.062	0.073	0.071	0.029	0.09**	0.092**	0.081*	0.067
		(1.36)	(1.53)	(1.50)	(0.54)	(2.08)	(2.08)	(1.80)	(1.25)
	2	0.07	0.069	0.051	0.043	0.077*	0.069	0.046	0.038
		(1.49)	(1.46)	(1.09)	(0.72)	(1.78)	(1.59)	(1.06)	(0.71)

Money Managers' Short Proportion Growth

		Panel A: Equal-Weight				Panel B: Value-Weight			
Interval	J	(3−1)	C4 α	FF5 α	SY4 α	(3−1)	C4 α	FF5 α	SY4 α
Wed–Tue	1	−0.229***	−0.245***	−0.243***	−0.275***	−0.253***	−0.264***	−0.257***	−0.275***
		(−2.99)	(−3.09)	(−3.05)	(−2.86)	(−3.47)	(−3.53)	(−3.42)	(−2.98)
	2	−0.231***	−0.232***	−0.223***	−0.307***	−0.192***	−0.193***	−0.186***	−0.249***
		(−2.99)	(−2.97)	(−2.89)	(−3.25)	(−2.70)	(−2.69)	(−2.61)	(−2.86)
Wed–Fri	1	−0.199***	−0.204***	−0.207***	−0.27***	−0.189***	−0.188***	−0.194***	−0.23***
		(−3.17)	(−3.19)	(−3.23)	(−3.59)	(−3.20)	(−3.13)	(−3.19)	(−3.20)
	2	−0.166***	−0.163***	−0.171***	−0.258***	−0.113**	−0.109*	−0.118**	−0.172***
		(−2.72)	(−2.65)	(−2.76)	(−3.54)	(−2.03)	(−1.96)	(−2.07)	(−2.59)
Mon–Tue	1	−0.036	−0.044	−0.043	0.008	−0.07	−0.065	−0.052	−0.014
		(−0.80)	(−0.93)	(−0.92)	(0.15)	(−1.64)	(−1.49)	(−1.21)	(−0.27)
	2	−0.067	−0.065	−0.048	−0.044	−0.082*	−0.071	−0.05	−0.054
		(−1.36)	(−1.34)	(−0.97)	(−0.73)	(−1.79)	(−1.58)	(−1.09)	(−0.98)

TABLE B.13 Announcement Effect at 3:30 p.m. on Fridays, Fama-MacBeth Regressions

This table shows results from Fama-MacBeth cross-sectional regressions (average slopes, and t-statistics based on White standard errors in parentheses) of firms' equity returns on the signal release date from 3:30 p.m. to 4:00 p.m. ($R_{i,t}^{3:30pm-4pm}$) on the MM signal and other lagged control variables for expected returns. The signal from the futures market is constructed either as a 1-week ($J = 1$) lag (i.e., compiled using positions data as of the same week's Tuesday) or as a 2-week backward moving average ($J = 2$). ret_{-1day} is the stock return in the previous trading day, 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, $ln(ME)$ is the log of the market value of equity at the end of the previous calendar year, and $ln(BE/ME)$ is the log of the book-to-market value of equity, where the book value is measured at the end of the previous fiscal year. The row labeled Adj. R^2 displays 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 release days utilized in the regression. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

