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Destabilizing or passive? The impact of commodity index traders on equilibrium prices[☆]

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ABSTRACT

We examine the price impact of traders on commodity futures markets. Following the framework of De Long et al. (1990), we empirically identify the existence of positive feedback traders, passive investors, and rational speculators in major global commodity futures markets. Our results show that index trader demand is negatively related to past commodity returns and is positively related to future commodity returns, as De Long et al. (1990) model predicts for passive investors. Furthermore, "non-reportable traders," who are not obligated to report their positions to the regulators, behave like positive feedback traders, and interact significantly with commodity futures returns as well.

1. Introduction

This paper analyzes whether index traders have an impact on equilibrium prices of commodity futures around 2008. The academia has been studying the phenomenon until recently (Ordu et al., 2018; Aït-Youcef, 2019). This question arises since the growth in importance of commodity markets as financial investment vehicles has been accompanied by significant changes in equilibrium prices, resulting in a higher volatility of commodity indices. This situation is illustrated in Fig. 1. The upper panel of Fig. 1 shows the price process of the S&P GSCI index, a major commodity price index. It can be seen that commodity prices have been subject to several boom and bust cycles. A possible explanation for this pattern, that naturally arises, would be a shift in the demand and supply for commodities, for example, the shift in energy demand of emerging economies, and biofuel production changing supply. Papers that provide an analysis along these lines include Hamilton (2009), Mueller et al. (2011), and Kilian and Murphy (2014). However, results of these studies show that fundamentals alone do not constitute the sole reason for the observed patterns in prices.

A further reason put forward for the increasing price volatility is the flow of investment capital into and out of commodity markets. As noted by Domanski and Heath (2007), "commodity markets have become more like financial markets in terms of the motivations and strategies of participants." The can be evidenced by the lower panel of Fig. 1, which shows the estimated long positions of index traders during the period between 2006 and 2014. The consistency between the lines makes it clear why the connection between index trading and market volatility has been pointed out in media outlets and has been the target of investigation in academic papers.

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Fig. 1. S&P GSCI and Estimated CIT Net Long Positions
"CIT" stands for Commodity Index Traders. Their net long positions were estimated with the Rectified Hamilton–Wu Algorithm.

The most prominent proponent of this "financialization" theory is Michael W. Masters, a hedge fund portfolio manager. He argued in front of the United States Commodity Futures Trading Commission (CFTC) that the inflow of money into commodity index funds caused the price spike observed in 2008 (Masters, 2009). Following the terminology of Irwin and Sanders (2012), we refer to the claim made by Mr. Masters as the "Masters Hypothesis" hereafter.

Our goal is to shed further light on the role that commodity index funds play in the futures markets. To do this, we follow the theoretical model of De Long et al. (1990) (hereinafter DSSW), in which the futures market is populated by three investor categories: positive feedback traders, passive investors, and rational speculators. Our main contribution consists of identifying each of these categories of investors, in line with the model, so that we can clearly establish the role each category plays in changing the equilibrium prices we observe. We find that commodity index traders (CITs), as well as a special class of traders called "nonreportable traders," who are not obligated to report their positions to the regulators, behave like passive traders and positive feedback traders respectively. After the recognition of the trader classes, we are able to analyze the price impacts of each category of these traders.

We first show that commodity index trader (CIT) positions are negatively affected by past returns and that they positively predict future returns. CITs therefore behave in line with the passive investor category in the DSSW model. Therefore, we may conclude that the flows caused by index traders are unlikely to constitute a destabilizing factor in the price-finding process that caused the increase in price volatility.

Next, we try to investigate the existence of financial trading positions that resemble the positive feedback traders in the DSSW model. To do so, we analyze the flows of the non-reportable traders collected by the Commodity Futures Trading Commission (CFTC). The CFTC demands that all clearing members, futures commission merchants, and foreign brokers should report to them daily; therefore, we can identify the trading positions of numerous trader categories.[1] We concentrate on the trading positions of non-reportable traders because they are generally smaller in scale, and as has been shown in, e.g., Abraham and Ikenberry (1994), Lee et al. (1998), and Bange (1994), smaller investors are more likely to follow simplistic trading strategies as postulated positive feedback traders would. Indeed, in our empirical applications we find that the change in positions of non-reportable traders are positively related to commodity returns and negatively related to future returns - a characteristic that resembles the positive feedback traders in DSSW.[2]

Our final step consists of combining both results. We show that although the financialization of commodity markets can have contributed to the increasing price volatility, commodity index traders are unlikely to be the source of this destabilization. Here we retain two caveats. First, we certainly do not argue that nonreportable traders are all positive feedback traders and that none of the reportable traders are sophisticated non-feedback traders. Given the large proportion of reportable traders' open interest in the market, the majority of these positive feedback traders should be concealed in the reportable section of the COT report. Second, we do not exclude commercial hedgers, which represent a separate type of investor in commodity futures markets. We simply do not differentiate financial from commercial traders or "speculators" from "hedgers." Nothing prevents commercial hedgers from being positive feedback traders, since commercial hedgers also strive for the lowest hedging costs as well as minimum commodity price risk. To empirically examine what happens when positive feedback traders meet passive investors in commodity futures markets is no an easy task. Specifically, we need to try to establish two key aspects of CITs' actions: whether and how they affect commodity prices, and how their activities are, in turn, affected by market conditions, including price trends.

The first aspect is exactly what the Masters Hypothesis addresses. Aside from the informal evidence shown by Masters (2009) in his testimony, Singleton (2014) is the first formal attempt to discover some trace of the predictive power of CIT positions on commodity prices. He finds that changes of CIT net long positions significantly predict crude oil futures returns. However, evidence to the contrary also exists. Irwin and Sanders (2012) argue that the mapping algorithm employed by Singleton (2014) is problematic. Hamilton and Wu (2015) improve the Masters algorithm and find that the relationship discovered by Singleton (2014) between CIT positions and commodity futures becomes insignificant, using to-date data. Liu and Zhang (2019) also find that magnitude of excess spillovers across different commodities is significantly positively related to the extent of participation by financial investors.

However, when we take a broader look at the impact of CITs covering 35 different commodity futures,[3] we indeed find commodity returns across markets are predicted by CITs flows, in contrast with Hamilton and Wu (2015), but consistent with the DSSW model. In addition to these results, we also contribute to the topic methodologically. Employing the algorithm invented by Chow and Lin (1971), we further improve the Hamilton and Wu (2015) estimation by rectifying the estimated values with the monthly reporting Index Investment Data (IID).[4]

Putting the commodity futures price puzzle together also requires looking at another aspect of the presence of CITs. However, the question of to what extent CIT positions themselves are the result of market conditions has not been addressed much. Cheng et al. (2014) find that VIX changes can significantly predict CIT position changes. It has also been found that CITs' investment is related to high market liquidity (Ordu et al., 2018) and Ordu-Akkaya and Soytas (2020).[5] Palazzi et al. (2020) do not find causal relationship between index funds and agricultural commodity prices.

