Does Trading Behaviour Converge across Commodity Markets? Evidence from a Hedgers' Sentiment Perspective

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Abstract: This paper analyses the connectedness network for commercial traders' sentiment across agriculture, energy, metals and livestock futures markets. The findings find that: (a) producer/merchant/processor/user (PMPU) in agricultural and energy markets are mainly engaged in cross-hedging in the futures market, and most of them would avoid risks in these markets by operating in the metal markets, which can be considered safe for PMPU traders, and that the cross-hedging strategies may play the role of PMPU sentiment spillover across futures markets; (b) as index traders, the swap dealers operate more in two markets, namely between the agricultural and metal markets, or between the agricultural and energy markets; (c) the influence of geopolitical risks in some countries can affect the stability of energy markets, which in turn can cause PMPU system-wide connectedness.

Keywords: Investor sentiment, commodity market, connectedness, spillover effect

1. Introduction

Since the creation of the Commodity Futures Trading Commission (CFTC) in the 1970s, academics and practitioners have used the data on traders' open positions reported in Commitments of Traders (COT) reports to analyse the stability and functioning of futures and options markets in the United States. COT reports categorize

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the open interest data into non-reporting (small) and reporting (large) traders, where the reporting traders are also split into commercials (hedgers) or non-commercials (speculators). The past 20 years have seen a number of significant changes regarding new types of market traders and new trading strategies. Some new traders' categories have entered futures markets, and today they hold a significant share of open positions in futures markets. Meanwhile, over the past decade, the open interest in many commodities futures rose dramatically, and the composition of participants in these markets has also changed dramatically. In response to requests for more transparency in COT weekly data, the CFTC created a new report called the Disaggregated Commitments of Traders (DCOT) report. The DCOT reports breakdown the data further by separating traders on futures markets into 4 categories: producer/merchant/processor/user (PMPU), which includes traders engaged in production, processing, packing, or handling of a physical commodity and uses futures markets to manage or hedge risks associated with those activities; swap dealer (SD) which includes commodity index traders in the majority of markets; money manager, which represents hedge funds traders; and other reportable, which includes every other reportable trader that is not placed into one of the other 3 categories.

As defined in the DCOT explanatory notes, commercial traders are not only PMPU traders engaging in the production, packing, processing or handling of a physical commodity and using futures markets for managing or hedging risks associated with those activities, but this category of traders also includes swap dealers' traders with no commercial interest in the physical commodities. According to Sanders and Irwin (2011), given that an important number of the commodity index-based investment is delivered through swaps in a variety of markets, including metals and energy futures markets, the positions held by this category of traders is assumed to reflect index-type investments. From the definition, we can say that, by using index trading activity, swap dealers can link a number of markets since index trade is based on a benchmark or an index which includes different assets. Hence, we can also expect that swap dealers in futures markets can create cross-market linkages through their sentiment dynamics[1].

This study will concentrate on the cross-market linkages that can be created through commercial traders' sentiment. The analysis on the trading sentiment connectedness across commodity markets can provide detail understanding for the trader behaviour compared to the price data. Furthermore, it would help us grasp the differences of the strategies for different traders when they make trading across commodity markets.

This study seeks to contribute to the literature by understanding the linkages in commodities futures markets by analysing the sentiment dynamics across commercial traders. The trading categories proposed by the CFTC in their DCOT reports for a set of 21 futures contracts can be grouped into 4 sectors – agricultural, energy, metal and livestock – traded over the period of 2 September 2008 to 27 December 2016. For this purpose, the method of measuring connectedness proposed by Diebold and Yilmaz (2009, 2012, 2014) is used to study the commercial traders' sentiment spillover across different futures markets. This method has been widely used to study systems in many areas of the economy, which can not only capture the static information spillover of trader sentiments across commodity market, but also exhibit the magnitude and dynamic information connectedness of trader sentiments across commodities (Ji et al., 2018b, 2019a,b; Luo and Ji, 2018; Ma et al., 2019a; Xia et al., 2019; Zhang et al., 2018). In this paper, we will use this method to measure and analyse the connectedness network for commercial traders' sentiment in commodity futures markets. We will

[1] This study will concentrate on the cross-market linkages that can be created through commercial traders' sentiment. However, in addition to the role that hedgers can play to link futures markets, others research on cross-market linkages deal with the importance of the role that speculators can also play to link futures markets (See Röthig, 2012; Röthig and Röthig, 2014). For this reason, we also tested the connectedness over futures markets based on the sentiment dynamics across non-commercial traders. The results show that the total connectedness of the system containing the sentiment indices of the money managers is also high and the different of money managers across commodity markets interact more with each other. In general, the main purpose of a money manager is to make speculative trades, and the energy market is used more as the intermediate market to avoid risks in the metal and agricultural markets. Meanwhile, the sentiments of other reportable traders is relatively dispersed across various commodities and do not have obvious clustering characteristics. More detailed results and discussions from the full-sample (static) analysis and rolling-sample (dynamic) analysis of connectedness for the "Money manager: MM" and "Other reportable: Oth" sentiments are reported in the Appendix.

focus on connectedness at a variety of levels, from pairwise connectedness for hedgers' sentiment across individual futures commodities and different futures sectors to the total connectedness among hedgers' sentiment system-wide and from the static connectedness that measures the unconditional average of connectedness over the full sample to the dynamic that represents the conditional connectedness and its movements during a particular period. Thus, there are main three contributions in this study. Firstly, we investigate the trader behaviour connectedness from the investor sentiment perspective. Secondly, the connectedness network used in this study can directly present the integration and linkage of the sentiment across commodity markets, and furthermore exhibit the time varying characteristics of the sentiment integration across commodity markets. Thirdly, the differences for the sentiment of different traders across commodity markets are compared, thus providing the deep understanding for the strategies of different traders.

We proceed as follows. In section 2, we discuss the construction of our investor sentiment measure by hedgers' category and introduce the connectedness method proposed by Diebold and Yilmaz (2014) to investigate hedgers' sentiment spillover across commodity markets. In section 3, we propose the data description and the summary statistics. In section 4, we provide results for the static and dynamic information spillover effect, and we conclude in section 5.

2. Literature review

Traditionally, linkages between different commodity futures markets were analysed using price data (Zhang and Broadstock, 2018). More recently, however, some authors in the literature have also considered open interest data for the different categories of traders in futures markets as an important source of information.

The majority of the literature focuses on the effect of open interest by traders' category on the price dynamics[2] . For example, Wang (2002), uses the trading demand, defined as the difference between the long open interest and the short open interest, to explore the relationship between the trading demand by the traders' type and the futures market index on S&P 500. Sanders et al. (2004) investigate the relationships between trader positions and market prices for crude oil, unleaded gasoline, heating oil, and natural gas futures contracts using the Commodity Futures Trading Commission (CFTC)'s Commitments of Traders (COT) data. Recently, some studies have employed open interest data on traders' category to analyse linkages between different futures markets. Research on cross-market linkages is concerned with cross-hedging that may arise when an agent tries to hedge a spot position for a specific asset with the respective futures market or when a futures contract may be affected because of information spillover[3] . Fleming et al. (1998), present a model that helps to identify how information creates cross-market linkages. In this model, the authors propose two distinct sources that can generate linkages across markets. According to this model, cross-hedging represents an important source of information and may play the role of a channel of information spillover if a hedger uses an asset to hedge his position in another asset affected by new information. Additionally, linkages can arise from information that simultaneously affects expectations in more than one market. According to Röthig and Röthig (2014), hedgers can link different markets. For instance, hedgers can hedge a spot position for a specific asset with the respective futures contract, and this will result in trading activity in both markets (spot and futures). In this type of hedging, only one asset type is used (some hedging strategies are based on several asset classes). These hedging strategies are labelled cross-hedging strategies where a trader uses the position in one asset to hedge risk in a position taken in different assets. Ji et al. (2019c) investigate the different role of various trader positions in influencing WTI returns. They find that speculator positions have the largest contribution to WTI returns variation. Ma et al. (2019b) introduce speculator positions into financial predictor and find its effectiveness on oil volatility forecasting.

Some scholars investigate the behaviour of the commercial traders. Fishe and Smith (2012) suggest that commercial traders (including natural hedgers such as producers, merchants and processors) are relatively less informed. Cheng and Xiong (2014) demonstrate that hedgers (and more precisely the producer/merchant/processor/user category) in wheat, corn, soybeans and cotton appear to engage not only in production but also in complex trading activities traditionally viewed as the province of financial firms, and they participate in significant non-output-related trading. Bahloul and Bouri (2016a) demonstrate that hedgers behave irrationally and overreact to information, which means they may trade because of both fundamental and non-fundamental factors. Bahloul and Bouri (2016b) also illustrate that the PMPU category in 13 major futures markets behaves like irrational traders. Based on this, we can expect that when PMPU traders use futures markets for speculation or for applying cross-hedging strategies, and given that they may be less informed and trade as irrational traders, they can create market linkages across futures commodities through their sentiment dynamics in different markets.

3. Methodology

In this section, we first measure investor sentiment by traders' types and then introduce a connectedness framework proposed by Diebold and Yilmaz (2014) to investigate investor sentiment spillover across commodity markets.

3.1 Investor sentiment measure

Baker and Wurgler (2006, 2007) define investor sentiment as the measure of investors' beliefs about future asset prices and risks. Therefore, sentiment reflects the degree of investor optimism or pessimism about the market in general. In his illuminative article, Briese (1990) illustrates that we can use data on open interest coming from the CFTC's COT reports to construct a sentiment index which can help to understand the trend changes in the sugar market. Based on the open interest data published in the COT reports, Wang (2001) proposed a measure for sentiment by traders' category in commodity futures markets. Tornell and Yuan (2012) indicate that such a sentiment measure largely reflects the investors' belief in the degree of bearishness or bullishness of the markets and provides a more intuitive reading of traders' actions than the number of short or long contracts.

In this paper, we follow Bahloul (2018) to construct a sentiment index for the two categories of commercials traders (PMPU and swap dealers) proposed by the CFTC

DCOT reports. Based on data provided in these reports, the sentiment index for each contract for traders' type *i* at week *t*, $SI_t^i(l)$ can be calculated as follow:

$$SI_t^i(l) = \frac{NP_t^i - NP_{t,l}^{i,\min}}{NP_{t,l}^{i,\max} - NP_{t,l}^{i,\min}} \tag{1}$$

Where $NP_{t,l}^{i,\max} = \max\left\{NP_{t-l}^i, NP_{t-l+1}^i, ..., NP_t^i\right\}$ represents the maximum of the net positions of trader type *i* over the most recent periods *l* prior to the current observation, and $NP_{t,l}^{i,\min} = \min\left\{NP_{t-l}^i, NP_{t-l+1}^i, ..., NP_t^i\right\}$ represents the minimum of the net positions of trader type *i* over the most recent periods *l* prior to the current observation. Given that historical data for the DCOT report are available back to 13 June 2006 and to get a weekly observation of the data sample, the conventional period selection for the lookback (*l*) is 1 year which is equal to 52 on a weekly basis.