$Y = R_{i,t}^{3:30pm-4pm}$	**MM Net Change**		**MM Long Proportion Growth**		**MM Short Proportion Growth**	
	J=1	J=2	J=1	J=2	J=1	J=2
Signal	−0.084	0.162	−0.418	0.827	−0.002	−0.493
	(−0.31)	(0.50)	(−0.56)	(0.99)	(−0.01)	(−1.25)
ln(BE/ME)	0.037	0.035	0.021	0.021	0.037	0.033
	(0.70)	(0.69)	(0.43)	(0.44)	(0.69)	(0.65)
ln(ME)	−0.174***	−0.176***	−0.170***	−0.168***	−0.174***	−0.178***
	(−2.75)	(−2.79)	(−2.75)	(−2.74)	(−2.74)	(−2.80)
ret_{-1day}	−3.323	−3.531	−3.405	−3.219	−3.407	−3.642
	(−1.09)	(−1.12)	(−1.10)	(−1.06)	(−1.11)	(−1.15)
ret_{-1}	−1.017	−1.112	−0.972	−0.988	−0.999	−1.104
	(−1.36)	(−1.46)	(−1.31)	(−1.33)	(−1.34)	(−1.45)
$ret_{-2;-12}$	−0.282**	−0.275**	−0.267**	−0.260**	−0.277**	−0.260**
	(−2.16)	(−2.09)	(−2.17)	(−2.12)	(−2.16)	(−2.03)
intercept	2.703***	2.714***	2.621***	2.583***	2.695***	2.727***
	(2.86)	(2.90)	(2.87)	(2.85)	(2.86)	(2.90)
N–Observations	529	529	529	529	529	529
N–Companies	221	221	221	221	221	221
Adj. R^2	0.06	0.06	0.06	0.06	0.06	0.06

B.3 Supplementary Results to Section V

TABLE B.14 Double-Sort: Money Managers' Long Proportion Growth (%, per Week)

This table presents results of a three-by-two double-sort cross-sectional exercise. AD, VOL, and LIQ stand for the ex ante analyst dispersion, the 90-day historical stock volatility, and the Amihud's illiquidity measure, respectively. In each week, all the producer stocks are first sorted into three friction portfolios using one of the three firm-level proxies of friction (AD, VOL, and LIQ) with the requirement that each commodity appears across those three portfolios. Column "3" is associated with the highest friction. Within each friction portfolio, the producers' stock returns belonging to the same commodity are either equal-weighted (Panel A) or value-weighted (Panel B) into commodity-equity portfolios. Then, the commodity-equity portfolios are sorted dependently within each friction portfolio based on the sign of the MM Long Proportion Growth signal to form two signal portfolios, by being long (short) on positive (negative) signals, which yields the long-short portfolio returns (2−1). The MM signal is constructed as a 2-week backward moving average. We evaluate the α's relative to the Carhart four-factor model (C4), the Fama and French five-factor model (FF5), and the Stambaugh and Yuan mispricing factor model (SY4). We pay attention to the row "2−1" and whether the four- or five-factor alphas arise in the difference between the high- and low-friction bins that corresponds to the (3−1) column, marked in bold. The weekly average returns and α's, multiplied by 100 so they can be interpreted as percentages, are reported together with their t-statistics in parentheses (based on White standard errors). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Panel A: Equal-Weight				**Panel B: Value-Weight**			
AD / Signal	1	2	3	(3–1)	1	2	3	(3–1)
(2–1)	0.053	0.079*	0.191***	**0.138****	0.044	0.072	0.19***	**0.146****
	(1.28)	(1.83)	(3.04)	**(2.34)**	(1.09)	(1.64)	(2.99)	**(2.49)**
C4 α	0.062	0.086*	0.208***	**0.146****	0.055	0.083*	0.211***	**0.156****
	(1.51)	(1.93)	(3.18)	**(2.35)**	(1.36)	(1.92)	(3.27)	**(2.54)**
FF5 α	0.06	0.075*	0.195***	**0.135****	0.054	0.073*	0.199***	**0.145****
	(1.47)	(1.75)	(3.07)	**(2.23)**	(1.36)	(1.74)	(3.16)	**(2.42)**
SY4 α	0.058	0.08	0.253***	**0.195****	0.05	0.075	0.263***	**0.213*****
	(1.13)	(1.54)	(3.08)	**(2.47)**	(1.00)	(1.44)	(3.29)	**(2.74)**
VOL / Signal	1	2	3	(3–1)	1	2	3	(3–1)
(2–1)	0.048	0.077*	0.184***	**0.136****	0.057	0.058	0.189***	**0.132****
	(1.22)	(1.80)	(2.93)	**(2.48)**	(1.37)	(1.34)	(2.97)	**(2.35)**
C4 α	0.058	0.085*	0.197***	**0.14****	0.07*	0.068	0.203***	**0.133****
	(1.52)	(1.96)	(3.00)	**(2.40)**	(1.78)	(1.55)	(3.08)	**(2.23)**
FF5 α	0.055	0.073*	0.182***	**0.127****	0.066*	0.058	0.192***	**0.125****
	(1.49)	(1.74)	(2.85)	**(2.22)**	(1.73)	(1.35)	(2.95)	**(2.10)**
SY4 α	0.061	0.08	0.225***	**0.165****	0.073	0.057	0.233***	**0.16****
	(1.31)	(1.52)	(2.79)	**(2.24)**	(1.49)	(1.08)	(2.85)	**(2.08)**
LIQ / Signal	1	2	3	(3–1)	1	2	3	(3–1)
(2–1)	0.067	0.114**	0.149***	**0.082**	0.072	0.111**	0.143**	**0.07**
	(1.41)	(2.47)	(2.64)	**(1.43)**	(1.51)	(2.51)	(2.48)	**(1.22)**
C4 α	0.083*	0.118**	0.162***	**0.079**	0.09*	0.117***	0.157***	**0.067**
	(1.79)	(2.55)	(2.78)	**(1.34)**	(1.95)	(2.62)	(2.65)	**(1.13)**
FF5 α	0.075*	0.107**	0.151***	**0.076**	0.081*	0.107**	0.147**	**0.065**
	(1.66)	(2.40)	(2.62)	**(1.29)**	(1.82)	(2.46)	(2.51)	**(1.09)**
SY4 α	0.07	0.122**	0.2***	**0.13***	0.082	0.126**	0.187**	**0.105**
	(1.24)	(2.22)	(2.70)	**(1.66)**	(1.47)	(2.37)	(2.48)	**(1.31)**