We take a slightly different view from previous researchers, and try to ascertain whether or not CITs behave like the passive investor class in the DSSW model, which hypothesizes that passive investors' positions are negatively correlated with the departure of prices from the values of underlying assets. Unfortunately, it is nearly impossible to know the exact value of physical commodities. Therefore we test a simpler hypothesis, which says positive innovations in commodity futures prices lead to negative changes in CIT net long positions. Of course the portfolios of CITs, usually large funds, are affected by many factors, including macro shocks. Since our sample period includes the 2008 financial crisis, these macro shocks are especially important (Etula, 2013). Once we control for these macro shocks, we find that CITs cut their net long positions when contract prices are going up. This observation is closely in line with the DSSW model and implies that CITs indeed do not represent a destabilizing power. Instead, positive feedback traders turn out to be a much more likely candidate for being the responsible party for recent commodity price volatilities. Making matters more complex, we find that the conditions for positive feedback traders to play this role are often the result of CIT activities.

In this paper, we do not try to test directly whether the speculators destabilize commodity prices. Instead, we focus on a more complex mechanism, under which the price destabilization is caused by the interaction between different classes of traders. This is the main distinction between our paper and the existing studies. As far as we know, no existing study shows the distinctive and necessary role of non-reportable traders in the formation of commodity price volatilities. We believe this makes another contribution of this

[1] According to the CFTC, "the aggregate of all traders" positions reported to the Commission usually represent 70 to 90 percent of the total open interest in any given market.

[2] Demirer et al. (2015) present some indirect evidence for herding behavior in commodity markets. Related to this, it is also documented that noise trading can enlarge commodity market volatilities, e.g., Peri et al. (2014). Also see Ramiah et al. (2015) for a review.

[3] Wu et al. (2020) demonstrate the connections among different commodity futures.

[4] Before June 2010, the IID reports were announced every quarter instead of every month. [5]Shang et al. (2016) also study the behavior of long-only commodity investors.

[5] S&P GSCI and DJ UBSCI are the two most popular commodity price indices used during our sample period, which are managed by S&P and Dow Jones, respectively.

paper.

This paper is directly related to the existing literature on the causes of commodity price volatilities. We briefly discuss three types of existing hypotheses. First, some studies argue that commodity price volatilities are driven by limits of arbitrage due to traders' capital constraints. Therefore, if short traders (typically commercial hedgers) are more constrained by their capitals, or long traders (typically CITs) are less constrained by their capitals, commodity prices are expected to rise. Specifically, Acharya et al. (2013)introduce a formal model and empirically assess how producers' hedging demand is met by increase activities of speculative traders. Mou (2010) provides evidence that CITs (used to) suffer significant losses when they have to go through the Goldman Roll, if their counter-parties are financially incapable of fully neutralizing the massive opening and closing of CIT positions. A second view emphasizes information frictions, resulting in asymmetric information and opposite interpretations of the same observable information, known as "agree to disagree." Singleton (2014) supports this view and shows that the front-month NYMEX WTI futures prices and the cross-sectional dispersion of forecasts of oil prices one-year ahead by professionals are correlated. The third view attributes commodity price volatilities to the benchmark effect of commodity prices indices. Basak and Pavlova (2013) construct a theoretical model, and argue that institutional investors enter commodity markets and drive up commodity prices because their performances are benchmarked against commodity index returns. In relation to this paper, the first two views tend to regard "speculators" as a homogeneous group that trades in the same manner. On the contrary, the work of Basak and Pavlova (2013) is more closely related to De Long et al. (1990) and our paper, as the former is among the earliest attempts to recognize different subgroups of "speculators."

The rest of this paper is organized as follows: Section 2 presents the hypotheses to be tested and the empirical strategy employed in the tests, and Section 3 describes the data used in the tests. Test results are reported in Section 4. Finally, Section 5 concludes this paper.

2. Hypothesis development and empirical strategy

2.1. Investor categories

Our analysis is based on the theoretical framework put forward by De Long et al. (1990). In the model, the futures market for commodities is populated by three classes of investors: (1) positive feedback traders, (2) passive investors, and (3) rational speculators.

De Long et al. (1990) introduce a three period model with an underlying asset that pays a risky cash flow at the end of period three. Investors base the demand for the underlying asset on different information sets. Positive feedback traders buy the asset in case there is a price increase and sell otherwise. Passive investors' demand is a function of the difference between the fundamental value of the asset and its current market price. Rational speculators' demand function has two components. First, they react to price differences between fundamental value and the current price of the asset. Second, they seek to take advantage of the behavior of the positive feedback traders by anticipating the increased demand due to price movements. De Long et al. (1990) show that an increase in the number of rational speculators or positive feedback traders leads to a divergence of market prices from fundamental values and to an increase in price volatility.

Naturally, the model is too stylized to be applied directly to the data. Instead, we use it as guidance to make predictions regarding what we should observe in terms of demand functions for the different investor classes assumed in the model. First, we need to make is that the demand functions of the investors are not as simple as postulated in the theoretical model, because they do not only depend on the price movements of the underlying asset. We therefore control for other factors that have been shown in the literature to have an impact on fund flows. Second, we are not able to observe the fundamental value of a commodity, and therefore we need to work with a modified demand function for the passive investor class. We argue that the probability for the market price to be higher than the fundamental value is increasing with the returns of that commodity, and vice versa. This brings us to our first two predictions:

Prediction 1: Regressing the change in investor positions on returns and control variables results in the negative coefficient for the returns for passive investors.

Prediction 2: Regressing the change in investor positions on returns and control variables results in the positive coefficient for the returns for positive feedback investors.

In a second step we use the assumption that fundamental value do not change in a short period of time. This implies that if the demand of an investor is driven by price differences from the fundamental value it should be positively related to future returns. For example, if prices are below the fundamental value, then the passive investor has a positive demand. If prices revert to the fundamental value, that means that the return is positive in the next period. This observation leads us to the second set of predictions.

Prediction 3: The demand of passive investors positively predict future returns.

Prediction 4: The demand of positive feedback traders negatively predict future returns.

Taken together, we are able to classify the trading positions of commodity index traders and non-reportable traders into either passive investor or feedback trader, investment classes postulated in the paper by De Long et al. (1990). Following De Long et al. (1990), we hypothesize that the net long positions of passive traders (CITs) positively predict commodity future returns, and the net long positions of positive feedback traders (non-reportable traders) positively predict commodity future returns. However, we do not try to lock the identity of the rational speculators, as apparently every investor can be fully rational. CITs and non-reportable traders can be passive traders or positive feedback traders on average, but individually they can still be rational. Nevertheless, Miffre and Brooks (2013) do not find common long-short speculation strategies cause changes in the volatilities of the portfolios.

2.1.1. Modeling CIT positions

We first model the change in the holdings of commodity index investors. The returns are defined as the full collateralized returns of the front contracts. Hereinafter, we denote commodity futures returns and CIT net long positions growth as ComRet and CITPosGr respectively. We use a set of control variables that are closely related to the macroeconomic environment and therefore to the demand and supply of commodities. In addition, as we observe positions at a weekly basis, we assume that the slow-moving fundamentals of commodities do not change within a week.

We examine 35 major commodity futures markets, including all major commodity futures traded in the United States (Tang & Xiong, 2012), except for pork bellies futures, as that market is not liquid. Our sample also includes several metal contracts traded in London that are included in the S&P GSCI or DJ UBSCI indexes,[5] as well as an obsolete contract known as unleaded gas, which used to be a component of the indices. A detailed list of these contracts can be found in Table 1.

