Journal of Commodity Markets 31 (2023) 100330

Contents lists available at ScienceDirect

Journal of Commodity Markets

journal homepage: www.elsevier.com/locate/jcomm

Regular article

The impact of financialization on the efficiency of commodity futures markets

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ARTICLE INFO

JEL classification:
G14
Q02

Keywords:
Commodity financialization
Price informativeness
Index investing
Real economic effects

ABSTRACT

The pronounced inflow of financial capital from index investors over the last 15 years and the accompanying substantial fluctuations in commodity futures markets have aroused public and academic interest. A common accusation made in this context is that commodity index traders (CITs) negatively influence the quality of commodity futures markets and keep them far from fundamentally justified price levels. In this paper, we focus on quantifying market efficiency, and investigate empirically the suggested effect of CITs over the period from 1999 to 2019 for 34 commodity futures markets. In contrast to recent studies, we find empirical evidence that the financialization positively affected the market efficiency of indexed commodity futures markets. Consistently, we observe that the degree of commodity index trader activity is associated with higher degrees of informational efficiency.

1. Introduction

Recent decades have witnessed a sharp increase in the amount of capital devoted to index-related investment products. This structural change in investor composition has been especially evident in commodity futures markets. Starting around 2004, financial traders began a large build-up of positions in commodity futures markets, a process often referred to as financialization (Tang and Xiong, 2012). To a great extent, this structural change took place through investment vehicles that replicate the performance of one of the main commodity price indices. Indeed, the surge in commodity index trader (CIT) activity was accompanied by a shift in price and volatility dynamics with pronounced boom-bust cycles (Cheng and Xiong, 2014). A potential causal link between these two chronologically related developments has been widely-discussed by politicians, media, and throughout the academic literature (e.g., Singleton, 2014; Hamilton and Wu, 2015).

An issue that has only recently begun to receive attention is the impact of the growing market share of commodity index investments on informational efficiency, which is of particular importance because futures markets aggregate and convey valuable information to producers and consumers (Black, 1976). According to Grossman (1976), prices aggregate private signals of market participants, and thus, reveal information. Any disruption to this process can have serious real economic consequences. This paper addresses this topic. It examines the extent to which the financialization of commodity futures markets and CIT trading activity have led to changes in the efficiency of information processing.

The presence of CITs may influence the degree of informational efficiency in different ways. In this respect, market microstructure theory (e.g., Kyle, 1985; Glosten and Milgrom, 1985) suggests three different trader types: (i) market makers that provide liquidity

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https://doi.org/10.1016/j.jcomm.2023.100330
Received 23 June 2022; Received in revised form 28 February 2023; Accepted 18 April 2023
Available online 7 June 2023
2405-8513/

to the market, (ii) traders with private information, and (iii) so-called noise traders, who trade for non-fundamental objectives (e.g., hedging needs). According to Sockin and Xiong (2015), the overall effect of CIT trading may depend on whether CITs utilize commodity futures contracts to speculate (informed trading) or diversify (uninformed trading).

In this regard, Glosten et al. (2021) suggest that index investing may improve informational efficiency by helping commodity futures to reflect systemic information in a more timely manner. If they are associated with higher liquidity, and hence, lower transaction costs compared to the individual futures markets, index products will be used by market participants trading on systemic information. In this respect, CITs differ significantly from traditional speculators, whose trading behaviour may also be affected by private commodity-specific information. If this assumption holds, then the improvement of information efficiency should be most notable in commodity futures markets that fail to incorporate systemic information on a timely basis (e.g., due to low liquidity). Concerning this matter, Glosten et al. (2021) show that improvement in short-run informational efficiency is most pronounced among firms with low market capitalization and analyst coverage. However, according to the authors, it is also conceivable that CITs trade in commodity futures based on idiosyncratic information, and use index products to hedge against systematic risk. This, in turn, may induce noise in the return process.

Index investing may also have an indirect effect on the information production process in commodity futures markets, in that growth in index investments may lead informed investors to be less inclined to collect and process information (Brown et al., 2021). A common assumption is that market participants have to incur costs to gather information (Grossman and Stiglitz, 1980). This effort, in turn, is compensated with profits acquired via trading with uninformed market participants, and ultimately ensures that new information is incorporated into prices. However, index investment may disrupt this mechanism. Due to low adverse selection costs and the opportunity to diversify asset-specific risk, noise traders may be attracted by index investments (Subrahmanyam, 1991; Gorton and Pennacchi, 1993), leaving only informed traders in the underlying markets. Without trading gains at the expense of uninformed investors, remaining informed traders trade less, leading to illiquidity and increased transaction costs (Grossman and Stiglitz, 1980).