TABLE B.15 Double-Sort: Money Managers' Short Proportion Growth (%, per Week)

This table presents results of a three-by-two double-sort cross-sectional exercise. AD, VOL, and LIQ stand for the ex ante analyst dispersion, the 90-day historical stock volatility, and the Amihud's illiquidity measure, respectively. In each week, all the producer stocks are first sorted into three friction portfolios using one of the three firm-level proxies of friction (AD, VOL, and LIQ) with the requirement that each commodity appears across those three portfolios. Column "3" is associated with the highest friction. Within each friction portfolio, the producers' stock returns belonging to the same commodity are either equal-weighted (Panel A) or value-weighted (Panel B) into commodity-equity portfolios. Then, the commodity-equity portfolios are sorted dependently within each friction portfolio based on the sign of the MM Short Proportion Growth signal to form two signal portfolios, by being long (short) on positive (negative) signals, which yields the long-short portfolio returns (2−1). The MM signal is constructed as a 2-week backward moving average. We evaluate the α's relative to the Carhart four-factor model (C4), the Fama and French five-factor model (FF5), and the Stambaugh and Yuan mispricing factor model (SY4). We pay attention to the row "2−1" and whether the four- or five-factor alphas arise in the difference between the high- and low-friction bins that corresponds to the (3−1) column, marked in bold. The weekly average returns and α's, multiplied by 100 so they can be interpreted as percentages, are reported together with their t-statistics in parentheses (based on White standard errors). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