To test whether CITs reduce their positions following negative commodity returns, we could directly regress CIT position adjustments on lagged commodity returns. This can either be specified as

Table 1
List of contracts studied in this paper

Ticker	Contract Name	Exchange Board	S&P GSCI Weights	DJ UBSCI Weights	Market Average Weights	Adjusted Weights	Is Reported in COT
Energy CL	WTI Crude Oil	NYM	.2568	.1038	.1311	.5339	Yes
HO	Heating Oil	NYM	.0652	.0393	.0439	.5932	Yes
HU	Unleaded Gas	NYM	.0000	.0000	.0000	.2765	No
NG	Natural Gas	NYM	.0284	.1389	.1192	.2157	Yes
RB	RBOB Gasoline	NYM	.0583	.0372	.0410	.4330	Yes
LCO	Brent Crude Oil	ICE-UK	.2348	.0647	.0951	.6209	No
LGO	Gasoil	ICE-UK	.0889	.0000	.0159	.5906	No
Grains BO	Soybean Oil	CBT	.0000	.0242	.0151	.5979	Yes
C	Corn	CBT	.0321	.0488	.0458	.3136	Yes
O	Oats	CBT	.0000	.0000	.0000	.2438	Yes
RR	Rough Rice	CBT	.0000	.0000	.0000	.2528	Yes
S	Soybeans	CBT	.0258	.0568	.0512	.4573	Yes
SM	Siybean Meal	CBT	.0139	.0381	.0338	.2706	Yes
W	Chicago Wheat	CBT	.0319	.0336	.0333	.3083	Yes
KW	Kansas Wheat	KBT	.0068	.0128	.0112	.3455	Yes
MWE	Minneapolis Wheat	MGE	.0000	.0000	.0000	.2609	Yes
Softs CC	Cocoa	ICE-US	.0028	.0000	.0005	.2235	Yes
CT	Cotton #2	ICE-US	.0100	.0202	.0183	.1962	Yes
KC	Coffee	ICE-US	.0047	.0197	.0170	.3526	Yes
OJ	Orange Juice	ICE-US	.0000	.0000	.0000	.1434	Yes
SB	Sugar #11	ICE-US	.0139	.0381	.0338	.1880	Yes
LB	Lumber	CME	.0000	.0000	.0000	.1390	Yes
Livestock							
FC	Feeder Cattle	CME	.0059	.0000	.0011	.1877	Yes
LH	Lean Hogs	CME	.0166	.0215	.0207	.0449	Yes
LC	Live Cattle	CME	.0297	.0364	.0352	.3336	Yes
Metals							
GC	Gold	CMX	.0227	.0883	.0766	.5090	Yes
SI	Silver	CMX	.0031	.0271	.0228	.3514	Yes
HG	New York Copper	NYM	.0000	.0689	.0566	.4666	Yes
PA	Palladium	NYM	.0000	.0000	.0000	.3420	No
PL	Platinum	NYM	.0000	.0000	.0000	.4547	Yes
MAL	Aluminum	LME	.0181	.0450	.0402	.5005	No
MCU	London Copper	LME	.0298	.0000	.0053	.4733	No
MNI	Nickel	LME	.0045	.0192	.0166	.2603	No
MPB	Lead	LME	.0041	.0000	.0007	.2495	No
MZN	Zinc	LME	.0050	.0256	.0219	.3082	No

This table lists the 35 different commodity futures contracts used by this paper, together with their demonstrative dollar weights as of December 3, 2013. Tickers for contracts traded in United Kingdom follows the handbooks of S&P GSCI Index Methodology. Weights are rounded to four digits. Market average weights are the dollar weights averaged across S&P GSCI and DJ UBSCI by their estimated market shares. These weights are then adjusted by their historical return correlations, and the results are put in the respective column. Adjusted weights do not sum to one. RBOB stands for Reformulated Blendstock for Oxygenate Blending, which is a major gasoline product consumed in the U.S.

$$\mathrm{CITPosGr}_t = \alpha_i + \beta_1 \mathrm{CITPosGr}_{t-1} + \beta_2 \mathrm{ComRet}_{i,t-1} + \mathbf{Controls}_{t-1} \cdot \gamma + \varepsilon_{it}, \tag{1}$$

Where the dependent variable is the growth rate of total CIT positions ($\mathrm{CITPosGr}_t$), or, alternatively,

$$\mathrm{CITPosGr}_{it} = \alpha_i + \beta_1 \mathrm{CITPosGr}_{i,t-1} + \beta_2 \mathrm{ComRet}_{i,t-1} + \mathbf{Controls}_{t-1} \cdot \gamma + \varepsilon_{it}, \tag{2}$$

Where the dependent variable is the growth rate of CIT positions in Contract i ($\mathrm{CITPosGr}_{it}$).[6] In both Regressions (1) and (2), α_i is contract-fixed effects, $\mathrm{ComRet}_{i,t-1}$ is lagged return of Contract i, and ε_{it} is the error term. Other control variables are described below:

In a pioneering empirical study on the decision of CIT positions, Cheng et al. (2014) focus on the VIX and its interaction with the CDS spread. Etula (2013) model how financial constraints of investors affect their willingness to invest in the risky commodity markets. Of course, market conditions especially important because our sample period contains the crisis period. We include a number of control variables to capture changes in market conditions, including the CDS spread of major investment banks (CDSSprd), major investment bank returns (IBRet),[7] first-order difference of VIX (DiffVIX), the LIBOR, the term spread (TermSprd), the TED spread (TEDSprd), and S&P 500 returns (SPRet).

Because the contract weights in either index are relatively stable, we expect β_2 in both Regressions (1) and (2) are negative.

In addition to the basic test specified by Regression (1) or (2), we can see in Table 1 that the weight allocation of each contract in the two indices is very unbalanced. For example, on December 3, 2013, the WTI crude oil contract has a dollar weight of 0.36 in the S&P GSCI index and a weight of 0.10 in the DJ UBSCI, but the weights of lean hogs are only about 0.02 in both indices. Furthermore, some contracts are not included in both indices. These unbalanced allocation of contract weights can be exploited to construct a more efficient test of Prediction 1, as we expect that price changes in contracts with larger weights have a significantly larger negative impact on CIT positions. We thus calculate the market average weights of each contract by weighted-averaging the weights designated by the two indices based on respective estimated market shares, and test whether this average weight has an interactive effect together with ComRet. The variable is abbreviated as MktWt. We can thereby perform the following test:

$$\begin{aligned}\mathrm{CITPosGr}_t &= \alpha_i + \beta_1 \mathrm{CITPosGr}_{t-1} + \beta_2 \mathrm{ComRet}_{i,t-1} + \beta_3 \mathrm{MktWt}_{i,t-1} \\ &+ \beta_4 \mathrm{ComRet}_{i,t-1} \times \mathrm{MktWt}_{i,t-1} + \mathbf{Controls}_{t-1} \cdot \gamma + \varepsilon_{i,t},\end{aligned} \tag{3}$$

Where t represents the weekly index of observations, i represents different contracts, **Controls** are the controlling variables to be introduced below, and ε is the error term.