3.2 Connectedness network modelling

Diebold and Yilmaz (2014) proposed a new connectedness framework based on a vector autoregressive model (VAR) and the generalized forecasting variance decomposition method. Due to its simplicity and flexibility, Diebold and Yilmaz's (2014) connectedness measure has been widely applied in information spillover and systemic risk (Diebold and Yilmaz, 2016; Zhang, 2017; Ji et al., 2018). The detailed modelling procedure is as follows.

First, a VAR model with a *p* lagged number is constructed:

$$R_t^m = \sum_{i=1}^{p} \Phi_i^m R_{t-i}^m + \varepsilon_t^m \tag{2}$$

where R_t^m is the vector of investor sentiment for traders' type *m* (*m* = producer/merchant/processor/user and swap dealer, respectively). Φ_i^m is the autoregressive coefficient matrix, and ε_t^m is the vector of error terms that are assumed to be serially uncorrelated. Given a stationary covariance of the VAR system, a moving average representation is written as $R_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$, where $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \ldots + \Phi_p A_{j-p}$. A_0 is the $n \times n$ identity matrix and $A_j = 0$

for $j < 0$.

Koop et al. (1996) and Pesaran and Shin (1998) proposed the following H-step ahead generalized forecast-error variance decomposition:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)}, \tag{3}$$

where $\theta_{ij}(H)$ is the variance contribution of the variable j to variable i. Σ is the variance matrix of the vector of errors ε, and σ_{jj} is the standard deviation of the error term of the j^{th} equation. Finally, e_i is a selection vector with a value of 1 for the i^{th} element, and 0 otherwise. The spillover index yields an $n \times n$ matrix $\theta(H) = \left[\theta_{ij}(H)\right]$, where each entry gives the contribution of variable j to the forecast-error variance of variable i. Own-variable and cross-variable contributions are contained in the main diagonal and off-diagonal elements, respectively, of the $\theta(H)$ matrix. Each entry in the $\theta(H)$ matrix is normalized by the row sum to make sure the row sum is equal to one. Then, employing the generalized forecast-error variance decomposition (FEVD) approach, we can construct net pairwise connectedness, directional connectedness and total connectedness.

3.2.1 Net pairwise connectedness

In general, there is an asymmetric effect between two variables according to the definition of FEVD. So, the difference between θ_{ij} and θ_{ji} can be measured as the net pairwise connectedness. $\theta_{ij} - \theta_{ji}$ can measure the net spillover effect from variable j to variable i. Subsequently, a directional connectedness network can be further built based on net pairwise connectedness. In this network, each market is set as a node and the condition in which a directional edge from i to j exists in the network if $\theta_{ji} - \theta_{ij} > 0$.

3.2.2 Total directional connectedness "From" and "To"

We use total directional connectedness "From" and "To" to measure the total information spillover from and to each market. Total directional connectedness "From" $C_{i\leftarrow\bullet}$ is defined as the information inflow from other markets to one market, while total directional connectedness "To" $C_{\bullet\leftarrow i}$ is defined as the information outflow from one market to other markets.

$$C_{i\leftarrow\bullet} = \sum\nolimits_{j=1}^{N} \theta_{ij},\ j \neq i \tag{4}$$

$$C_{\bullet\leftarrow i} = \sum\nolimits_{j=1}^{N} \theta_{ji}, i \neq j \tag{5}$$

3.2.3 Net total directional connectedness

The net total connectedness measures the net information spillover contribution by the difference between total directional connectedness "To" and "From" of one market.

$$C_i = C_{\bullet\leftarrow i} - C_{i\leftarrow\bullet} \tag{6}$$

3.2.4 Total connectedness for the system

Finally, the sum of total directional connectedness "From" or "To" for all the variables is defined as the total connectedness of the system, which is a good indicator to measure market integration and convergence.

$$Total = \frac{1}{N}\sum\nolimits_{i,j=1}^{N} \theta_{ij}, i \neq j \tag{7}$$

3.3 Data description and summary statistics

The primary sources of data on traders' positions used in this study were collected from the DCOT reports published by the CFTC since 4 September 4 2009. The DCOT report separates commercials traders, traditionally labelled hedgers, into two principal categories which are producer/merchant/processor/user and swap dealer. Open interest positions of market participants reported in the DCOT report are published every Tuesday, and historical data are available back to 13 June 2006 for some futures commodities and from 04 September 2007 for others. Based on the available historical data and given that the investor sentiment measure calculation is based on a 52-week lookback period, our sample ranges from 2 September 2008 to 27 December 2016 (435 observations). The sample contains data on hedgers' positions collected from 21 futures markets that include 11 agricultural (cocoa, coffee, corn, cotton, orange juice, soybean meal, soybean oil, soybean, sugar no. 11, wheat and Kansas wheat), 4 energy (light sweet crude oil, gasoline, heating oil no. 2 and natural gas), 4 metal (gold, palladium, platinum and silver) and 2 livestock (lean hogs and live cattle). Table 1 reports mean and standard deviations on sentiment by hedgers' type and reports the correlation between sentiments by type of traders in the 21 futures markets.

Table 1
Summary statistics of investor sentiment in each commodity market.

Commodity	Type	Sentiment Mean		Sentiment Std. dev		Correlation
		PM	SD	PM	SD	PM, SD
Cocoa	Agricultural	0.518	0.525	0.331	0.297	−0.417
Coffee	Agricultural	0.530	0.490	0.350	0.373	−0.153
Corn	Agricultural	0.575	0.471	0.320	0.355	−0.066
Cotton	Agricultural	0.493	0.474	0.349	0.346	−0.608
Orange juice	Agricultural	0.519	0.322	0.320	0.281	0.327
Soybean meal	Agricultural	0.489	0.576	0.315	0.329	−0.387
Soybean oil	Agricultural	0.493	0.484	0.335	0.310	−0.400
Soybean	Agricultural	0.511	0.522	0.330	0.365	−0.299
Sugar	Agricultural	0.547	0.525	0.321	0.358	−0.200
Wheat	Agricultural	0.605	0.377	0.324	0.328	−0.369
K. Wheat	Agricultural	0.547	0.514	0.318	0.342	−0.173
Crude oil	Energy	0.438	0.479	0.376	0.351	−0.503
Gasoline	Energy	0.453	0.590	0.283	0.343	−0.172
Heating oil	Energy	0.436	0.590	0.309	0.347	−0.436
Natural gas	Energy	0.499	0.526	0.334	0.352	−0.254
Gold	Metal	0.486	0.486	0.327	0.322	0.214
Palladium	Metal	0.559	0.465	0.342	0.340	0.233
Platinum	Metal	0.432	0.483	0.305	0.324	0.556
Silver	Metal	0.557	0.492	0.310	0.322	0.645
Lean hogs	Livestock	0.514	0.493	0.339	0.339	−0.486
Live cattle	Livestock	0.561	0.349	0.352	0.319	−0.525

Note: PM denotes Producer/Merchant/Processor/User and SD denotes swap dealer.

4. Empirical results

This section mainly analyses the trading behaviour convergence across commodity markets for different categories of commercials traders. The hedgers category is mainly divided into two categories: producer/merchant/processor/user and swap dealer traders. This paper mainly analyses the static and dynamic information spillover effect across the commodity markets for the sentiment indices in the two categories of commercial traders.

Table 2
Full-sample connectedness matrix for Producer/Merchant/Processor/User sentiment of in commodity futures markets.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	From
1	0.665	0.017	0.005	0.005	0.000	0.003	0.003	0.036	0.005	0.074	0.033	0.003	0.033	0.049	0.016	0.007	0.019	0.017	0.003	0.005	0.000	**0.335**
2	0.042	0.627	0.007	0.003	0.014	0.016	0.026	0.027	0.006	0.006	0.018	0.005	0.007	0.001	0.007	0.035	0.003	0.011	0.021	0.032	0.086	**0.373**
3	0.026	0.061	0.273	0.012	0.045	0.023	0.034	0.103	0.013	0.145	0.099	0.001	0.042	0.021	0.031	0.010	0.024	0.007	0.001	0.012	0.018	**0.727**
4	0.001	0.002	0.026	0.504	0.002	0.093	0.006	0.075	0.001	0.035	0.005	0.001	0.046	0.066	0.023	0.009	0.032	0.001	0.062	0.001	0.009	**0.496**
5	0.026	0.027	0.029	0.005	0.529	0.023	0.015	0.093	0.001	0.008	0.031	0.006	0.018	0.019	0.074	0.015	0.009	0.050	0.002	0.001	0.018	**0.471**
6	0.008	0.067	0.014	0.059	0.007	0.447	0.019	0.198	0.009	0.019	0.008	0.033	0.018	0.017	0.008	0.012	0.012	0.017	0.014	0.005	0.011	**0.553**
7	0.005	0.104	0.028	0.019	0.006	0.018	0.396	0.029	0.054	0.067	0.049	0.024	0.030	0.015	0.004	0.005	0.016	0.022	0.042	0.001	0.065	**0.604**
8	0.009	0.022	0.036	0.009	0.011	0.107	0.088	0.480	0.047	0.019	0.028	0.001	0.037	0.014	0.009	0.001	0.008	0.006	0.037	0.011	0.019	**0.520**
9	0.002	0.038	0.003	0.038	0.021	0.004	0.037	0.079	0.579	0.011	0.011	0.008	0.020	0.005	0.003	0.008	0.016	0.021	0.022	0.072	0.002	**0.421**
10	0.004	0.052	0.064	0.004	0.060	0.014	0.051	0.067	0.001	0.424	0.139	0.002	0.024	0.005	0.008	0.004	0.017	0.010	0.003	0.005	0.042	**0.576**
11	0.002	0.074	0.025	0.022	0.000	0.033	0.010	0.081	0.004	0.153	0.443	0.001	0.031	0.022	0.030	0.024	0.004	0.005	0.009	0.009	0.017	**0.557**
12	0.022	0.003	0.000	0.028	0.021	0.000	0.003	0.014	0.001	0.001	0.001	0.749	0.020	0.011	0.032	0.069	0.002	0.004	0.002	0.014	0.000	**0.251**
13	0.006	0.005	0.043	0.007	0.009	0.014	0.066	0.006	0.004	0.004	0.026	0.002	0.606	0.125	0.005	0.013	0.010	0.011	0.016	0.016	0.004	**0.394**
14	0.009	0.007	0.003	0.012	0.005	0.007	0.032	0.006	0.001	0.010	0.019	0.038	0.158	0.528	0.016	0.012	0.017	0.019	0.064	0.009	0.028	**0.472**
15	0.019	0.015	0.014	0.008	0.013	0.028	0.003	0.041	0.000	0.016	0.099	0.004	0.004	0.009	0.563	0.047	0.065	0.036	0.011	0.000	0.007	**0.437**
16	0.004	0.006	0.000	0.023	0.003	0.024	0.011	0.016	0.014	0.005	0.075	0.035	0.006	0.002	0.028	0.465	0.060	0.050	0.147	0.021	0.006	**0.535**
17	0.001	0.018	0.003	0.079	0.051	0.035	0.018	0.011	0.004	0.008	0.066	0.020	0.041	0.024	0.018	0.090	0.324	0.097	0.076	0.006	0.011	**0.676**
18	0.004	0.015	0.010	0.002	0.011	0.010	0.008	0.035	0.012	0.003	0.088	0.010	0.158	0.066	0.012	0.075	0.051	0.323	0.089	0.016	0.001	**0.677**
19	0.002	0.004	0.003	0.012	0.005	0.006	0.011	0.007	0.007	0.002	0.039	0.015	0.085	0.046	0.003	0.147	0.029	0.040	0.487	0.045	0.003	**0.513**
20	0.045	0.036	0.002	0.001	0.001	0.004	0.005	0.031	0.003	0.018	0.001	0.003	0.011	0.017	0.062	0.014	0.009	0.020	0.045	0.601	0.071	**0.399**
21	0.001	0.024	0.003	0.032	0.003	0.029	0.006	0.012	0.000	0.019	0.025	0.015	0.013	0.010	0.003	0.027	0.058	0.017	0.074	0.100	0.529	**0.471**
To	**0.238**	**0.597**	**0.318**	**0.381**	**0.289**	**0.491**	**0.451**	**0.970**	**0.190**	**0.623**	**0.859**	**0.226**	**0.801**	**0.544**	**0.393**	**0.625**	**0.462**	**0.461**	**0.739**	**0.381**	**0.418**	**Total = 0.498**
Net	**-0.097**	**0.225**	**-0.409**	**-0.115**	**-0.182**	**-0.063**	**-0.153**	**0.451**	**-0.231**	**0.047**	**0.302**	**-0.025**	**0.407**	**0.072**	**-0.044**	**0.090**	**-0.214**	**-0.215**	**0.226**	**-0.017**	**-0.053**	