Apart from attracting noise traders, index investment products may affect informational efficiency through market conditions. More volatile and illiquid markets complicate converting private information into profits. In the case of market volatility, Basak and Pavlova (2013) and Baruch and Zhang (2019) provide a theoretical explanation for rising volatility in indexed assets due to index investing. This prediction has received empirical confirmation by Ben-David et al. (2018). For market liquidity, the theoretical model of Bhattacharya and O'Hara (2018) predicts a positive impact on liquidity. Boehmer and Boehmer (2003), Hegde and McDermott (2004), and Holden and Nam (2019) show that the initiation of exchange traded funds (ETFs) increases liquidity of the underlying assets.

A recent study by Brogaard et al. (2019) presents evidence that commodity index investing feeds back into the real economy in a negative manner. More specifically, the informational efficiency of index commodities is reported to have declined substantially due to CIT trading, with the decline in efficiency on the order of 75%. The decline in informational efficiency is predicted to have caused production and investment decisions for firms using indexed commodities to become less efficient due to the increased noise in futures price quotations. Analysis of individual commodity firm data reveals that firms who are heavy users of index commodities earn significantly lower profits, and have higher costs than control firms over 2000–2007.

The results found in Brogaard et al. (2019) are troubling from a public policy standpoint. Specifically, their results indicate that financialization substantially reduced the informational efficiency of indexed commodity futures markets, and materially harmed the financial performance of firms that are heavy users of these commodities. Given the relatively large real economy impacts reported in Brogaard et al. (2019), and the fact that theirs is the only study to date reporting such results, the need for additional research on this topic should be obvious. The results of Brogaard et al. (2019) also raise the question of how it was possible for speculators and arbitrageurs to eliminate predictable movements in commodity prices before financialization, but not afterwards. This is particularly questionable given the fact that sophisticated investors such as hedge funds have increasingly entered the market during the financialization period.

In the present study, we focus on the informational efficiency of index and non-index commodity futures markets, as Brogaard et al.'s (2019) identification strategy is based on this characteristic. We examine 34 commodity futures markets spanning the period 1999 through 2019. Based on the classification into index and non-index commodity futures markets we calculate for each commodity the absolute value of centred variance ratio (VR), and the delay (DL) measures of Hou and Moskowitz (2005). We use daily rather than weekly futures price time series. We argue that information processing in commodity futures markets is fast, and as such, daily data are preferable to weekly. In addition, the aggregation to weekly data may mask economically important dynamics that may only be discovered with the use of daily futures prices. Furthermore, we use daily data to ensure that our results are not driven by time-varying expected returns (Ahn et al., 2002).

We use two different approaches to examine the question of whether financialization and index investing affect price informativeness in commodity futures markets. First, we utilize CIT position data provided by the U.S. Commodity Futures Trading Commission (CFTC) to investigate directly how variation in market participant composition is related to informational efficiency in commodity futures markets. Relying on ordinary least squares (OLS) regressions, we find that CIT activity is significantly associated with higher degrees of informational efficiency. Next, we decompose CIT activity in the number of new CITs and existing CITs expanding their market positions. We demonstrate that the identified relationship between informational efficiency and CIT activity is mainly driven by CITs increasing their portfolio holdings.

In the OLS regressions we control for several observable commodity futures characteristics, and consider both commodity and month fixed effects. Nevertheless, we cannot rule out the possibility that CIT activity is endogenous, and the observed relationship may be driven by an omitted variable bias. To address this concern, we replicate and extend the difference-in-differences regression results of Brogaard et al. (2019). In this part of the analysis, we focus on the build-up in CIT positions around the year 2004. We split the sample between treatment and control group based on whether the commodity futures contract is a constituent of a commodity index or not. By doing this, we assume that the financialization represents an exogenous shock that is orthogonal to other factors affecting the level of price informativeness. To control for the effect of temporal variations in economic conditions and any potentially persistent differences between index and nonindex commodity futures markets, we add commodity and month fixed effects. In general, our results stand in sharp contrast to those of Brogaard et al. (2019). For a similar sample of commodity futures contracts, we find no significant degradation in informational efficiency that is experienced by only index commodity futures contracts. On the contrary, difference-in-differences regressions reveal that price informativeness of index commodities improved significantly compared to non-index commodities.