However, the above test does not consider the natural price correlations between the commodity contracts that are mutually substitute or complement goods. For example, the prices of RBOB and WTI crude oil co-move closely. Therefore, a one-percent change in the price of an RBOB futures contract is also expected to have large impact on CIT positions, even though it carries only a small weight in the index. The unadjusted MktWt cannot reflect such inherent price relationship between substitute or complement goods; in the above example, RBOB price shocks would have an influence that is not proportional to the nominal weight of RBOB. In response to the natural relationship between contracts, we could improve our experimental design. Specifically, we adjust the simple market average weights as follows. Let $\mathbf{w}_t$ be the vector containing the market average weights of the contracts at time t, and let $\mathbf{r}_{it}$ and $\mathbf{r}_{jt}$ respectively be vectors of full collateralized returns of contracts i and j ($\neq i$). For the regression $\mathbf{r}_{jt} = a_{ij}\mathbf{r}_{it} + \varepsilon_t$, we have $\widehat{a}_{ij}$ as the OLS estimation of a_{ij}. Square matrix $\mathbf{A}$ is defined as $(\widehat{a}_{ij})_{n\times n}$, where $\widehat{a}_{ii}$ for any i, and n is the number of different contracts, and then our adjusted average weights $\widetilde{\mathbf{w}}_t = \mathbf{A}\mathbf{w}_t$. We denote the adjusted weights as AdjWt hereinafter. Note that AdjWt can be significantly larger than MktWt because we do not scale the sum of AdjWt to one. This leads to the following modified specification:

$$\begin{aligned}\mathrm{CITPosGr}_t &= \alpha_i + \beta_1 \mathrm{CITPosGr}_{t-1} + \beta_2 \mathrm{ComRet}_{i,t-1} + \beta_3 \mathrm{AdjWt}_{i,t-1} \\ &+ \beta_4 \mathrm{ComRet}_{i,t-1} \times \mathrm{AdjWt}_{i,t-1} + \mathbf{Controls}_{t-1} \cdot \gamma + \varepsilon_{i,t},\end{aligned} \tag{4}$$

Next, we describe how we analyze the implications of changes in CIT positions.

2.1.2. Implications of changes in CIT positions

In the DSSW model, passive investors are indispensable in keeping a constant risk-bearing capacity. They thereby help stabilize the market, whereas positive feedback traders have the opposite effect. We therefore use the growth rates of CIT net long positions in a second test to categorize the movements of CIT investors.

Hamilton and Wu (2015) test a similar hypothesis. For each commodity contract, they directly test whether CIT positions changes have significant predictive power for the returns in the following week, controlling for one lag of the returns. In contrast, in this paper we test the hypothesis in the panorama of 35 contracts, and the test can either be specified as

$$\mathrm{ComRet}_{it} = \alpha_i + \beta_1 \mathrm{ComRet}_{i,t-1} + \beta_2 \mathrm{CITPosGr}_{i,t-1} + \mathbf{Controls}_t \cdot \gamma + \varepsilon_{it}, \tag{5}$$

Where i stands for different contracts. We also try adding the same set of control variables as Regressions (1–4) here to control for the financial environment for the commodity markets.

[6] Specifically, $\mathrm{CITPosGr}_{it} = \mathrm{CITPosGr}_t \cdot (w_t^{SP} w_{it}^{SP} + w_t^{DJ} w_{it}^{DJ})$, where w_t^{SP} and w_t^{DJ} are respectively the proportions of CIT positions invested according S&P GSCI and DJ UBSCI at time t, and w_{it}^{SP} and w_{it}^{DJ} are respectively the weights of Contract i in S&P GSCI and DJ UBSCI at time t.

[7] These banks include Bear Stearns, Citigroup, Credit Suisse, Goldman Sachs, HSBC, JP Morgan, Merril Lynch, and Morgan Stanley. The two variables related to these investment banks, i.e., CDS and IBRet, are the market value weighted averages.

2.2. Non-reportable traders

Now that we have started to consider CIT traders, we move on to the behavior of positive feedback traders and their contribution to price discovery and development.

The so-called non-reportable traders are traders not identified as clearing members, futures commission merchants, and foreign brokers. They tend to be smaller in size and therefore are more likely to take the naïve positive feedback strategy.

Both the long and short positions on each commodity contract are reported by the COT report. Nonrepotable traders' net long positions are often considered to be the most intuitive indicator of their strategies. However, the simple net long open interests of non-reportable traders are likely to largely represent capital flows into and out of commodity markets instead of a pure reflection of the traders' true opinions towards the markets. Since commodity markets are known to have relatively high entry barriers, an increase in non-reportable net long open interests may simply indicate that more investors have passed the barrier to entry.

Based on the above considerations, we represent non-reportable traders' strategies with the long-to-total open interests ratio, defined as the percentage of long open interests in total open interests. In doing so, we cancel out the effect of investors' in- and outflows. The resulting variable will be abbreviated as PctLong in the following parts of the paper.

2.2.1. Modeling the change in non-reportable trader holdings

The construction of the test in this section is similar to the regressions used for Prediction 1 in Section 2.1.1. However, we do not have to concern ourselves with weights of contracts in this part, since non-reportable positions are known for each individual contract and these positions are mutually independent. Instead, we run the following regression:

$$\mathrm{PctLong}_{it} = \alpha_i + \beta_1 \mathrm{PctLong}_{i,t-1} + \beta_2 \mathrm{ComRet}_{it} + \mathbf{Controls}_{t-1} \cdot \gamma + \varepsilon_{i,t}, \tag{6}$$

Where **Controls** are the same as for prediction 1. It should be noted that we regress on ComRet_{it} instead of $\mathrm{ComRet}_{i,t}1$ because the dependent variable $\mathrm{PctLong}_{it}$ is not a difference or change rate that depends on $\mathrm{PctLong}_{i,t}1$. According to the DSSW model, we care

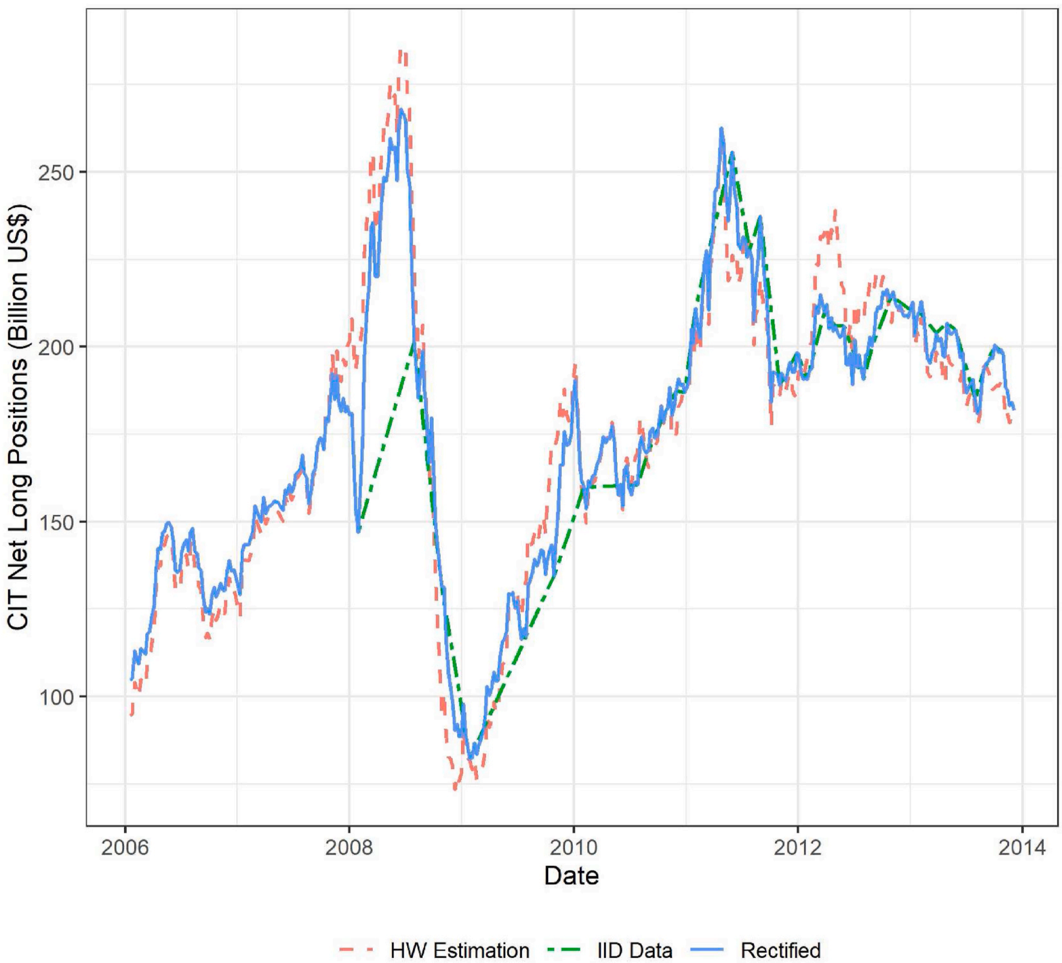

Fig. 2. CIT net long positions estimations.