Note: each number denotes investor sentiment in one selected commodity market (1 = cocoa, 2 = coffee, 3 = corn, 4 = cotton, 5 = orange juice, 6 = soybean meal, 7 = soybean oil, 8 = soybean, 9 = sugar, 10 = wheat, 11 = K. wheat, 12 = crude oil, 13 = gasoline, 14 = heating oil, 15 = natural gas, 16 = gold, 17 = palladium, 18 = platinum, 19 = silver, 20 = lean hogs, 21 = live cattle). This table presents the estimated contribution to the variance of the 20-day forecast variance error of i coming from innovations to variable j. The diagonal elements ($i = j$) are the own variance shares estimates, which show the fraction of the forecast-error variance of market i from its own shocks. The last column 'From' shows the total spillovers received by a particular market from all other markets, whereas the row 'To' shows the spillover effect from a particular market on all other markets. The row 'Net' indicates the gap between 'From' and 'To', measuring the total net directional spillover for each market.

4.1 Static analysis of connectedness network for investor sentiment by traders' types

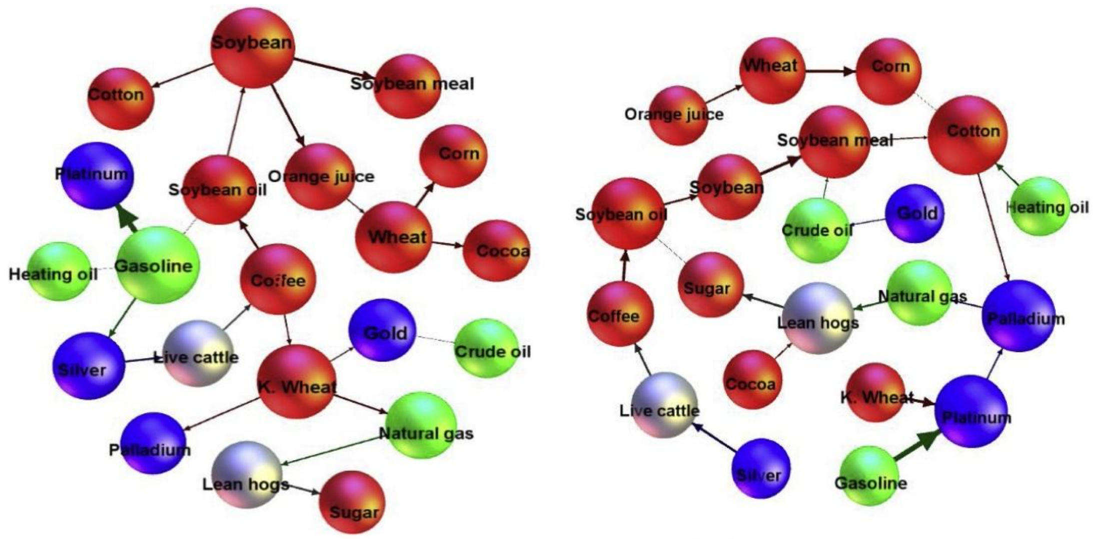
4.1.1 Full-sample connectedness analysis for producer/merchant/processor/user sentiment

First, the static connectedness of the sentiment indices of the PMPU across the commodity markets for the full sample is estimated using the VAR model and the generalized variance decomposition model. Table 2 shows the full-sample connectedness matrix for PMPU sentiment in commodity futures markets. The total connectedness of the system containing the sentiment indices of the PMPU across the commodity futures markets is 49.8%, which indicates that the integration of the PMPU sentiment indices across the commodity futures markets is high and the different PMPUs across different commodity markets interact more with each other.

By comparing "From" and "To" in each futures market, the results showed that the sentiments for soybean (0.970), K. wheat (0.859), gasoline (0.801), silver (0.739), gold (0.625), wheat (0.623), coffee (0.597), heating oil (0.544), palladium (0.462) and platinum (0.461) have a relatively large contribution to the system. At the same time, the results showed that the sentiments for corn (0.727), platinum (0.677), palladium (0.676), soybean oil (0.604), wheat (0.576), K. wheat (0.557), wheat meal (0.553), gold (0.535) and silver (0.513) gain more information in the system. These mainly belong to the sentiment indices in agricultural and metal markets. In other words, the sentiments of the PMPU in agricultural and metal markets play an important role in connecting the system and are critical for information spillover within the system.

Next, the net connectedness in the analysis of the PMPU sentiment across various commodities was investigated. The sentiment indices of soybean (0.451), gasoline (0.407), K. wheat (0.302), silver (0.226) and coffee (0.225) are the net information transmitters that have a large net positive contribution to the system. The sentiment indices of corn (-0.409), sugar (-0.231), platinum (-0.215), palladium (-0.214), orange juice (-0.182) and soybean oil (-0.153) are the net information receivers. The PMPU sentiment for soybean is the largest net information transmitter with the largest positive contribution to the system, while the PMPU sentiment of corn is the largest net information receiver in the system.

Figure 1 shows the directional connectedness network based on net pairwise connectedness for PMPU sentiment across commodity markets, and each node represents the sentiment of PMPU in each commodity market. Each node's in-degree is 1, which only reflects the maximum information inflow from other nodes in Figure 1 (a). When each node's out-degree is 1, it only reflects the maximum information outflow from each node to other nodes in Figure 1 (b). In Figure 1 (a), the sentiment for soybean in the agricultural market has the largest direct impact on the other commodities in the agricultural market, while the sentiment for K. wheat in the agricultural market has the largest direct impact on the majority of the commodities in the metal market. The energy market also has the largest direct influence on most of the commodities in the metal market, and the energy and metal markets have the largest direct influence on the livestock market.



(a) Directional connectedness network (in) (b) Directional connectedness network (out)

Fig. 1. Directional connectedness network based on net pairwise connectedness for PMPU sentiment.

In Figure 1 (b), the sentiments for the commodities in the agricultural market are mainly influenced by themselves, and the sentiments for coffee and sugar are influenced by the sentiment in the livestock market. The sentiment in the metal market is most directly affected by the sentiment for refined oil in the energy market and the sentiments in the agricultural market, while the sentiment for primary energy is most directly affected by the sentiment for the metal market. The sentiment for the livestock market is directly influenced by the sentiments for the agricultural, metals and energy commodity markets. Generally, the sentiments in the agricultural market and the sentiment for gasoline in energy market have the most direct influence on the metal market. And the sentiments in the agricultural, energy and metal markets have the biggest direct influence on the livestock market. The results also show that the sentiments move from the agricultural and energy markets to the metal and livestock markets.

Figure 2 shows the centrality connectedness network for PMPU sentiment, which is based on total pairwise connectedness (the sum of two directional pairwise connectedness $\theta_{ji} + \theta_{ij}$). It can be clearly seen that PMPU sentiments of different types of commodities present obvious clustering characteristics, and the internal connection of the sentiments for the same type of commodities is relatively close. Further, we can see that the sentiment indices in the livestock market is closely related to the sentiment indices in the agricultural market. Further, the sentiment indices in the agricultural market are closely related to the sentiment indices in metal and livestock markets. The sentiment indices in the energy market are closely related to the metal market, while the sentiment indices for the natural gas in the energy market is strongly related to the sentiment indices for K. wheat in the agricultural market.

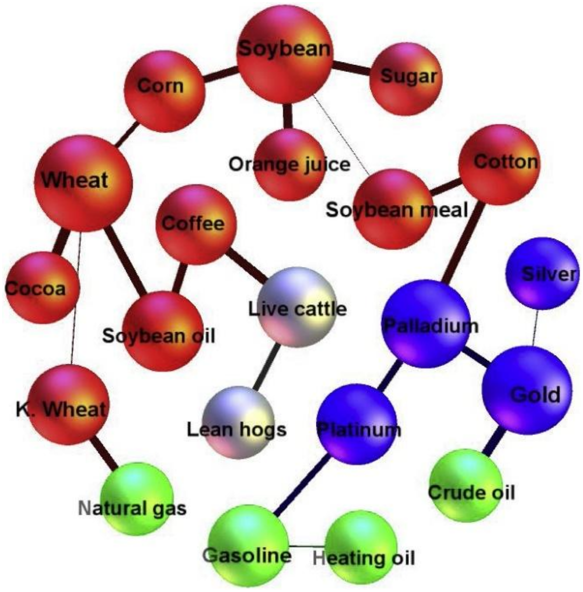


Fig. 2. Centrality connectedness network for PMPU sentiment.

(Note: this figure is based on total pairwise connectedness (the sum of two directional pairwise connectedness $\theta_{ji}+\theta_{ij}$). For simplicity and visualization, we employ Prim's (1957) minimal spanning tree algorithm. Then Fig. 2 only retains 21−1 = 20 links with the closest (maximum) connectedness.).

To conclude, the result of the total connectedness shows that for PMPU, the investment portfolio is more likely to be among the agricultural, metal and livestock markets, or between the energy and metal markets, and the sentiments in the agricultural market is relatively unrelated to the sentiments in the energy market. This result confirms the obtained results from the pairwise connectedness where we find that the PMPU sentiments move from the agricultural and energy markets to the metal and livestock markets. Additionally, the result from net connectedness confirms that sentiments in the agricultural market have the largest direct impact on the majority of the commodities in the metal market and that the energy market also has the largest direct influence on most of the commodities in the metal market.