The contributions of this article are threefold. First, we contribute to the literature studying the impact of the financialization on underlying commodity futures markets. There is already a substantial literature debating the link between the sharp increase in commodity index trading and commodity futures and spot prices in 2007–08. Among others, Stoll and Whaley (2010), Hamilton and Wu (2015), and Brunetti et al. (2016) find no empirical evidence that the rapid growth in CIT trading affected commodity futures prices or volatility. In contrast, Henderson et al. (2015) and Cheng et al. (2015) find the opposite. Moreover Singleton (2014) provides empirical evidence of correlation but states that more investigation is needed. Moreover, Tang and Xiong (2012) and Büyükşahin and Robe (2014) document increasing comovement between stock and commodity indices following the financialization, whereas Le Pen and Sévi (2018) find particularly high excess co-movement of commodity prices after 2007 that is driven by speculative trading in the context of financialization. However, the effect of the financialization on the informativeness of futures prices is not well understood. A major exception is the study of Brogaard et al. (2019) who alleged that indexed commodity futures markets are significantly more affected than non-indexed futures markets.

Second, this paper draws on recent work (Brogaard et al., 2019; Goldstein and Yang, 2019), emphasizing real economic consequences from the financialization. This literature heavily relies on the assumption of a feedback channel, i.e. that financialization harms price informativeness of futures markets, which in turn harms production and investment decisions of exposed companies. Based on a broad set of empirical tests, our results document that the suggested feedback-channel is not present in commodity futures markets.

Finally, we add to the literature studying how investment in index-related products (e.g. ETFs) affects the informational efficiency of the underlying securities. For instance, Israeli et al. (2017) and Coles et al. (2020) show that higher index investor ownership leads to decreased informational efficiency. However, on the contrary, Glosten et al. (2021) find that ETFs positively affect informational efficiency at the individual stock level. Similar positive effects for industry level ETFs are illustrated by Huang et al. (2021) and Bhojraj et al. (2018). Contributing to this strand of the literature, we provide additional evidence for a different market setting.

The paper proceeds as follows. In the next section, we describe the data and variable construction. Section 3 outlines the empirical findings, before Section 4 draws some conclusions.

2. Data and variable construction

2.1. Futures data

The selection of commodity futures markets and the identification of indexed commodities belonging to the S&P GSCI or Bloomberg Commodity Index (former Dow Jones UBS Commodity Index) relies on Brogaard's et al. (2019) approach.[1] However, we make few adjustments. In principle, we only use futures contracts that have been traded for some time both before and after the suspected break around 2004. For this reason, we do not use time series for molybdenum and cobalt, as trading in futures contracts for these commodities did not start until February 2010.[2] For the same reason, we also refrain from including ethanol and RBOB gasoline (for both started trading in 2005). Finally, we do not include soybean meal, although it is a current member of the Bloomberg Commodity Index. However, indexing of soybean meal futures contracts only began in 2013. We consider a total of 34 commodity futures markets of which 24 were classified as indexed, and 10 as non-indexed (see Table 1). Our sample of daily futures prices covers the period from January 1999 to November 2019.[3] The data are sourced from Datastream and Barchart.

Consistent with Bakshi et al. (2019), we roll over the contract with the second shortest maturity T_2 to the next nearby contract T_3 on the first trading day of the month prior expiration to construct a daily time series of futures prices. Therefore, we avoid the first notice day and the associated risk of physical delivery, which may lead to liquidity and pricing irregularities in the futures series (Szymanowska et al., 2014; Bakshi et al., 2019).[4] However, the adopted methodology complicates the computation of returns

1 While the weighting of individual commodities varies depending on relative global production, index membership has remained fairly stable over time. For example, rice, palladium, platinum, and steel are still not considered in the index construction, despite their importance in global production & consumption.

2 The use of molybdenum in Brogaard et al. (2019) is particularly puzzling because the investigation period covers the period from 2000 to 2007, but futures trading in molybdenum only started in February 2010.

3 Since we compute efficiency measures based on a rolling-window of 250 trading days, and the investigation period starts in 2000, we utilize data starting in January 1999.

4 This approach mimics the roll behaviour of, for example, the S&P GSCI with the exception of the day on which the roll is performed. Sensitivity of the empirical results with respect to the choice of roll day is checked in Section 4. For more details on the roll procedure of the S&P GSCI, the reader is referred to Mou (2010).

Table 1
Commodity futures contracts by exchange.