about levels, but not changes, of non-reportable traders' views and positions in the market; therefore, we do not use differences of PctLong. We expect that in Week *t*, a larger proportion of non-reportable traders in Market *i* will take long positions if they experience price increases in the previous week shown by positive values of $\mathrm{ComRet}_{i,t}$. This expectation corresponds to a significantly positive value for β_2. Note that this does means that every non-reportable trader employs the positive feedback strategy. Nonetheless, as a whole, the class of non-reportable traders is a good parallel to that of the positive feedback traders in the DSSW model.

2.2.2. Impact of the change in non-reportable trader holdings on returns

To construct the second set of tests, in the case of the non-reportable traders, we must regress returns on the change of the positions of this investor category.

This hypothesis can be tested with

$$\mathrm{ComRet}_{it} = \alpha_i + \beta_1 \mathrm{ComRet}_{i,t-1} + \beta_2 \mathrm{PctLong}_{i,t-1} + \mathbf{Controls}_{t-1} \cdot \gamma + \varepsilon_{it}, \tag{7}$$

And similar to the test for Prediction 2 in Section 2.1.2, we again add the same set of control variables to control for the financial environment. We expect β_2 to be negative. Additionally, if we find that $\mathrm{CITPosGr}_{i,t-1}$ can significantly predict $\mathrm{ComRet}_{i,t}$ in Regression (5), we will also add $\mathrm{CITPosGr}_{i,t-1}$ into the regression, after which the regression becomes

$$\mathrm{ComRet}_{it} = \alpha_i + \beta_1 \mathrm{ComRet}_{i,t-1} + \beta_2 \mathrm{PctLong}_{i,t-1} + \beta_3 \mathrm{CITPosGr}_{i,t-1} + \mathbf{Controls}_{t-1} \cdot \gamma + \varepsilon_{it}. \tag{8}$$

We expect β_2 to be negative, and we expect β_3 to be positive. Because of the COT report does not cover all the contracts, we can consider only 26 of the 35 contracts traded in the US when testing for the behavior and influence of non-reportable traders. The list of contracts used can be found in Table 1.

3. Data

Since we try to test directly how CITs interact with commodity futures markets, we have to know their positions. However, the highest frequency at which public data of CIT positions in all futures markets are available is monthly, as released by the CFTC in their IID report. This frequency is too low for our study. A popular weekly estimation of CIT positions is proposed by Masters (2009), who utilizes weekly positions data of agricultural futures markets released in the Commodity Index Trader Supplement (CITS) of the COT report by the CFTC. He maps CIT positions in agricultural futures markets to the total positions of CITs in all commodity futures markets based on the index weights of popular commodity indices. However, Irwin and Sanders (2012) point out that the original algorithm proposed by Masters (2009) has various problems. In response to the criticism, the algorithm is then revised by Hamilton and Wu (2015, HW).

Nevertheless, there is still a gap between the HW estimation and the official monthly data released in the IID report. In Fig. 2, the HW estimation and the IID data are displayed with dashed and double-dashed lines, respectively. We can see that the two lines have roughly similar trends but are separated by a spread. Correlation analysis shows that the HW estimation and the IID data have a Pearson correlation coefficient of 0.79 and a Spearman correlation coefficient of 0.83.

Dashed, double-dashed, and solid lines represent estimations of CIT net long positions in billion US$ estimated with the HW Algorithm, reported by the CFTC IID (Index Investment Data) report, and rectified values.

In this paper, we argue that the HW estimation can be further improved by intelligently combining the information from the IID report. While the IID report only provides monthly data, we can still use it to rectify the weekly HW estimation with the method

Table 2
Descriptive statistics.

	Min.	L. Quartile	Median	H. Quartile	Max.	Mean	SD
ComRet	−0.330	−0.0230	0.000310	0.0261	0.396	0.00195	0.0453
MktWt	0	0	0.0166	0.0379	0.317	0.0286	0.0445
AdjWt	0.00898	0.244	0.325	0.474	0.723	0.352	0.155
PctLong	0.176	0.427	0.532	0.644	0.958	0.536	0.137
CITPosGr	−0.148	−0.0161	0.00193	0.0195	0.188	0.00200	0.0373
TermSprd	−0.598	1.12	2.13	2.93	3.77	1.92	1.25
TEDSprd	−0.422	0.488	0.788	1.80	5.98	1.36	1.43
LIBOR	0.00500	1.23	4.93	5.75	6.78	3.95	2.18
DiffVIX	−14.8	−1.14	−0.104	1.09	16.2	0.0175	2.77
CDSSprd	23.3	79.3	133	166	296	126	63.9
SPRet	−0.119	−0.00776	0.00168	0.0107	0.0614	0.000571	0.0173

This table reports minimums, lower quartiles, medians, higher quartiles, maximums, means, and standard deviations of the variables used in this paper. The first four lines are the pooled statistics of the weekly observations for all the 35 contracts as is listed in Table 1 from January 17, 2006 to December 3, 2013, which sum to 14,420 observations. The remaining lines are time series statistics of the 412 weekly observations in the same period. ComRet is the weekly return on commodity futures; MktWt is the market average weight of CIT positions; AdjWt is the same weight after the Chow and Lin (1971) adjustment; PctLong is the percentage of long open interests in total open interests of non-reportable traders; CITPosGr is the CIT net long positions growth; TermSprd is the term spread; LIBOR is the London Interbank Offer Rate; DiffVIX is first difference of the VIX; CDSSprd is the CDS spread; SPRet is the return on the S&P500.

invented by Chow and Lin (1971).

The Chow and Lin (1971) algorithm interpolates a lower-frequency time series into to a higher-frequency series with the help of another higher-frequency series. It is a popular strategy in macroeconomics to estimate monthly GDP based on quarterly GDP statistics and monthly series such as industrial added values (e.g., Groenewold & He, 2007; Jardet, 2004). The algorithm consists of a linear part and an residual part. First, for the linear part, we assume that there is a linear relation between the HW estimations and CITs' actual weekly positions. However, although CIT's actual positions at a weekly basis are unobservable, these data are known at lower frequencies from the IID report. We can therefore project the HW-estimated series onto the IID monthly series using a generalized least squares estimator, and have an estimation of the linear relation between the two series. Next, for the residual part, we relax the assumption of the strict linear relation between the HW estimations and CITs' actual weekly positions. We can thus find the best interpolation of the IID data series by additionally allocating the residuals generated in the preceding step along the linear projection in an optimal way. To achieve the optimal allocation of the residuals, we to the projection of the HW series such that the error covariance of the estimated CITs' actual positions (i.e., the rectified HW estimations) is minimized. The rectified HW estimations become consistent with the IID data while retaining the weekly structure of the original HW estimations. Details of this procedure can be found in Appendix A. We plot the corrected values in Fig. 2 with the solid line. We can see here that these estimations are more closely aligned with the IID values, although the overall pattern is similar to the original HW estimations. Both Pearson and Spearman correlation coefficients between the rectified and original values are 0.97, and the correlation coefficients do not diminish even after we keep the interpolated data points only.