In general, the sentiments move from the agricultural and energy markets to the metal and livestock markets. As explained by Li and Lucey (2017), the 4 precious metals (gold, silver, platinum and palladium) can be seen as safe havens, and portfolios that contain precious metals perform better than portfolios that do not. Sakemoto (2018) also found that precious metals, and more precisely gold and silver, act as hedges and safe havens for all currency portfolios. Therefore, one possible explanation of the obtained result is that as commercial traders, PMPUs in agricultural and energy markets are mainly engaged in cross-hedging in the futures market, and most of them would avoid risks in these markets by operating in the metal market. In such cases, cross-hedging in the metal markets represents an important source of information and is a channel of sentiment spillover when PMPUs in the agricultural and energy markets use the metal markets to hedge their positions. Hence, linkages can arise from information that simultaneously affects expectations in more than one market.

4.1.2 Full-sample connectedness analysis for swap dealer sentiment

Table 3 shows the connectedness matrix of the swap dealers. The total connectedness of the system containing the sentiment indices of the swap dealers across the commodity markets is 44.5%, which indicates that the integration of swap dealers' sentiment across various commodity markets is high and the different swap dealers in different commodity markets interact more with each other.

Generally speaking, when comparing *"From"* and *"To"* in each market, the sentiment indices in the metal market contribute more to the system. It is worth noting that the sentiment indices for the most of commodities in the energy market contribute least to the system, while the sentiment for crude oil contributes more to the system, reaching 0.639. In the agricultural market, the sentiment indices for wheat, K. wheat,

Table 3
Full-sample connectedness matrix for swap dealer sentiment in commodity futures markets.

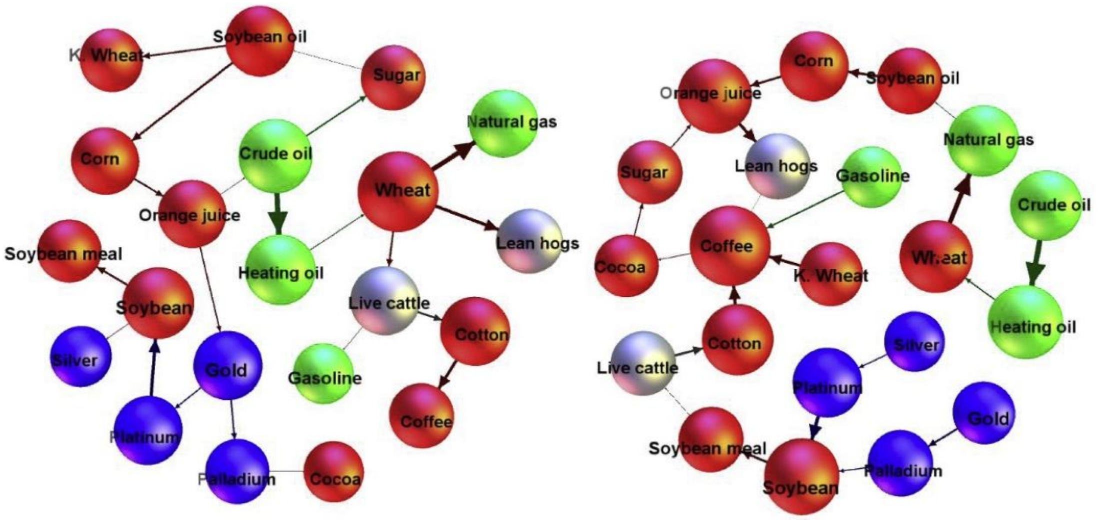
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	From
1	0.717	0.032	0.007	0.002	0.027	0.001	0.003	0.004	0.015	0.047	0.009	0.007	0.001	0.001	0.023	0.012	0.035	0.000	0.046	0.006	0.006	**0.283**
2	0.000	0.525	0.009	0.121	0.017	0.001	0.025	0.002	0.001	0.011	0.104	0.012	0.073	0.003	0.001	0.017	0.008	0.022	0.002	0.018	0.029	**0.475**
3	0.053	0.007	0.496	0.058	0.004	0.003	0.096	0.041	0.008	0.015	0.063	0.008	0.009	0.004	0.036	0.010	0.002	0.017	0.035	0.031	0.006	**0.504**
4	0.003	0.009	0.009	0.496	0.036	0.003	0.019	0.056	0.015	0.020	0.123	0.012	0.017	0.000	0.003	0.002	0.060	0.010	0.011	0.008	0.089	**0.504**
5	0.007	0.010	0.081	0.013	0.726	0.001	0.001	0.008	0.059	0.003	0.034	0.007	0.000	0.003	0.001	0.005	0.004	0.004	0.025	0.006	0.003	**0.274**
6	0.029	0.012	0.045	0.023	0.014	0.546	0.003	0.086	0.016	0.008	0.017	0.118	0.029	0.003	0.000	0.006	0.028	0.002	0.005	0.004	0.006	**0.454**
7	0.033	0.012	0.007	0.034	0.004	0.002	0.667	0.012	0.041	0.025	0.054	0.018	0.001	0.034	0.031	0.003	0.003	0.004	0.007	0.004	0.003	**0.333**
8	0.020	0.009	0.035	0.003	0.061	0.001	0.000	0.526	0.012	0.003	0.035	0.004	0.003	0.040	0.018	0.002	0.046	0.123	0.016	0.033	0.009	**0.474**
9	0.065	0.008	0.007	0.061	0.013	0.022	0.004	0.001	0.555	0.007	0.085	0.075	0.002	0.031	0.003	0.006	0.021	0.013	0.014	0.005	0.002	**0.445**
10	0.014	0.026	0.016	0.012	0.050	0.001	0.035	0.024	0.012	0.545	0.064	0.002	0.015	0.054	0.016	0.046	0.028	0.004	0.006	0.014	0.015	**0.455**
11	0.003	0.003	0.014	0.057	0.018	0.001	0.130	0.044	0.018	0.033	0.566	0.021	0.004	0.004	0.016	0.000	0.007	0.044	0.001	0.011	0.004	**0.434**
12	0.002	0.005	0.004	0.012	0.047	0.116	0.004	0.010	0.004	0.032	0.005	0.611	0.064	0.012	0.013	0.021	0.010	0.005	0.011	0.009	0.004	**0.389**
13	0.001	0.013	0.008	0.027	0.023	0.014	0.012	0.001	0.001	0.001	0.030	0.041	0.621	0.060	0.002	0.026	0.011	0.037	0.005	0.003	0.063	**0.379**
14	0.006	0.003	0.013	0.010	0.004	0.020	0.016	0.000	0.034	0.002	0.015	0.195	0.112	0.473	0.011	0.007	0.016	0.020	0.005	0.014	0.025	**0.527**
15	0.012	0.004	0.059	0.007	0.005	0.017	0.004	0.000	0.007	0.182	0.007	0.006	0.005	0.052	0.525	0.071	0.027	0.003	0.003	0.001	0.001	**0.475**
16	0.022	0.032	0.003	0.005	0.071	0.005	0.008	0.024	0.003	0.011	0.011	0.016	0.003	0.001	0.004	0.483	0.038	0.057	0.190	0.008	0.005	**0.517**
17	0.000	0.009	0.002	0.036	0.005	0.013	0.004	0.001	0.001	0.007	0.000	0.003	0.002	0.009	0.012	0.108	0.646	0.107	0.023	0.004	0.009	**0.354**
18	0.022	0.007	0.002	0.039	0.007	0.016	0.003	0.001	0.033	0.008	0.001	0.017	0.021	0.003	0.002	0.121	0.148	0.437	0.109	0.001	0.002	**0.563**
19	0.019	0.013	0.003	0.007	0.024	0.005	0.007	0.059	0.005	0.037	0.002	0.010	0.001	0.010	0.020	0.152	0.013	0.063	0.547	0.004	0.001	**0.453**
20	0.011	0.000	0.017	0.017	0.113	0.006	0.008	0.053	0.015	0.136	0.007	0.009	0.003	0.010	0.000	0.063	0.001	0.020	0.047	0.394	0.070	**0.606**
21	0.012	0.025	0.001	0.005	0.055	0.027	0.010	0.009	0.007	0.091	0.021	0.058	0.022	0.009	0.005	0.020	0.000	0.020	0.029	0.017	0.557	**0.443**
To	**0.333**	**0.239**	**0.339**	**0.549**	**0.599**	**0.276**	**0.390**	**0.437**	**0.306**	**0.680**	**0.687**	**0.639**	**0.385**	**0.342**	**0.217**	**0.697**	**0.506**	**0.576**	**0.591**	**0.203**	**0.351**	**Total = 0.445**
Net	**0.050**	**-0.236**	**-0.164**	**0.046**	**0.324**	**-0.178**	**0.058**	**-0.038**	**-0.139**	**0.225**	**0.253**	**0.250**	**0.006**	**-0.185**	**-0.257**	**0.180**	**0.152**	**0.013**	**0.137**	**-0.403**	**-0.092**	

Note: see Table 2.

cotton and orange juice make greater contribution to the system, while the sentiment for the other commodities' contributions is smaller. Thus, it can be concluded that the sentiment indices of swap dealers in the metal market and for crude oil in the energy market as well as on some commodities in the agricultural market are important for the system. At the same time, we found that the sentiments on the lean hogs in livestock market gain the most information from the system.

Swap dealer sentiments on all the commodities in the metal market are net information transmitters that have a large net positive contribution to the system, and the swap dealer sentiments of all the commodities in the livestock market are the net information receiver in the system. Furthermore, swap dealer sentiment for orange juice (0.324) is the largest net positive information transmitter to the system, while the swap dealer sentiment for lean hogs (-0.403) is the largest net information receiver in the system.

Figure 3 shows the directional connectedness network based on net pairwise connectedness for swap dealer sentiment across various commodity markets. Each node represents the swap dealer sentiment of each commodity market. In Figure 3 (a), the sentiment for crude oil in the energy market has the largest direct impact on the sentiment for heating oil in the energy market. The sentiment for wheat in the agricultural market has the largest direct impact on the sentiment for natural gas in the energy market and lean hogs in the livestock market. The sentiment for platinum in the metal market has the largest direct impact on the sentiment for soybean in the agricultural market. In Figure 3 (b), the sentiment for heating oil in the energy market has the most direct impact on the sentiment for crude oil in the energy market, while the sentiment for natural gas in the energy market has the most direct impact on the sentiment for wheat and platinum.



(a) Directional connectedness network (in) (b) Directional connectedness network (out)

Fig. 3. Directional connectedness network based on net pairwise connectedness for swap dealer sentiment.

(Note: refer to Fig. 1).

Figure 4 shows the centrality connectedness network for swap dealer sentiment across various commodity markets. It can be clearly seen that many kinds of commodities have obvious clustering characteristics. The sentiment indices in the livestock market are closely related to the sentiment in the agricultural market, especially with wheat. The sentiment in the metal market is also closely related to the sentiment in the agricultural market, especially with soybean and cotton. The sentiment in the energy market is closely related to the sentiment in the agricultural market, especially with wheat and soybean meal. However, the sentiments in the livestock, metal and energy markets are not closely connected. In general, the sentiment in the agricultural market is closely related to the sentiment in the metal and energy markets, while the sentiment in the metal market is not closely related to the sentiment in the energy market. As index traders, based their trade on a benchmark or an index which includes different assets, the swap dealers operate more in two markets, namely between the agricultural and metal markets, or between the agricultural and energy markets.