A. Index commodities		B. Nonindex commodities	
Commodity	Exchange	Commodity	Exchange
Energy		Energy	
Brent oil	ICE	Propane	NYMEX
Crude oil	NYMEX		
Gasoil	ICE		
Heating oil	NYMEX		
Natural gas	NYMEX		
Agriculture		Agriculture	
Corn	CBOT	Rice	CBOT
Soybeans	CBOT	Oats	CBOT
Chicago wheat	CBOT	Lumber	CME
Kansas wheat	KBOT	Orange Juice	ICE
Soybean oil	CBOT	Pork bellies	CME
Coffee	ICE	Minneapolis wheat	MGE
Cotton	ICE		
Sugar	ICE		
Cocoa	ICE		
Feeder cattle	CME		
Live cattle	CME		
Lean hogs	CME		
Metals		Metals	
Gold	COMEX	Palladium	COMEX
Silver	COMEX	Platinum	COMEX
Copper	COMEX	Tin	LME
Aluminium			LME
Lead	LME		
Nickel	LME		
Zinc	LME		

Note: The exchange abbreviations CME, ICE, LME and NYMEX refer to the Chicago Mercantile Exchange, the Intercontinental Exchange U.S. (New York), the London Metal Exchange and the New York Mercantile Exchange. The classification in index and non-index commodities follows the approach suggested in Brogaard et al. (2019). Indexed futures markets are constituents of the S&P GSCI and/or the Bloomberg Commodity Index (former Dow Jones UBS Commodity Index).

since on the roll-over day t the third nearby contract in $t-1$ becomes the second nearby contract. We overcome this issue and derive continuously compounded returns based on settlement prices of the same contract:

$$R_{t,i}^{2} = \begin{cases} log F_{t,i}^{2} - log F_{t-1,i}^{3}, & \text{if } t-1 \text{ represents a roll-over day} \\ log F_{t,i}^{2} - log F_{t-1,i}^{2}, & \text{otherwise,} \end{cases} \tag{1}$$

where $F_{t,i}^{T}$ denotes the settlement price of commodity i's Tth nearby contract on day t. Detailed information on the statistical of the return time series is presented in Table 2. It becomes obvious that the majority of return time series shows negative skewness and excess kurtosis. Moreover, no obvious differences between index and non-index commodities are evident from the descriptive statistics.

Finally, we derive several futures market related control variables. First, consistent with Kang et al. (2020), we compute the log basis as

$$B_{i,t} = \frac{\ln(F_i(t,T_2)) - \ln(F_i(t,T_1))}{T_2 - T_1}, \tag{2}$$

where $F_i(t,T_n)$ denotes the nth-nearby contract for commodity i on day t. We include $B_{i,t}$ as a control variable, as it is closely related to the commodity futures risk premium (see, among others, Working, 1949; Brennan, 1958; Fama and French, 1987; Erb and Harvey, 2006). To control for varying degrees of market illiquidity, we use the commonly adopted Amihud (2002) measure, which is defined as:

$$IQ_{i,t} = \frac{|r_{i,t}|}{\text{Trading Volume}_{i,t}(\text{in \$billion})}. \tag{3}$$

2.2. CIT activity

In order to measure the degree of CITs' market activity, we rely on trader positioning data published by the CFTC in their Supplemental Commitment of Traders (SCOT) report. In total, the SCOT report covers aggregate trading positions held by CITs for 12 selected agricultural futures markets. According to the CFTC's definition, CITs comprise the class of institutional investors who

Table 2
Descriptive statistics of futures return time series.