	Panel A: Equal-Weight				**Panel B: Value-Weight**			
Signal \ **AD**	1	2	3	(3–1)	1	2	3	(3–1)
(2–1)	−0.036	−0.093**	−0.209***	**−0.173*****	−0.024	−0.081*	−0.208***	**−0.183*****
	(−0.84)	(−2.14)	(−3.27)	**(−2.98)**	(−0.59)	(−1.86)	(−3.25)	**(−3.19)**
C4 α	−0.042	−0.096**	−0.225***	**−0.183*****	−0.032	−0.09**	−0.229***	**−0.197*****
	(−1.01)	(−2.15)	(−3.40)	**(−3.00)**	(−0.78)	(−2.07)	(−3.54)	**(−3.28)**
FF5 α	−0.04	−0.085**	−0.213***	**−0.173*****	−0.031	−0.08*	−0.218***	**−0.187*****
	(−0.97)	(−1.97)	(−3.31)	**(−2.90)**	(−0.78)	(−1.89)	(−3.46)	**(−3.17)**
SY4 α	−0.029	−0.093*	−0.279***	**−0.25*****	−0.019	−0.086*	−0.29***	**−0.271*****
	(−0.56)	(−1.78)	(−3.33)	**(−3.21)**	(−0.38)	(−1.65)	(−3.60)	**(−3.55)**
Signal \ **VOL**	1	2	3	(3–1)	1	2	3	(3–1)
(2–1)	−0.027	−0.088**	−0.201***	**−0.175*****	−0.038	−0.072*	−0.215***	**−0.177*****
	(−0.67)	(−2.05)	(−3.19)	**(−3.24)**	(−0.91)	(−1.65)	(−3.36)	**(−3.19)**
C4 α	−0.035	−0.091**	−0.214***	**−0.179*****	−0.049	−0.077*	−0.229***	**−0.18*****
	(−0.91)	(−2.09)	(−3.24)	**(−3.13)**	(−1.23)	(−1.74)	(−3.47)	**(−3.06)**
FF5 α	−0.032	−0.079*	−0.2***	**−0.168*****	−0.045	−0.066	−0.219***	**−0.174*****
	(−0.86)	(−1.88)	(−3.12)	**(−2.97)**	(−1.15)	(−1.56)	(−3.37)	**(−2.96)**
SY4 α	−0.031	−0.085	−0.251***	**−0.22*****	−0.045	−0.066	−0.272***	**−0.227*****
	(−0.65)	(−1.63)	(−3.10)	**(−3.03)**	(−0.90)	(−1.27)	(−3.32)	**(−2.99)**
Signal \ **LIQ**	1	2	3	(3–1)	1	2	3	(3–1)
(2–1)	−0.067	−0.118**	−0.16***	**−0.093**	−0.071	−0.11**	−0.16***	**−0.088**
	(−1.43)	(−2.55)	(−2.76)	**(−1.63)**	(−1.50)	(−2.46)	(−2.71)	**(−1.53)**
C4 α	−0.08*	−0.12**	−0.173***	**−0.092**	−0.086*	−0.113**	−0.173***	**−0.087**
	(−1.73)	(−2.55)	(−2.87)	**(−1.57)**	(−1.87)	(−2.50)	(−2.85)	**(−1.46)**
FF5 α	−0.072	−0.107**	−0.162***	**−0.09**	−0.078*	−0.102**	−0.163***	**−0.085**
	(−1.61)	(−2.39)	(−2.74)	**(−1.52)**	(−1.75)	(−2.32)	(−2.74)	**(−1.43)**
SY4 α	−0.07	−0.123**	−0.212***	**−0.142***	−0.08	−0.122**	−0.205***	**−0.125**
	(−1.24)	(−2.21)	(−2.77)	**(−1.79)**	(−1.44)	(−2.26)	(−2.64)	**(−1.55)**

References

Arnott, Robert, Chaves, Denis, Gunzberg, Jodie, Hsu, Jason and Tsui, Peter. (2014). 'Getting Smarter About Commodities', *Journal of Indexes* p. 52–60.

Bakshi, Gurdip, Gao, Xiaohui and Rossi, Alberto G. (2019). 'Understanding the sources of risk underlying the cross section of commodity returns', *Management Science* 65(2), 619–641.

Bessembinder, Hendrik. (2018). 'The "roll yield" myth', *Financial Analysts Journal* 74(2), 41–53.