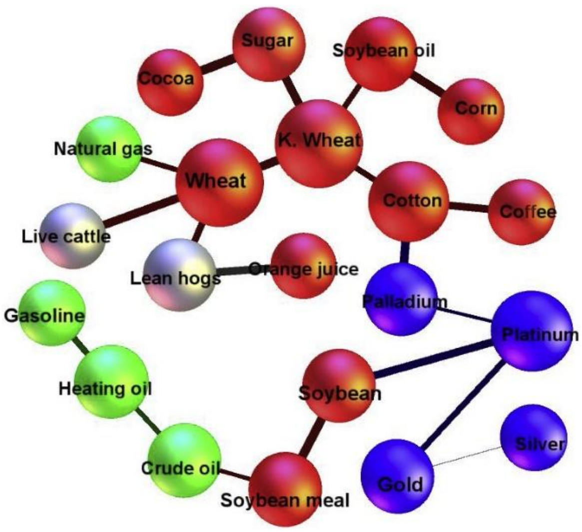


Fig. 4. Centrality connectedness network for swap dealer sentiment.

(Note: refer to Fig. 2).

4.1.3 Sentiment spillover across commodity market types

Generally, for the connectedness network of PMPU sentiment, the sentiment for soybean and gasoline have the most positive net contribution to the system, while the sentiment for corn is the largest information receiver. The PMPU sentiment is transmitted from the agricultural and energy markets to the metal and livestock markets. There is little connection between the PMPU sentiment in the agricultural market and the energy market. The sentiment in the metal market, however, plays an important role in the connection between the PMPU sentiment in the agricultural market and energy markets.

For the connectedness network of swap dealer sentiment, all the sentiment indices of the metal markets are the net positive information transmitters in the system, while all the sentiment indices of the livestock markets are the net information receivers in the system. Further, the sentiment for orange juice (0.324) is the largest net positive information transmitter in the system, while the sentiment for lean hogs (-0.403) is the largest net information receiver in the system. The sentiment in the agricultural market is closely related to the sentiment in metal and energy markets, while the sentiment in the metal market is not closely related to the sentiment in the energy market. As commercial dealers, swap dealers are mainly engaged in speculative trading, mainly operating between two markets, namely the agricultural and metal markets, or the agricultural and energy markets. The sentiment of the agricultural market plays a very important role in the linkage between the metal and energy markets.

Table 4 shows the full-sample total connectedness matrix of sentiment among different commodities. It can be seen that: (1) for the PMPU connectedness network, the sentiment in the energy market is the main information transmitter, while the sentiments in the other three markets are the main information receivers; (2) for the swap dealers' connectedness network, the sentiments in metal and agricultural markets are the main information transmitters, while the sentiments in the livestock and energy markets are the main information receivers.

Table 4
Full-sample total connectedness matrix of sentiment among different commodity types.

	PM				SD			
	Agricultural	Energy	Metal	Livestock	Agricultural	Energy	Metal	Livestock
Agricultural	9.049	0.839	0.672	0.440	9.163	0.762	0.762	0.313
Energy	0.654	2.868	0.399	0.079	0.801	2.803	0.277	0.119
Metal	0.771	0.568	2.551	0.109	0.592	0.134	3.241	0.033
Livestock	0.300	0.135	0.264	1.302	0.645	0.115	0.201	1.039
Net	**-0.226**	**0.410**	**-0.113**	**-0.071**	**0.201**	**-0.186**	**0.481**	**-0.496**

Note: this table presents the connectedness spillover of sentiment across commodity market types. Each element in the table is calculated by the sum of all pairwise connectedness from one type of commodity market to another type of commodity market. 'Net' denotes the total net connectedness from one type of commodity market to all the other types of commodity markets.

4.2 Dynamic analysis of connectedness spillover for investor sentiment across markets

4.2.1 Dynamic convergence of investor sentiment in the commodity market system

Figure 5 shows the dynamic total connectedness for PMPU sentiment in the commodity market system. The total spillover index has time-varying characteristics and ranges from 70% to 88%. This suggests that PMPU sentiment indices in the commodity markets have remained highly integrated. From the sentiment spillover across commodity market types reported in table 4, we can see that the sentiment in the energy market is the main information transmitter. Hence, understanding the evolution in the energy markets over the period can lead to an understanding of the dynamics of connectedness spillover for PMPU sentiment across markets. From mid-2010 to early 2013, the system-wide connectedness fluctuated between 79% and 88%. Meanwhile, it reached a peak of nearly 88% in early 2012. This increase in PMPU sentiment connectedness can be explained by worries about the political disorder in North Africa in 2011, which then transmitted to the Middle East. Given that this region is an important energy producer, such disorders increase the energy price volatility. In these situations, PMPU in energy markets will search to hedge their positions by using metal markets, which in turn increases the system-wide sentiment connectedness. Early 2014 to the end of 2016, shows an overall downward trend from high to low, and the system-wide connectedness fluctuated between 73% and 80%. Over this period, the prices in energy, agricultural and metal commodities followed a downward trend that started in mid-2014 to the end of our sample. The decline in energy prices was more limited than the decline in the prices of other commodities, especially the metals. This resulted in the lowest connectedness in system-wide sentiments. In the summer of 2015, the energy prices ended their downward spiral and the price of oil settled at around $50 per barrel. Combined with the reduction of geopolitical risks in some countries in the Middle East and North Africa, the system-wide connectedness bottoms out at nearly 73% at the end of 2015. This decrease in the PMPU sentiment connectedness over this period can be explained by the fact that PMPU in the energy market became less exposed to the risk, and therefore they reduced their cross-hedging strategies, which resulted in less information spillover across futures markets.

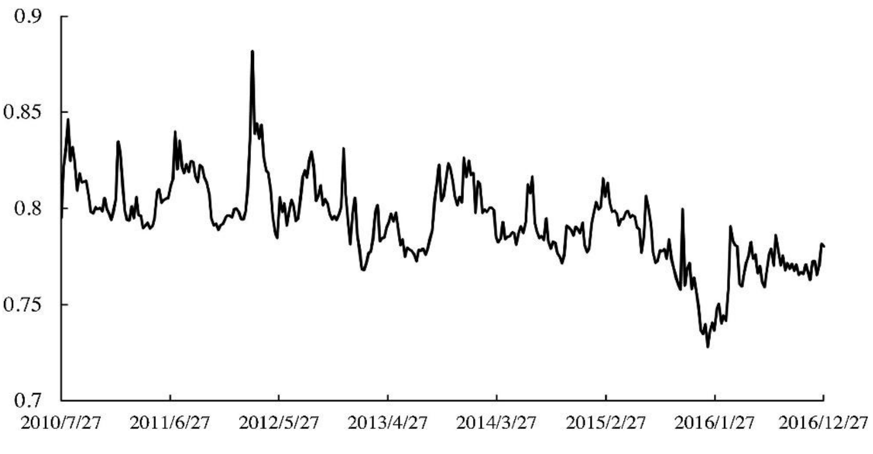


Fig. 5. Dynamic total connectedness for PMPU sentiment in the commodity market system.

(Note: The size of the rolling window is set 100).

Figure 6 shows the dynamic total connectedness for swap dealer sentiment in the commodity market system. The total spillover index has time-varying characteristics and ranges from 70% to 90%, which indicates that the swap dealers' sentiments for various commodities maintained a high degree of integration. From September 2010 to April 2013, it had a downward trend from high to low. In April 2013, it reached a low point of nearly 72%, and then began to rise. In April 2014, it began to decline again, and reached a low in October 2016 and began to rise. In general, the swap dealers' sentiment fluctuates greatly for the full sample.

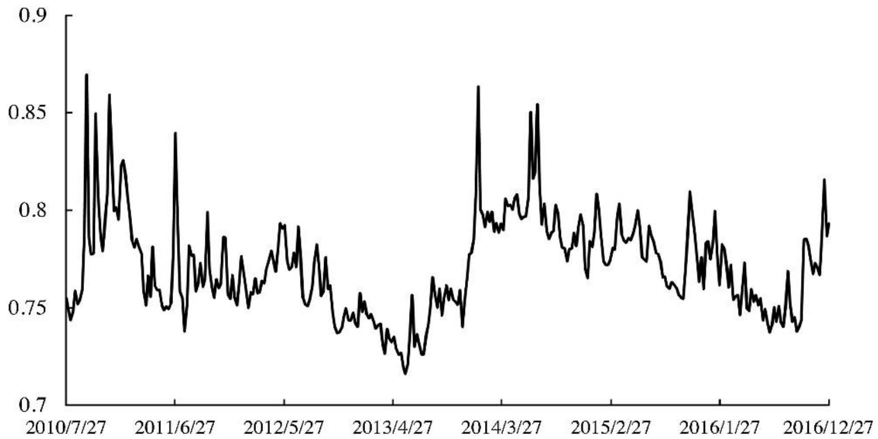


Fig. 6. Dynamic total connectedness for swap dealer sentiment in the commodity market system.

(Note: The size of the rolling window is set 100)

In general, the sentiment indices of PMPU and swap dealer traders have maintained a high degree of integration in all commodity markets, indicating that the two categories of hedgers pay close attention to all kinds of commodities. There is an overall downward trend from high to low in the PMPU sentiments. There is no obvious single downward trend from high to low in the swap dealers' sentiments, but there are multiple upward and downward trends for the full sample period. In general, the sentiments of the swap dealers fluctuate greatly in the full sample period.

4.2.2 Dynamic spillover effect of investor sentiment from each commodity market

Table 5 shows the summary statistics of dynamic net total directional connectedness. Regarding the PMPU sentiment, the average values of the sentiments on soybean, gasoline and wheat are larger, at 0.335, 0.288 and 0.221, respectively, indicating that the sentiment indices of these 3 commodities play an important role in the sentiment connectedness network and have an impact on the sentiment of other commodities. For swap dealers, all the market sentiments have little impact on the other commodities. However, the average value of sugar is -0.294, indicating that sugar is most affected by the sentiments of the other commodities.

Table 5
Summary statistics of dynamic net total directional connectedness.