Our dataset ranges from 17 January 2006 to 3 December 2013, containing 412 weekly observations. The estimations of CIT positions have been addressed above. Positions of non-reportable traders are directly obtained from the weekly COT reports. Commodity index weights are collected from the handbooks of S&P GSCI and DJ UBSCI. All other data are taken from either Datastream or CRSP. Descriptive statistics for variables used in this paper can be found in Table 2.

4. Empirical results

In this empirical section, we combine the three parts that jointly allow us to assess the impact of commodity index traders on equilibrium prices. First, we test for the impact of returns on CIT positions. Then we assess how CIT demand affects commodity returns. Finally, we analyze non-reportable trader positions.

4.1. Impact of returns on CIT positions

We begin by investigating whether CITs indeed behave like negative feedback traders. We first show results for Regressions (1–2) in Table 3.

Table 3 contain two groups of regression results, and the dependent variables are respectively CITGr_t and CITGr_{it}. In columns (1)

Table 3
Predicting CIT net long positions with commodity returns.

	CITPosGr		CITPosGr	
	(1)	(2)	(3)	(4)
$\text{ComRet}_{i,t-1}$	−0.0450***	−0.0605***	−0.0623***	−0.0962***
	(0.0084)	(0.0084)	(0.0174)	(0.0178)
CITPosGr_{t-1}	0.2053***	0.1747***		
	(0.0103)	(0.0104)		
$\text{CITPosGr}_{i,t-1}$			0.0975***	0.0981***
			(0.0117)	(0.0117)
CDSSprd_{t-1}		−0.0001***		−0.0001***
		(0.0000)		(0.0000)
DiffVIX_{t-1}		−0.0009***		−0.0016***
		(0.0002)		(0.0003)
IBRet_{t-1}		0.1556***		0.1456***
		(0.0308)		(0.0542)
LIBOR_{t-1}		−0.0014**		−0.0016
		(0.0007)		(0.0011)
TermSprd_{t-1}		−0.0005		−0.0007
		(0.0007)		(0.0012)
TEDSprd_{t-1}		−0.0014*		−0.0015
		(0.0008)		(0.0014)
SPRet_{t-1}		−0.1350***		−0.1914***
		(0.0257)		(0.0452)
R^2	0.0367	0.0602	0.0069	0.0187
Num. obs.	10705	10705	10705	10705

This table reports the results of Regressions 1 and 2 in Section 2.1.1 concerning the trading behavior of CITs. The dependent variable is CITPosGr_t for columns (1–2) and CITPosGr_{it} for columns (3–4). All regressions are estimated with contract fixed effects. Standard errors of the estimations are shown in the brackets. Significant levels: *** for 0–0.01, ** for 0.01–0.05, and * for 0.05–0.1.

and (3), we do not control the additional control variables. For these regressions, we also drop a part of observations, where there is no CIT investment. This is because some contracts are not represented by either S&P GSCI or DJ UBSCI, and, therefore, CITs do not invest in them. We do not expect CITs to adjust their positions following price changes of these contracts. Nonetheless, these dropped contracts become useful for Regression (3–4), the results for which are reported in Table 4.

The coefficients for the focal coefficient, ComRet (commodity returns), are negative, for all the four columns. This shows that CITs decrease their positions after experiencing negative returns, which is consistent with the behavior of passive investors in the model of De Long et al. (1990).

Among the control variables, only the coefficients for term spread are insignificant for both specifications (2 and 4). The remaining control variables are significant for at least one specification, which shows that the inflows and outflows of CITs have a close relation with macro market situations. This is another direct reflection of the traits of CITs as financial investors. The choice of the measure of market weights does not have a material impact on the coefficients for the control variables.

The coefficients for the CDS spread and for the differences of the VIX are significantly negative for both specifications. This is consistent with Cheng et al. (2014), implying that financial investors reallocate to less risky assets when they (think they) need to. This can also be seen from the negative coefficients for TED spreads, another indicator of perceived credit risk. The positive coefficients of IB returns are also intuitive, since higher IB returns indicate that the financial sector is doing better. The coefficient for LIBOR is significantly negative for only specification (2), but it is negative as well for specification (4) as well, though insignificant. When funding costs reflected by LIBOR are higher, it is natural that CITs hold less long open interests in commodity futures. The negative coefficients for the term spreads for specification (2) may be driven by CITs' hedge demands against inflation. Finally, the negative coefficient S&P 500 returns may reflect the inter-market money flows: institutional investors could withdraw funds from the stock market and reinvest in the commodity market, if the stock market does not perform well.

Next, we report results for Regressions (3) and 4 in Table 4. Because the contract weights in both contracts vary substantially, these tests could show CITs' behavior more clearly. In these tests, we use all the 35 contracts, as those contracts that are not covered by the indices can serve as good contrasts.

Table 4 also contains two groups of results. The first group includes the results for the regression using nominal market weights for the commodities (Regression 3) and the second group includes the results using adjusted weights (Regression 4). The main coefficients of interest are the coefficients for ComRet and the interaction terms of returns with adjusted weights. We also report results for the

Table 4
CITs are affected more by contracts of higher adjusted weights.

	$CITPosGr_t$					
	Nominal Weights			Adjusted Weights		
	(1)	(2)	(3)	(4)	(5)	(6)
$CITPosGr_{t-1}$	0.2012***	0.2015***	0.1705***	0.2009***	0.2041***	0.1734***
	(0.0088)	(0.0088)	(0.0089)	(0.0088)	(0.0089)	(0.0090)
$ComRet_{i,t-1}$	−0.0374***	−0.0337***	−0.0482***	−0.0376***	−0.0019	−0.0074
	(0.0073)	(0.0084)	(0.0084)	(0.0073)	(0.0165)	(0.0163)
$MktWt_{i,t-1}$	0.0069	0.0089	0.0115			
	(0.0281)	(0.0282)	(0.0278)			
$ComRet_{i,t-1} \times MktWt_{i,t-1}$		−0.1263	−0.1218			
		(0.1436)	(0.1419)			
$AdjWt_{i,t-1}$				0.0145	0.0171	0.0322
				(0.0199)	(0.0199)	(0.0197)
$ComRet_{i,t-1} \times AdjWt_{i,t-1}$					−0.1111**	−0.1402***
					(0.0461)	(0.0456)
$CDSSprd_{t-1}$			−0.0001***			−0.0001***
			(0.0000)			(0.0000)
$DiffVIX_{t-1}$			−0.0009***			−0.0009***
			(0.0001)			(0.0001)
$IBRet_{t-1}$			0.1542***			0.1547***
			(0.0266)			(0.0266)
$LIBOR_{t-1}$			−0.0014**			−0.0015***
			(0.0006)			(0.0006)
$TermSprd_{t-1}$			−0.0005			−0.0005
			(0.0006)			(0.0006)
$TEDSprd_{t-1}$			−0.0014**			−0.0014*
			(0.0007)			(0.0007)
$SPRet_{t-1}$			−0.1329***			−0.1361***
			(0.0222)			(0.0222)
R^2	0.0360	0.0360	0.0592	0.0360	0.0364	0.0599
Num. obs.	14350	14350	14350	14350	14350	14350

This table reports the results of Regressions 3 and 4 in Section 2.1.1 regarding the trading behavior of CITs. "Nominal Weights" and "Adjusted Weights" stand for the regressions using MktWt and AdjWt respectively. The dependent variable is $CITPosGr_t$ (CIT position growth). All regressions are estimated with contract fixed effects. Standard errors of the estimations are shown in the brackets. Significant levels: *** for 0–0.01, ** for 0.01–0.05, and * for 0.05–0.1.

regressions that do not include the interaction terms in columns (1) and (4). For columns (2) and (5), we do not include the control variables, and in columns (3) and (6), we report the results for the regressions with all the control variables.