Bessembinder, Hendrik, Carrion, Allen, Tuttle, Laura and Venkataraman, Kumar. (2016). 'Liquidity, resiliency and market quality around predictable trades: Theory and evidence', *Journal of Financial Economics* 121(1), 142–166.

Bhardwaj, Geetesh, Gorton, Gary B and Rouwenhorst, K Geert. (2014). 'Fooling some of the people all of the time: The inefficient performance and persistence of commodity trading advisors', *Review of Financial Studies* 27(11), 3099–3132.

Boons, Martijn and Prado, Melissa Porras. (2019). 'Basis-momentum', *Journal of Finance* 74(1), 239–279.

Carhart, Mark M. (1997). 'On persistence in mutual fund performance', *Journal of Finance* 52(1), 57–82.

Cheng, Ing-Haw, Kirilenko, Andrei and Xiong, Wei. (2015). 'Convective risk flows in commodity futures markets', *Review of Finance* 19(5), 1733–1781.

Cheng, Minder and Madhavan, Ananth. (2009). 'The dynamics of leveraged and inverse exchange-traded funds', *Journal of Investment Management* 16(4), 43.

Christoffersen, Peter, Lunde, Asger and Olesen, Kasper V. (2019). 'Factor structure in commodity futures return and volatility', *Journal of Financial and Quantitative Analysis* 54(3), 1083–1115.

Cochrane, Donald and Orcutt, Guy H. (1949). 'Application of least squares regression to relationships containing auto-correlated error terms', *Journal of the American Statistical Association* 44(245), 32–61.

Durbin, James and Watson, Geoffrey S. (1950). 'Testing for serial correlation in least squares regression: I', *Biometrika* 37(3/4), 409–428.

Erb, Claude B and Harvey, Campbell R. (2006). 'The strategic and tactical value of commodity futures', *Financial Analysts Journal* 62(2), 69–97.

Fama, Eugene F and French, Kenneth R. (2015). 'A five-factor asset pricing model', *Journal of Financial Economics* 116(1), 1–22.

Fevurly, Keith R. (2013), Exchange-Traded Funds, *in* 'The Handbook of Professionally Managed Assets', Springer, p. 145–161.

Gandhi, Priyank and Lustig, Hanno N. (2015). 'Size Anomalies in U.S. Bank Stock Returns', *Journal of Finance* 70(2), 733–768.

Gorton, Gary B, Hayashi, Fumio and Rouwenhorst, K Geert. (2013). 'The fundamentals of commodity futures returns', *Review of Finance* 17(1), 35–105.

Gorton, Gary and Rouwenhorst, K Geert. (2006). 'Facts and fantasies about commodity futures', *Financial Analysts Journal* 62(2), 47–68.

Greene, William H. (2000). 'Econometric analysis 4th edition', *International edition, New Jersey: Prentice Hall* p. 201–215.

Miffre, Joëlle and Rallis, Georgios. (2007). 'Momentum strategies in commodity futures markets', *Journal of Banking & Finance* 31(6), 1863–1886.

Moskowitz, Tobias J, Ooi, Yao Hua and Pedersen, Lasse Heje. (2012). 'Time series momentum', *Journal of Financial Economics* 104(2), 228–250.

Savin, Nathan E and White, Kenneth J. (1977). 'The Durbin-Watson test for serial correlation with extreme sample sizes or many regressors', *Econometrica* p. 1989–1996.

Schwarz, Krista. (2012). 'Are speculators informed?', *Journal of Futures Markets* 32(1), 1–23.

Stambaugh, Robert F and Yuan, Yu. (2016). 'Mispricing factors', *Review of Financial Studies* 30(4), 1270–1315.

Szymanowska, Marta, De Roon, Frans, Nijman, Theo and Van Den Goorbergh, Rob. (2014). 'An anatomy of commodity futures risk premia', *Journal of Finance* 69(1), 453–482.