	PM		SD	
	Mean	Std. dev	Mean	Std. dev
Cocoa	−0.164	0.308	−0.020	0.301
Coffee	−0.047	0.296	0.004	0.265
Corn	0.047	0.332	−0.090	0.397
Cotton	−0.172	0.314	0.033	0.303
Orange juice	−0.126	0.309	0.034	0.342
Soybean meal	0.043	0.280	−0.144	0.285
Soybean oil	−0.148	0.295	0.050	0.345
Soybean	0.335	0.404	0.052	0.343
Sugar	−0.083	0.335	−0.294	0.195
Wheat	0.221	0.428	0.148	0.421
K. Wheat	0.027	0.349	0.121	0.593
Crude oil	0.052	0.478	−0.137	0.248
Gasoline	0.288	0.457	0.165	0.418
Heating oil	0.057	0.388	−0.189	0.327
Natural gas	−0.144	0.291	−0.039	0.387
Gold	−0.089	0.321	0.127	0.294
Palladium	0.117	0.418	0.037	0.324
Platinum	0.058	0.432	0.045	0.343
Silver	−0.050	0.264	0.083	0.384
Lean hogs	−0.056	0.371	−0.121	0.303
Live cattle	−0.164	0.316	0.137	0.453

Note: this table calculates the mean and standard deviation of dynamic net total directional connectedness for each type of sentiment in each commodity.

5. Conclusions

In this paper, we have used the Diebold–Yilmaz connectedness model to study the linkages between commodities futures markets based on the sentiment dynamics across commercial traders by category as proposed by the CFTC in their DCOT reports for a set of 21 futures contracts. The pairwise directional connectedness of commercials sentiment allowed us to understand how each individual commercial traders' sentiment by category in a specific futures markets contributed to the connectedness in each futures contract and how it contributes to the sentiment system in futures markets. Given that there are many futures contracts that need to be included in the analysis, we aggregated the individual futures markets at the sector level and analysed sentiment spillover across commodity market types, which can help to understand how the sentiments by hedgers' category in one or several market types affect sentiments in other sectors. In addition to the static analysis of connectedness network for investor sentiment by hedger types, we provide a dynamic analysis which relies on rolling estimation windows.

Several interesting results from the analysis of sentiment connectedness of major futures markets was obtained. From the PMPU sentiments connectedness analysis, our most important results are that PMPU in agricultural and energy markets are mainly engaged in cross-hedging in the futures market, and most of them would avoid risks in these markets by operating in the metal markets, which are considered safe havens (Li and Lucey, 2017; Sakemoto, 2018) for PMPU traders. These cross-hedging strategies also play a role in PMPU sentiment spillover across futures markets. The results from the analysis of sentiment spillover across commodity market types and the dynamic analysis of the connectedness network show how geopolitical risks in some countries can influence the stability in energy markets which in turn can cause PMPU system-wide connectedness. From the swap dealer sentiment connectedness analysis, the most important results are that, as index traders, the swap dealers operate more in two markets, namely between the agricultural and metal markets, or between the agricultural and energy markets. The results from the dynamic analysis of the connectedness network illustrate that there is no obvious single downward trend from high to low in the swap dealers sentiments, but there are multiple upward and downward trends for the full sample period.

In this paper, we construct a trader-position-based sentiment index using the data provided by the CFTC on their DCOT reports. Even if the data provided by the DCOT gives more data on sentiment in more detailed groups of traders, these data remain published on a weekly basis. The CFTC collects data on more detailed categories of traders on a daily basis. These data are not publicly published, but researchers from the CFTC have used it in their work. Therefore, as part of future research, a detailed analysis of investor sentiment spillover across commodity markets based on an investor sentiment index calculated using daily non-public data from the Large Trader Reporting System maintained by the CFTC constitutes an interesting avenue for future research.

Acknowledgment

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Appendix A

In this appendix we mainly analyse the static and dynamic information spillover effect across the commodity markets for the sentiment indices in two categories of non-commercial traders.

A.1 Full-sample connectedness analysis for money manager sentiment

Table A1 shows the connectedness matrix of the money managers in the whole sample. The total connectedness of the system containing the sentiment indices of money managers is 52.2%, indicating that the integration of the sentiment of the swap dealers is also high and that different money managers across different commodity markets interact with each other.

Comparing *"From"* and *"To"* in each market, the money manager sentiment indices for soybean (1.302), wheat (0.799), crude oil (0.773), natural gas (0.743), gold (0.675), silver (0.652), corn (0.640), K. wheat (0.543), wheat meal (0.524) and coffee (0.521) make a great contribution to the system. The money manager sentiments in the agricultural, energy and metal markets play an important role in the system. Meanwhile, we see that money manager sentiment indices for platinum (0.729), corn (0.714), K. wheat (0.695), heating oil (0.659), wheat (0.620) and wheat (0.599) gain a large amount of information from the system. It can be also seen that the sentiment indices in the agricultural and metal markets play an important role in the system.

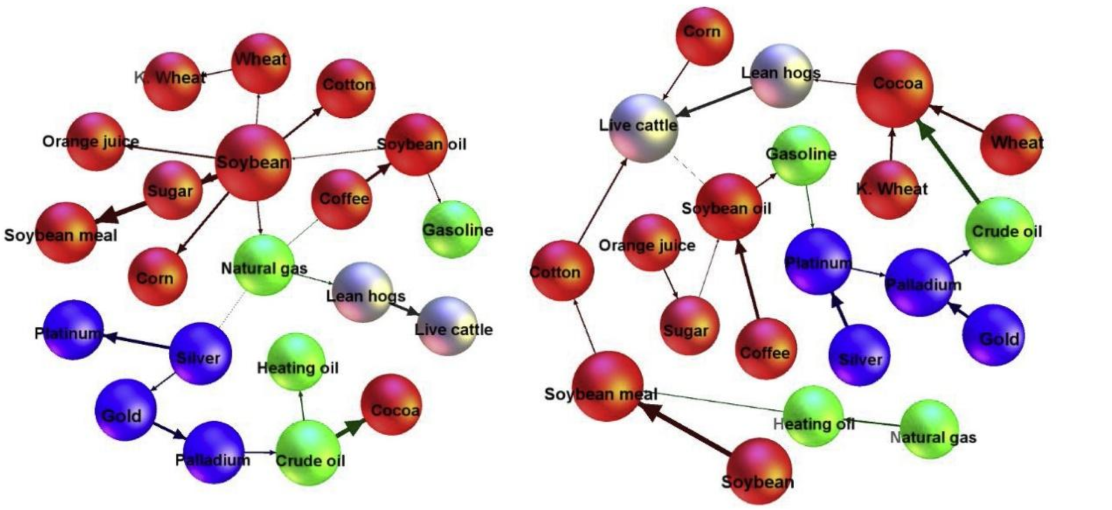
Money manager sentiment for soybean (0.749) is the largest net information transmitter that has a large net positive effect on the system, while money manager sentiment for live cattle (-0.373) is the largest net information receiver in the system.

Fig. A1.1 shows the directional connectedness network based on net pairwise connectedness for money manager sentiment across commodity markets. The money manager sentiment for silver has the largest direct impact on most of the commodities in the metal market. Money manager sentiment for lean hogs has the largest direct impact on the sentiment for other livestock commodities. The sentiment for cocoa in the agricultural market receives the most direct influence from the sentiment for crude oil in the energy market, and the sentiment for soybean meal receives the most direct influence from the sentiment for soybean.

Table A1
Full-sample connectedness matrix for money manager sentiment of in commodity futures markets.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	From
1	0.481	0.009	0.006	0.002	0.001	0.008	0.003	0.024	0.008	0.095	0.076	0.152	0.004	0.007	0.005	0.011	0.042	0.038	0.022	0.002	0.003	**0.519**
2	0.019	0.621	0.017	0.005	0.001	0.017	0.017	0.019	0.005	0.019	0.014	0.010	0.030	0.004	0.099	0.046	0.009	0.001	0.027	0.014	0.005	**0.379**
3	0.005	0.082	0.286	0.006	0.021	0.063	0.023	0.126	0.012	0.162	0.092	0.025	0.010	0.008	0.049	0.003	0.014	0.010	0.002	0.000	0.001	**0.714**
4	0.000	0.007	0.011	0.624	0.059	0.055	0.007	0.089	0.006	0.012	0.006	0.019	0.011	0.002	0.008	0.001	0.046	0.001	0.020	0.002	0.011	**0.376**
5	0.002	0.024	0.038	0.040	0.613	0.004	0.003	0.077	0.015	0.006	0.011	0.031	0.023	0.010	0.018	0.027	0.025	0.016	0.001	0.004	0.010	**0.387**
6	0.008	0.001	0.031	0.013	0.004	0.477	0.012	0.308	0.002	0.024	0.002	0.011	0.004	0.037	0.037	0.004	0.006	0.004	0.000	0.000	0.013	**0.523**
7	0.002	0.123	0.064	0.018	0.002	0.003	0.380	0.046	0.042	0.064	0.066	0.045	0.030	0.024	0.011	0.006	0.010	0.015	0.038	0.001	0.014	**0.620**
8	0.003	0.010	0.037	0.003	0.004	0.145	0.088	0.447	0.011	0.064	0.058	0.031	0.013	0.035	0.028	0.001	0.004	0.009	0.003	0.004	0.003	**0.553**
9	0.007	0.002	0.008	0.002	0.060	0.035	0.018	0.107	0.596	0.023	0.002	0.011	0.017	0.003	0.022	0.044	0.008	0.010	0.011	0.007	0.007	**0.404**
10	0.001	0.030	0.096	0.006	0.015	0.063	0.034	0.113	0.012	0.401	0.121	0.007	0.008	0.001	0.015	0.007	0.017	0.037	0.013	0.002	0.001	**0.599**
11	0.010	0.058	0.055	0.012	0.013	0.031	0.062	0.093	0.002	0.180	0.305	0.016	0.025	0.007	0.066	0.019	0.002	0.029	0.003	0.008	0.004	**0.695**
12	0.006	0.010	0.013	0.015	0.041	0.001	0.027	0.027	0.009	0.005	0.014	0.496	0.065	0.049	0.036	0.016	0.087	0.040	0.012	0.026	0.004	**0.504**
13	0.025	0.022	0.027	0.000	0.003	0.014	0.078	0.022	0.015	0.012	0.011	0.103	0.449	0.133	0.029	0.007	0.022	0.007	0.007	0.012	0.001	**0.551**
14	0.010	0.010	0.017	0.019	0.020	0.007	0.043	0.083	0.018	0.003	0.006	0.109	0.129	0.341	0.068	0.014	0.022	0.008	0.030	0.039	0.004	**0.659**
15	0.002	0.063	0.065	0.022	0.004	0.008	0.013	0.086	0.007	0.008	0.021	0.020	0.005	0.011	0.552	0.048	0.016	0.006	0.006	0.013	0.023	**0.448**
16	0.009	0.015	0.019	0.003	0.007	0.002	0.013	0.004	0.006	0.005	0.002	0.035	0.009	0.015	0.057	0.478	0.026	0.034	0.229	0.027	0.005	**0.522**
17	0.011	0.001	0.011	0.048	0.007	0.022	0.005	0.007	0.009	0.014	0.005	0.025	0.011	0.029	0.021	0.129	0.468	0.099	0.070	0.003	0.004	**0.532**
18	0.002	0.009	0.052	0.015	0.002	0.013	0.005	0.036	0.008	0.027	0.003	0.094	0.041	0.032	0.055	0.105	0.054	0.271	0.145	0.028	0.004	**0.729**
19	0.001	0.003	0.022	0.018	0.001	0.013	0.016	0.015	0.007	0.006	0.002	0.018	0.013	0.031	0.035	0.167	0.019	0.034	0.548	0.025	0.007	**0.452**
20	0.036	0.023	0.005	0.008	0.012	0.000	0.007	0.008	0.006	0.009	0.013	0.001	0.044	0.006	0.064	0.007	0.006	0.018	0.009	0.707	0.011	**0.293**
21	0.015	0.020	0.045	0.067	0.005	0.020	0.005	0.011	0.013	0.062	0.018	0.010	0.033	0.016	0.018	0.013	0.015	0.006	0.003	0.112	0.493	**0.507**
To	**0.173**	**0.521**	**0.640**	**0.325**	**0.281**	**0.524**	**0.480**	**1.302**	**0.213**	**0.799**	**0.543**	**0.773**	**0.526**	**0.460**	**0.743**	**0.675**	**0.449**	**0.421**	**0.652**	**0.331**	**0.134**	**Total = 0.522**
Net	**-0.345**	**0.142**	**-0.074**	**-0.050**	**-0.106**	**0.002**	**-0.139**	**0.749**	**-0.191**	**0.200**	**-0.152**	**0.269**	**-0.024**	**-0.199**	**0.295**	**0.152**	**-0.083**	**-0.308**	**0.200**	**0.038**	**-0.373**	

Note: see Table 2.