	#	Min	Mean	Max	St.dev.	Skew.	Kurt.
A. Index commodities							
Aluminium	5725	−8.22	−0.01	11.09	1.36	0.02	4.32
Brent oil	5808	−13.90	0.01	13.30	2.03	−0.08	3.24
Chicago wheat	5640	−9.76	−0.05	8.48	1.78	0.10	1.85
Cocoa	5643	−9.96	0.00	9.87	1.81	−0.12	2.37
Coffee	5669	−13.89	−0.04	20.05	2.15	0.08	4.81
Copper	5675	−11.71	0.01	11.64	1.67	−0.14	4.21
Corn	5560	−8.12	−0.03	8.48	1.62	0.07	2.20
Cotton	5703	−7.36	−0.03	6.93	1.54	−0.06	1.73
Crude oil	5707	−15.72	0.01	12.78	2.10	−0.19	3.21
Feeder cattle	5675	−6.00	0.00	4.47	0.93	−0.17	1.65
Gas oil	5748	−14.45	0.01	11.25	1.87	0.00	2.48
Gold	5692	−9.84	0.01	8.83	1.08	−0.12	6.39
Heating oil	5726	−13.97	0.01	10.30	2.03	−0.05	2.22
Kansas wheat	5670	−8.87	−0.03	8.01	1.66	0.11	1.77
Lead	5641	−17.86	0.05	24.20	2.13	0.46	10.52
Lean hogs	5635	−6.56	0.01	3.42	0.87	−0.18	1.57
Live cattle	5491	−6.60	−0.03	6.98	1.51	−0.05	1.11
Natural gas	5727	−19.18	−0.10	18.76	2.94	0.07	2.41
Nickel	5729	−29.93	−0.02	34.26	2.83	−0.41	19.47
Silver	5709	−19.48	0.01	12.45	1.87	−0.82	7.62
Soybeans	5684	−7.29	0.01	6.70	1.44	−0.12	2.29
Soybeans oil	5660	−7.14	−0.01	8.08	1.42	0.15	2.04
Sugar	5584	−13.20	−0.01	8.56	1.85	−0.22	2.33
Zinc	5704	−12.48	0.01	11.44	1.84	−0.14	3.54
B. Nonindex commodities							
Lumber	5681	−5.93	−0.03	6.22	1.63	0.15	0.27
Minneapolis wheat	5635	−8.41	−0.01	7.95	1.46	0.14	2.80
Oats	5439	−8.41	−0.01	8.34	1.78	−0.07	1.54
Orange juice	5651	−13.09	−0.03	15.08	1.82	−0.04	3.40
Palladium	5561	−14.36	0.05	15.54	2.07	−0.31	4.28
Platinum	5688	−9.48	0.02	10.28	1.41	−0.34	3.40
Pork bellies	3272	−7.08	0.00	7.44	1.97	0.00	0.60
Propane	2671	−22.07	0.05	13.91	2.21	−0.64	7.55
Rice	5568	−6.90	−0.04	7.28	1.41	0.06	1.38
Tin	5657	−11.46	0.02	15.03	1.58	−0.16	7.09

Note: Table 2 contains descriptive statistics for the employed return time series. Classified into index and non-index commodities, Table 2 contains information on number of observations, minimum, mean, maximum, standard deviation, skewness and kurtosis for the return time series. The data is sourced from Datastream and Barchart and spans the period from January 1997 to November 2019.

invest passively and unleveraged in commodity futures markets by means of commodity index investment vehicles. In addition, the CFTC assigns to CITs market participants who hedge commodity-index-related OTC derivative contracts in the underlying commodity futures markets. The SCOT report is published on a weekly basis (usually each Friday) and contains the long and short open interest held by CITs as of Tuesday market close for 12 selected agricultural commodities, beginning in January 2006. For a comprehensive overview of the limitations of this dataset, we refer the reader to Irwin and Sanders (2012).

Fig. 1 illustrates the evolution of index trader activity measured as the open interest held by market participants identified by the CFTC as index trader for CBOT corn, CBOT soybean, CBOT wheat, and KCBT wheat. For these grain futures markets, the CFTC collected additional data for the build-up period of index trader position data in 2004 and 2005 following a request from the U.S. Senate Permanent Subcommittee on Investigations in 2009. In addition, the corresponding futures price time series is shown in order to gain a first impression of the extent to which index traders' positions were accompanied by price movements. Looking at the period 2004 to 2009, there is no clear correlation between the build-up of long positions by CITs and the price fluctuations in agricultural futures markets. As frequently assumed, a large part of the position build-up took place during the period January 2004 to May 2006. For this period, however, no pronounced change in price dynamics in the selected agricultural futures markets can be identified. Assuming that index traders have significantly influenced the price process and consequently the efficiency of commodity futures markets, this should particularly be observed during the substantial position building between 2004 and 2006.