Consistent with results in Table 3, we can see that the coefficients for ComRet in both columns (1) and (4) are significantly negative. After adding the interaction terms into the regression, the coefficients for ComRet in columns (5–6) become insignificant. However, these coefficients only reflect the impact on CIT positions of contracts with zero weights (i.e., contracts that are not part of the commodity indices). The predictive power of returns of a non-zero weighted contract is given by the sum of the coefficients for ComRet and its interaction term with the adjusted weights, and we find the sum to be always significantly negative. In the meanwhile, the coefficients for the interaction terms between ComRet and MktWt in columns (2–3) are negative but insignificant. This is caused by the inherent substitute or complement relations among the contracts, which is discussed in Section 2.1.1. This issue can be corrected for by replacing MktWt with AdjWt. In columns (5–6), we report the results for Regression (4), where we consider AdjWt instead of MktWt. We indeed find that the coefficients for the interaction term between ComRet and AdjWt become significantly negative. This shows that CITs are influenced more by those contracts that are of larger weights in the indices. This confirms our hypothesis that the CIT investors can be classified as passive investors according to the model of De Long et al. (1990).

4.2. Influences of CIT demand on commodity returns

Now that we have established that CITs indeed behave like passive investors, we turn to the second piece of the puzzle and study the impact of CITs' trades on commodity returns according to Regression (5). The results can be found in Table 5.

We can see from Table 5 that changes in CIT positions positively predict commodity futures returns in the following weeks. In line with the finding above that CITs trade like negative feedback traders, CITs are now linked to the "passive investors" hypothesized in the DSSW model that help stabilize the market. This finding remains the same after we control for the returns of some other assets in column (2). We then add the other control variables, and the coefficient for CITPosGr remains significantly positive.

Besides the impacts of CIT flows on the levels of commodity prices, results in this and the previous subsection have an interesting implication with regard to the relationship among different commodity markets as well. Considering the quite unbalanced allocation of weights across different commodity contracts, it can be expected that a price shock in the "giant" markets such as crude oil affects CIT demands far more than in the "dwarf" markets such as coffee and consequently gains much larger influences on all commodity markets. This implies that an increase in the crude oil price will be followed by a decrease in the CIT demands of other commodities measured in numbers of contracts, as CITs must re-balance their dollar positions in different markets, if the amount of their funds does not change. This effect can actually reduce the prices correlations among the intra-index commodities, serving as an interesting footnote to the empirical findings of Cheng et al. (2014).

4.3. Analysis of Non-Reportable Trader Positions

The results for the analysis of the positions of non-reportable traders can be found in Table 6. In columns (1), the significantly

Table 5
Predicting commodity returns with CIT flows.

	$ComRet_{it}$	
	(1)	(2)
$ComRet_{i,t-1}$	−0.0235***	−0.0412***
	(0.0016)	(0.0022)
$CITPosGr_{i,t-1}$	0.0129***	0.0113***
	(0.0012)	(0.0010)
$CDSSprd_{t-1}$		0.0000***
		(0.0001)
$DiffVIX_{t-1}$		−0.0012***
		(0.0002)
$IBRet_{t-1}$		0.4984***
		(0.0727)
$LIBOR_{t-1}$		0.0025***
		(0.009)
$TermSprd_{t-1}$		0.0025***
		(0.0012)
$TEDSprd_{t-1}$		−0.0032***
		(0.0002)
$SPRet_{t-1}$		−0.1640***
		(0.0184)
R^2	0.0007	0.0154
Num. obs.	10705	10705

This table reports results for Regression (5) concerning the impacts of CITs net long positions growth on commodity returns. The dependent variable is $ComRet_{it}$. All regressions are estimated with contract fixed effects. Standard errors of the estimations are shown in the brackets. Significant levels: *** for 0–0.01, ** for 0.01–0.05, and * for 0.05–0.1.

Table 6
Predicting proportions of non-reportable long open interests with commodity returns.

$PctLong_{i,t-1}$	$PctLong_{it}$	
	(1)	(2)
	0.9215***	0.9210***
	(0.0038)	(0.0039)
$ComRet_{it}$	0.1568***	0.1548***
	(0.0057)	(0.0057)
$CDSSprd_{t-1}$		−0.0001**
		(0.0000)
$DiffVIX_{t-1}$		−0.0004***
		(0.0001)
$IBRet_{t-1}$		0.0321
		(0.0223)
$LIBOR_{t-1}$		0.0000
		(0.0003)
$TermSprd_{t-1}$		0.0002
		(0.0004)
$TEDSprd_{t-1}$		−0.0003
		(0.0004)
$SPRet_{t-1}$		−0.0494***
		(0.0188)
R^2	0.8560	0.8565
Num. obs.	9880	9880

This table reports results of Regressions 6 in Section 2.2.1 regarding the trading behaviors of non-reportable traders. The dependent variable is $PctLong_{it}$ (percentage of long open interests in total open interests of non-reportable traders). All regressions are estimated with contract fixed effects. Standard errors of the estimations are shown in the brackets. Significant levels: *** for 0–0.01, ** for 0.01–0.05, and * for 0.05–0.1.

positive coefficient for ComRet indicates that non-reportable traders collectively show positive feedback trading behaviors. When price increases, these non-reportable traders will prefer longing to shorting the contract. Positive feedback traders as are defined in the DSSW model.

Table 7
Predicting commodity returns with non-reportable long proportions.

	$ComRet_{it}$			
	Full Sample		Intra-Index Sample	
	(1)	(2)	(3)	(4)
$ComRet_{i,t-1}$	−0.0257***	−0.0399***	−0.0250***	−0.0540***
	(0.0013)	(0.0024)	(0.0008)	(0.0005)
$PctLong_{i,t-1}$	−0.0037*	−0.0060**	−0.0064***	−0.0097***
	(0.0022)	(0.0024)	(0.0007)	(0.0002)
$CITPosGr_{it}$				0.0148***
				(0.0005)
$CDSSprd_{t-1}$		0.0002***		0.0001
		(0.0001)		(0.0001)
$DiffVIX_{t-1}$		−0.0014***		−0.0013***
		(0.0002)		(0.0002)
$IBRet_{t-1}$		0.3669***		0.2570***
		(0.0743)		(0.0949)
$LIBOR_{t-1}$		0.0007		0.0016***
		(0.0007)		(0.0004)
$TermSprd_{t-1}$		−0.0005		0.0008
		(0.0013)		(0.0007)
$TEDSprd_{t-1}$		−0.0025***		−0.0037***
		(0.0008)		(0.0005)
$SPRet_{t-1}$		−0.2247***		−0.1668***
		(0.0345)		(0.0376)
R^2	0.0010	0.0201	0.0010	0.0224
Num. obs.	9880	9880	7165	7165

This table reports the results in Section 2.2.2 regarding influences of non-reportable long open interests proportions on commodity returns. The dependent variable is $ComRet_{it}$ (commodity futures returns). In columns (1–2), we keep all the available observations. In columns (3–4), we drop observations of contracts that are not covered by the commodity indices. All regressions are estimated with contract fixed effects. Standard errors of the estimations are shown in the brackets. Significant levels: *** for 0–0.01, ** for 0.01–0.05, and * for 0.05–0.1.