(a) Directional connectedness network (in) (b) Directional connectedness network (out)

Fig. A1.1. Directional connectedness network based on net pairwise connectedness for money manager sentiment.

(Note: refer to Fig. 1).

From Fig. A1.2 , it can be clearly seen that the sentiment indices of all categories of commodity markets have obvious clustering characteristics. The sentiment indices in the agricultural market are closely linked to the sentiment indices in the energy market. The sentiment indices in the metal market are close to the sentiment indices in the energy and agricultural markets. In general, money managers make speculative trades, and the energy market is used as an intermediate market to avoid risks in the metal and agricultural markets.

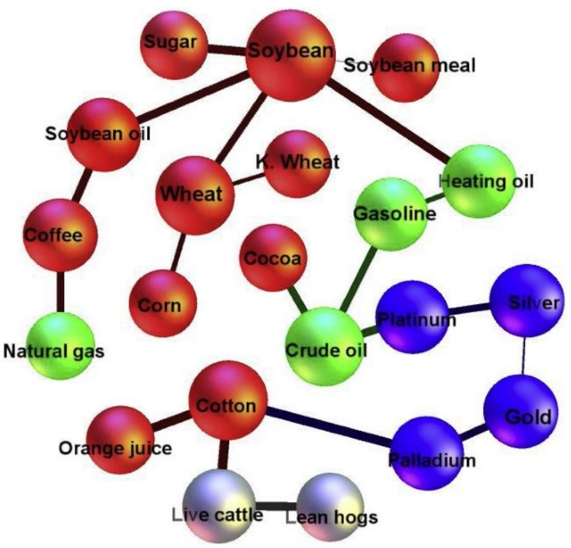


Fig. A1.2. Centrality connectedness network for money manager sentiment.

(Note: refer to Fig. 2).

Table A2
Full-sample connectedness matrix for other reportable sentiment of in commodity futures markets.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	From
1	0.641	0.009	0.009	0.019	0.012	0.004	0.018	0.011	0.021	0.020	0.034	0.003	0.030	0.056	0.009	0.060	0.007	0.002	0.027	0.001	0.008	**0.359**
2	0.009	0.589	0.010	0.023	0.070	0.011	0.030	0.005	0.005	0.011	0.013	0.006	0.005	0.064	0.025	0.053	0.018	0.043	0.003	0.004	0.001	**0.411**
3	0.028	0.010	0.649	0.023	0.013	0.093	0.008	0.039	0.005	0.005	0.006	0.005	0.001	0.004	0.006	0.005	0.047	0.002	0.011	0.038	0.003	**0.351**
4	0.011	0.002	0.083	0.657	0.000	0.056	0.026	0.004	0.004	0.003	0.004	0.023	0.050	0.002	0.007	0.001	0.001	0.010	0.027	0.003	0.025	**0.343**
5	0.062	0.031	0.016	0.020	0.556	0.047	0.001	0.019	0.029	0.041	0.011	0.010	0.059	0.032	0.004	0.033	0.010	0.004	0.006	0.002	0.009	**0.444**
6	0.004	0.021	0.032	0.003	0.008	0.603	0.057	0.078	0.010	0.056	0.002	0.001	0.001	0.025	0.008	0.018	0.005	0.017	0.008	0.003	0.041	**0.397**
7	0.008	0.009	0.007	0.009	0.008	0.033	0.722	0.023	0.005	0.005	0.024	0.002	0.010	0.043	0.010	0.016	0.021	0.021	0.002	0.013	0.006	**0.278**
8	0.005	0.015	0.032	0.004	0.006	0.133	0.032	0.575	0.008	0.010	0.036	0.005	0.018	0.034	0.018	0.001	0.003	0.039	0.021	0.001	0.005	**0.425**
9	0.017	0.050	0.010	0.003	0.011	0.010	0.036	0.018	0.590	0.005	0.001	0.002	0.007	0.007	0.015	0.124	0.004	0.017	0.062	0.002	0.010	**0.410**
10	0.015	0.065	0.020	0.030	0.049	0.005	0.001	0.001	0.013	0.556	0.005	0.000	0.013	0.000	0.019	0.079	0.014	0.019	0.020	0.047	0.026	**0.444**
11	0.008	0.036	0.001	0.008	0.005	0.010	0.002	0.018	0.006	0.006	0.737	0.008	0.015	0.004	0.004	0.006	0.039	0.033	0.013	0.007	0.035	**0.263**
12	0.032	0.085	0.008	0.009	0.005	0.015	0.032	0.004	0.021	0.022	0.009	0.507	0.021	0.112	0.023	0.036	0.002	0.002	0.005	0.037	0.012	**0.493**
13	0.049	0.001	0.009	0.002	0.019	0.007	0.008	0.002	0.012	0.001	0.002	0.041	0.699	0.082	0.001	0.006	0.003	0.033	0.006	0.001	0.017	**0.301**
14	0.006	0.002	0.005	0.004	0.025	0.004	0.078	0.001	0.003	0.009	0.000	0.024	0.005	0.665	0.005	0.052	0.000	0.021	0.008	0.074	0.009	**0.335**
15	0.010	0.013	0.010	0.067	0.010	0.004	0.027	0.013	0.028	0.009	0.055	0.004	0.043	0.025	0.531	0.013	0.014	0.053	0.009	0.058	0.006	**0.469**
16	0.002	0.003	0.001	0.021	0.005	0.009	0.017	0.002	0.009	0.003	0.006	0.001	0.015	0.032	0.106	0.600	0.021	0.004	0.082	0.005	0.057	**0.400**
17	0.028	0.006	0.001	0.114	0.025	0.004	0.010	0.000	0.011	0.012	0.008	0.022	0.029	0.002	0.007	0.036	0.573	0.014	0.069	0.006	0.022	**0.427**
18	0.008	0.056	0.000	0.007	0.005	0.031	0.023	0.007	0.006	0.017	0.011	0.001	0.001	0.012	0.099	0.004	0.016	0.622	0.014	0.029	0.029	**0.378**
19	0.005	0.015	0.013	0.013	0.003	0.067	0.064	0.001	0.009	0.013	0.019	0.006	0.018	0.030	0.018	0.123	0.059	0.001	0.482	0.002	0.041	**0.518**
20	0.015	0.032	0.041	0.087	0.003	0.001	0.041	0.002	0.001	0.023	0.015	0.008	0.001	0.177	0.076	0.010	0.009	0.006	0.002	0.438	0.012	**0.562**
21	0.037	0.027	0.008	0.022	0.013	0.001	0.028	0.002	0.038	0.013	0.004	0.001	0.014	0.004	0.011	0.074	0.001	0.018	0.001	0.008	0.674	**0.326**
To	**0.359**	**0.488**	**0.316**	**0.488**	**0.296**	**0.543**	**0.538**	**0.250**	**0.242**	**0.285**	**0.263**	**0.174**	**0.357**	**0.748**	**0.473**	**0.751**	**0.295**	**0.359**	**0.395**	**0.340**	**0.376**	**Total = 0.397**
Net	**-0.000**	**0.077**	**-0.035**	**0.144**	**-0.148**	**0.146**	**0.260**	**-0.175**	**-0.168**	**-0.159**	**0.000**	**-0.319**	**0.056**	**0.413**	**0.004**	**0.351**	**-0.132**	**-0.018**	**-0.123**	**-0.222**	**0.050**	

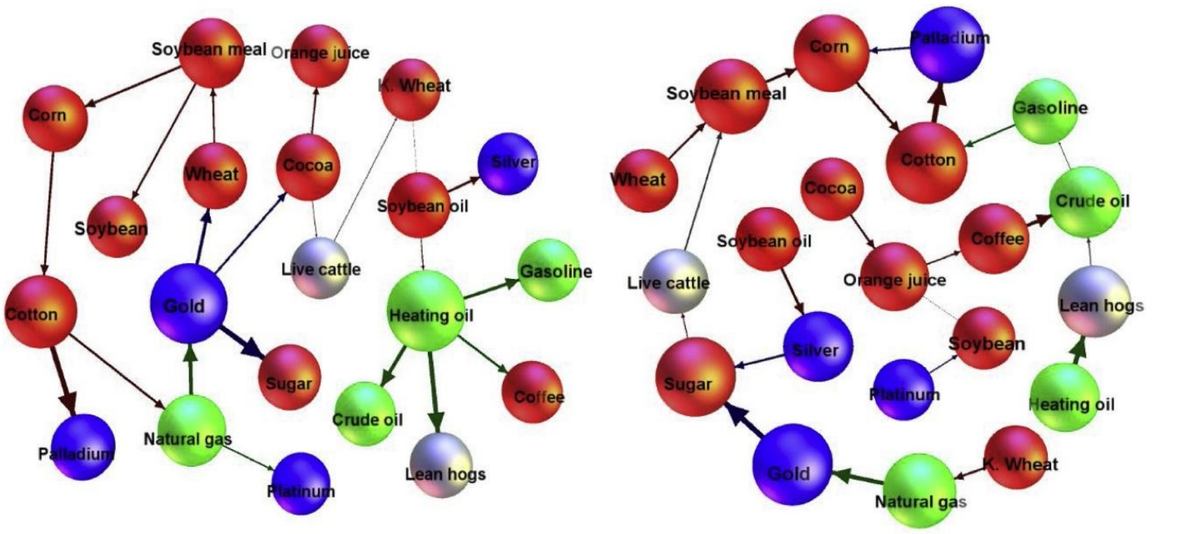
Note: see Table 2.

A2 Full-sample connectedness analysis for other reportable sentiment

Table A2 shows the connectedness matrix of the other reportable sentiment in the whole sample. The total connectedness of the system containing the other reportable sentiment indices is 39.7%, indicating that the integration of the other reportable sentiment indices is high and the different other reportable sentiment indices across different commodity markets interact with each other.

Compared with *"From"* and *"To"*, the other reportable sentiments for gold (0.751), heating oil (0.748), soybean meal (0.543) and soybean oil (0.538) make a great contribution to the system. These suggest that the other reportable sentiments in the metal, energy and agricultural markets play an important role in the system. At the same time, we found that the other reportable sentiment indices of lean hogs (0.562) and silver (0.518) received a large amount information from the system. Furthermore, the other reportable sentiment indices of heating oil (0.413) and gold (0.351) are the net information transmitters that have a net positive effect on the system, while the other reportable sentiment indices of crude oil (-0.319) are the net information receivers in the system.

Fig. A2.1 shows the directional connectedness network based on net pairwise connectedness for other reportable sentiment across commodity markets. The other reportable sentiment for gold has the largest direct impact on the other reportable sentiments for wheat, sugar, cocoa and other agricultural products, while the other reportable sentiment for heating oil has the largest direct impact on the other reportable sentiment for crude oil, gasoline, lean hogs and coffee. The other reportable sentiment for sugar receives the most direct influence from the other reportable sentiment in the gold market. The other reportable sentiment for lean hogs receives the most direct influence from the other reportable sentiment for heating oil. The other reportable sentiment for palladium receives the most direct influence from the other reportable sentiment for cotton.



(a) Directional connectedness network (in) (b) Directional connectedness network (out)

Fig. A2.1. Directional connectedness network based on net pairwise connectedness for other reportable sentiment.

(Note: refer to Fig. 1).

Fig. A2.2 shows the centrality connectedness network for the other reportable sentiment. It can be clearly seen that all the other reportable sentiment kinds for commodity markets are relatively dispersed and do not have obvious clustering characteristics. However, the other reportable sentiment indices for natural gas, gold and heating oil play an important role in network linkage. In general, the other reportable sentiments are scattered across various commodities.

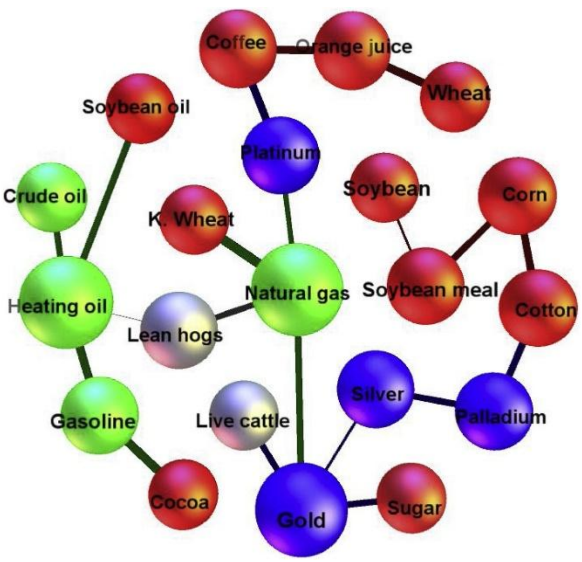


Fig. A2.2. Centrality connectedness network for other reportable sentiment.

(Note: refer to Fig. 2)

A3 Non-commercial sentiment spillover across commodity market types

For the connectedness network of money manager sentiment, the sentiment for soybean (0.749) is the larger net positive transmitter in the system, while the sentiment for live cattle (-0.373) and platinum (-0.308) are the net information receivers in the system. The sentiment in the agricultural market is closely linked to the sentiment in the energy market. The sentiment in the metal market is close to the sentiment in the energy and agricultural markets. In general, for money manager sentiment, the energy market serves as the intermediate market to avoid risks in the metal market and the agricultural market.

For the connectedness network of other reportable trader sentiment, the sentiment for heating oil (0.413) and gold (0.351) are the larger net positive information transmitters in the system, while the sentiment for crude oil (-0.319) is the net information receiver in the system. All the sentiment indices for the commodity markets are relatively dispersed and do not show obvious clustering characteristics. However, the sentiment indices for natural gas, gold and heating oil play an important role in network linkage.

Table A3 shows full-sample total connectedness matrix of speculators' sentiment among different commodities. It can be seen that: (1) for the connectedness network of money manager sentiment, the sentiment in the energy market is the main information transmitter, while the sentiment in the livestock market is the main information receiver; (2) for the connectedness network of the other reportable trader sentiment, the sentiment in the energy market is the main information transmitter, while the sentiment in the livestock market is the main information receiver.

Table A3
Full-sample total connectedness matrix of speculators sentiment among different commodity types.

	MM				Oth			
	Agricultural	Energy	Metal	Livestock	Agricultural	Energy	Metal	Livestock
Agricultural	9.19	1.032	0.661	0.117	9.064	0.673	0.973	0.29
Energy	0.935	2.595	0.348	0.121	0.736	2.788	0.261	0.215
Metal	0.5	0.522	2.874	0.104	0.689	0.399	2.721	0.191
Livestock	0.409	0.191	0.077	1.323	0.453	0.292	0.123	1.132
Net	**0.034**	**0.341**	**-0.04**	**-0.335**	**-0.058**	**0.152**	**0.078**	**-0.172**

Note: see Table 4.

A4 Dynamic convergence of speculators' sentiment in the commodity market system

Fig. A4.1 shows the dynamic total connectedness for money managers' sentiment in the commodity market system. The total spillover index has a time-varying characteristic and ranges from 75% to 85%, which indicates that the money manager sentiment of various commodities maintains a high degree of integration. From July 2010 to October 2014, the total spillover index showed a *W* shape, and from October 2014 to December 2016, the index showed a downward trend. In general, the index shows a relatively stable fluctuation for the full sample period.

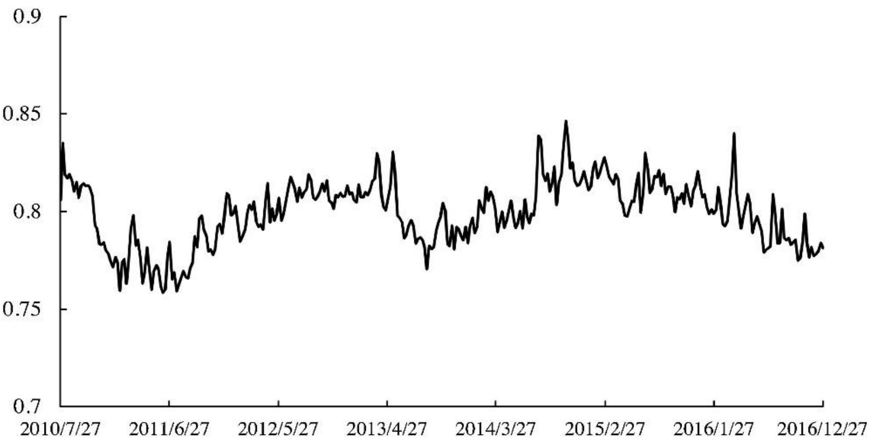


Fig. A4.1. Dynamic total connectedness for money manager sentiment in the commodity market system.

(Note: The size of the rolling window is set 100)

Fig. A4.2 shows the dynamic total connectedness for other reportable sentiment in the commodity market system. The total spillover index has time-varying characteristics and ranges from 67% to 77%, which indicates that other reportable sentiment of various commodities has also maintained a high degree of integration. Overall, its index showed a downward trend from July 2010 to January 2013, an upward trend from February 2013 to February 2016 and a downward trend from March 2016.

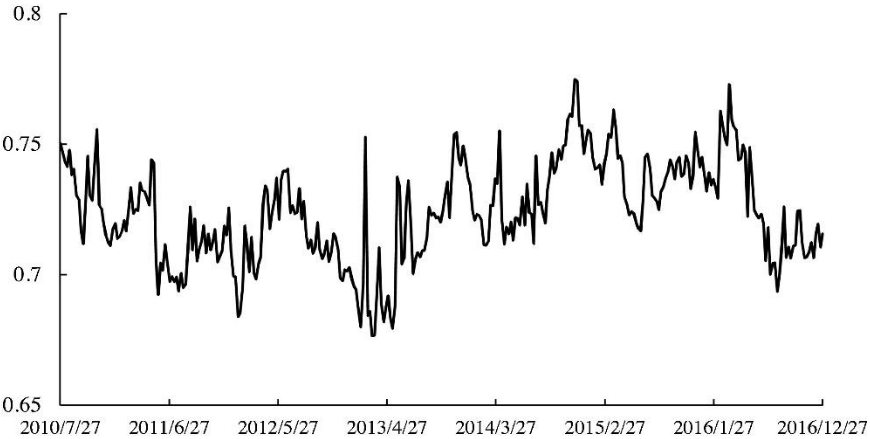


Fig. A4.2. Dynamic total connectedness for other reportable sentiment in the commodity market system.

(Note: The size of the rolling window is set 100).

In general, the sentiment indices of money managers and other reportable traders maintain a high degree of integration in all commodity markets, indicating that the two categories of non-commercial traders pay close attention to all kinds of commodities. There is no obvious single downward trend from high to low in the two types of sentiments, but there are multiple upward and downward trends for the full sample period. The sentiments of other reportable traders fluctuate greatly in the full sample period, while the money manager sentiment index presents a relatively stable fluctuation in the full sample period.

A5 Dynamic spillover effect of investor sentiment from each commodity market

Table A5 shows the summary statistics of dynamic net total directional connectedness. Regarding money manager sentiment, the mean value of the sentiments for soybean and wheat is larger, 0.378 and 0.352, respectively, indicating that the sentiments of these two commodities play an important role in the money manager sentiment connectedness network and have an impact on the sentiments of the other commodities. For the other reportable traders, the mean value of gold and cotton is relatively large, at 0.283 and 0.227 respectively, indicating that the sentiments for gold and cotton play an important role in sentiment connectedness of all commodities and have an impact on the sentiments of other commodities.

Table A5
Summary statistics of dynamic net total directional connectedness.

	MM		Oth	
	Mean	Std. dev	Mean	Std. dev
Cocoa	−0.212	0.218	−0.231	0.202
Coffee	−0.018	0.337	0.099	0.431
Corn	0.102	0.357	0.137	0.283
Cotton	−0.080	0.292	0.227	0.239
Orange juice	−0.107	0.301	−0.009	0.348
Soybean meal	0.029	0.330	−0.010	0.440
Soybean oil	−0.012	0.348	−0.114	0.255
Soybean	0.378	0.437	0.214	0.387
Sugar	0.079	0.408	0.070	0.308
Wheat	0.352	0.437	−0.017	0.223
K. Wheat	−0.189	0.326	0.040	0.278
Crude oil	0.047	0.344	−0.169	0.221
Gasoline	−0.021	0.244	−0.206	0.229
Heating oil	−0.202	0.238	−0.050	0.404
Natural gas	−0.147	0.208	−0.075	0.204
Gold	−0.098	0.305	0.283	0.281
Palladium	0.052	0.298	−0.082	0.220
Platinum	−0.014	0.368	−0.010	0.353
Silver	0.048	0.274	0.044	0.417
Lean hogs	−0.008	0.427	−0.133	0.266
Live cattle	0.019	0.461	−0.007	0.303

Note: See Table 5.