We next add the control variables into the regression to control for the market environment. A striking difference from the results in Table 3 is that most of the coefficients of the control variables are not significant. This finding suggests that as relatively small and naive positive feedback traders, non-reportable traders care not much about the market environment. Coefficients of CDS Spread and VIX remain significantly negative, showing that non-reportable traders are sensitive to general market risk levels as well. However, they are not affected by IB returns, LIBOR, Term Spread, and TED Spread. The coefficient of S&P 500 returns is also negative, which may be a result of the inter-market capital flow. between stock markets and commodity markets.

The results of our final analysis can be found in Table 7, in which we test the impact of the non-reportable trader holdings on the commodity returns. In columns (1–2), we keep all the available observations. In columns (3–4), we drop observations of contracts that are not covered by the commodity indices such that we can additionally control $\mathrm{CITPosGr}_{i,t}-1$ (column 4). We can see that non-reportable long open interests proportions negatively predicts commodity return in all the specifications (1–4). We also add other control variables in columns (2) and (4), and the focal results do not change significantly. We also quantitatively estimate the magnitude of the prediction power of CIT inflows and non-reportable trader position ratios: using a simple strategy where an investor longs a contract when CITPosGr is smaller than its median and lagged PctLong is bigger than its median, and shorts a contract when CITPosGr is bigger than its median and lagged PctLong is smaller than its median, this investor can earns a considerable weekly return of 2.8% on average. Taking these results together with those shown in Table 6, we find that non-reportable traders' behavior as well as their price influence is consistent with the assumption of positive feedback traders in the DSSW model.

5. Conclusion

We contribute to the discussion on the destabilizing effect of the financialization of commodity markets by relating the behavior of investor groups to the predictions in the model developed in De Long et al. (1990).

Our findings show that behavior of commodity index traders resembles the model predictions for passive investors. We find that the positions of CITs tend to decrease after a positive return and that an increase in their positions positively predicts commodity returns. In contrast, we find that the results are the opposite in the case of non-reportable traders, whose behavior resembles that of positive feedback traders.

In light of the concurrence of CIT capital flows and commodity price trends, it has been suggested that it was the CITs that destabilized the markets. It is helpful to test CITs' impacts by using CIT dollar positions to predict commodity returns. However, because of the sophistication of the market, even though CIT positions positively predict commodity prices, one may still be at risk of jumping to the conclusion that CITs are the ones to blame, especially if one fails to fully understand the determination of CITs' behaviors. In fact, based on our findings, we may call CITs a stabilizing power due to their negative feedback strategies. However, they are still a necessary condition for others to destabilize the markets. Furthermore, positive feedback traders do not either destabilize the markets by themselves. Rather, the destabilized price pattern is a collaboration of all the three classes of traders, none of which is dispensable. In light of policy recommendations, we believe that regulators should try to discourage the positive-feedback trading of the non-reportable traders, e.g., by raising the market threshold. Although index traders are necessary to the destabilization of commodity prices as well, they still offer a very useful investing instrument to the public, whereas restrictions on non-reportable traders are likely to affect less traders.

Author statement

Hang Sun: Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing - Review & Editing, Visualization, Funding acquisition. Jaap W. B. Bos: Conceptualization, Resources, Writing - Review & Editing, Supervision, Project administration. Paulo Rodrigues: Methodology, Writing - Review & Editing.

APPENDIX

Rectifying the HW Estimation with IID Reported Positions

Using the methodology of Chow and Lin (1971), we rectify the HW estimation of CIT positions in all futures markets with IID reported positions in the following way.

Let $y = \{y_t\}_{t=1}^{T}$ represent the true weekly positions of CITs, and $x = \{x_t\}_{t=1}^{T}$ be the original HW estimations. We want to estimate the linear model

$$y = x\beta + u, \tag{9}$$

Where $u = \{u_t\}_{t=1}^{T}$ is a covariance-stationary process uncorrelated with x with zero mean and a covariance matrix V, and β is regression coefficients.

However, not all y_t in y can be observed, and, therefore, Regression 9 cannot be estimated. However, we can observe is a series at a monthly frequency, y^*, which is released in the IID report. Denote the transformation matrix as C such that $y^* = Cy$. Premultiplying eq. (9) by C, we obtain

$$y^* = Cx\beta + Cu = x^*\beta + u^*, \tag{10}$$

where $x^* = Cx$ and $u^* = Cu$.

Regression (10) can be estimated with generalized least squares. The estimation of β is

$$\widehat{\beta} = \left[(x^*)'(V^{**})^{-1}x^*\right]^{-1}(x^*)'(V^{**})^{-1}y^*, \tag{11}$$

where

$$V^{**} = \mathrm{E}[u^*(u^*)'] = CVC'. \tag{12}$$

However, in eq. (12), V is still unknown thus far. We also have the estimation of $\widehat{u}^* = y^* - x^*\widehat{\beta}$. With β and u^*, we can obtain the estimation of CITs' actual positions y. The best linear unbiased estimator of y is

$$\widehat{y} = x\widehat{\beta} + \left[V^{\cdot *}(V^{**})^{-1}\right]\widehat{u}^*, \tag{13}$$

where

$$V^{\cdot *} = \mathrm{E}[u(u^*)'] = VC'. \tag{14}$$

We can see from eq. (13) that $\widehat{y}$ depends on the last remaining unknown parameter V. To estimate V, we assume u is a AR(1) process, following

$$u_t = au_{t-1} + \varepsilon_t, \tag{15}$$

Where a is the autoregressive coefficient, and ε_t is a white noise series with $\mathrm{E}[\varepsilon_t\varepsilon_s] = \delta_{ts}\sigma$.[2] Then the autocovariance of u_t is

$$V = \mathrm{E}[uu'] = \begin{pmatrix} 1 & a & a^2 & \cdots & a^{T-1} \\ a & 1 & a & \cdots & a^{T-2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a^{T-1} & a^{T-2} & a^{T-3} & \cdots & 1 \end{pmatrix} \frac{\sigma^2}{1-a^2} \triangleq A\frac{\sigma^2}{1-a^2}, \tag{16}$$

Where a and σ are unknown. With A, we have

$$V^{\cdot *}(V^{**})^{-1} = VC'(CVC')^{-1} = AC'(CAC')^{-1}. \tag{17}$$

However, by examining eqs. (13) and (17), we can notice that $\widehat{y}$ does not depends on σ, and we need to estimate only a. To estimate a, we notice that eq. (15) implies that

$$u^* = au^* + C\varepsilon_t. \tag{18}$$

Therefore, we can first choose an initial value of a, computes $\widehat{u}^*$ with a, and then updates a based on $\widehat{u}^*$. We can obtain a consistent estimate of a by iterating this step until convergence. After a is estimated, $\widehat{y}$ is obtained.

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