The total open interest (OI), reported by the CFTC can be subgrouped as follows:

$$2 \times OI = \underbrace{(\text{Long} + \text{Short} + 2 \times \text{Spread})}_{Non-commercial} + \underbrace{(\text{Long} + \text{Short})}_{Commercial} + \underbrace{(\text{Long} + \text{Short})}_{CIT} + \underbrace{(\text{Long} + \text{Short})}_{Non-reporting} \tag{4}$$

Utilizing the SCOT report data, we construct two measure to characterize the positions of CITs. First, we derive the market share of CITs as the sum of the number of contracts that CITs are long ($CITL$) and short ($CITS$), scaled by total open interest for commodity

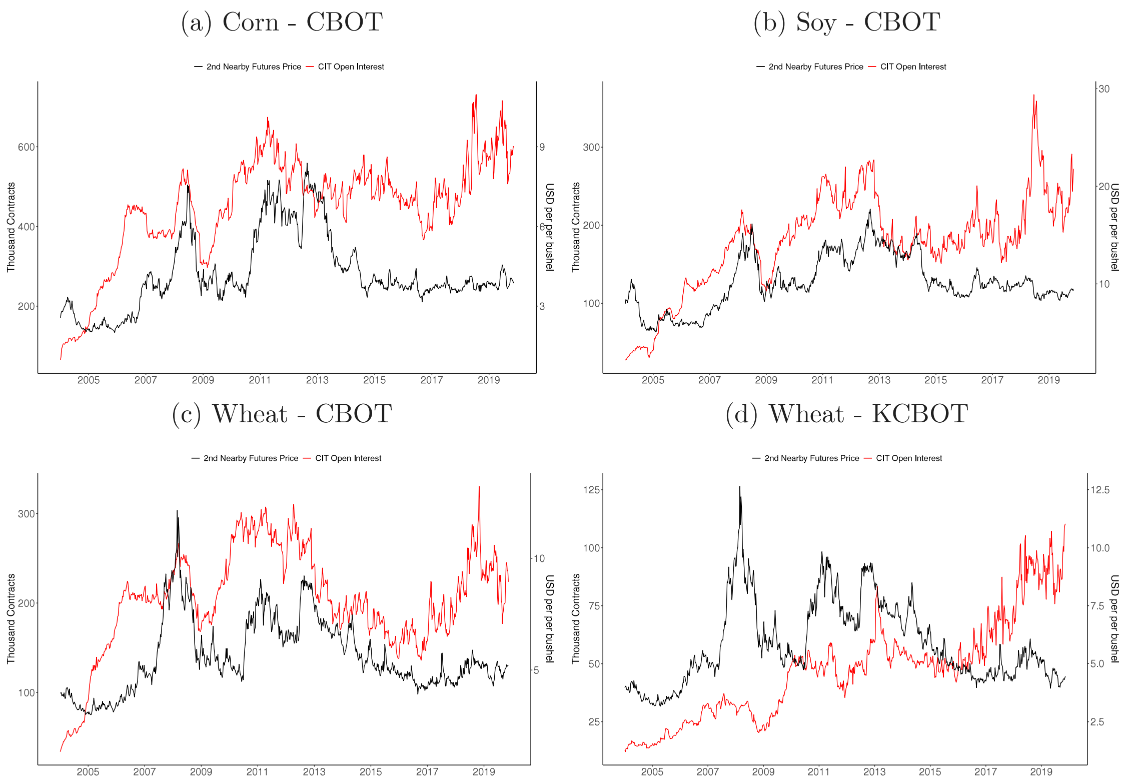

Fig. 1. CIT Positions & Futures Prices.
Note: The graphs show the weekly commodity index trader (CIT) positions based on position data obtained from the CFTC and corresponding next nearby futures prices, January 2004 to November 2019.

Table 3
Descriptive statistics of CIT measures.

	MS				NET				# CIT				OI			
	Min	Mean	Max	St.dev.	Min	Mean	Max	St.dev.	Min	Mean	Max	St.dev.	Min	Mean	Max	St.dev.
Chicago wheat	11.72	20.66	28.03	3.82	15.61	30.20	51.00	8.18	22	44.90	75	9.99	313.43	530.51	722.92	74.20
Cocoa	3.14	9.20	16.04	2.67	3.26	12.35	22.22	4.45	16	29.52	56	8.11	116.00	217.20	381.96	65.91
Coffee	7.61	12.87	21.60	2.61	8.02	20.49	42.20	6.77	18	37.81	76	12.51	111.94	217.54	434.12	60.90
Corn	8.66	13.56	18.46	1.75	9.10	20.21	32.73	4.59	26	46.50	86	11.61	996.90	1809.42	2708.87	303.98
Cotton	10.30	15.61	22.38	2.36	10.93	26.46	43.11	5.73	17	38.27	78	11.31	148.51	277.05	572.63	69.11
Feeder cattle	4.28	11.53	20.63	3.68	6.18	19.23	35.16	6.25	12	24.29	45	6.46	20.53	46.14	75.77	13.05
Kansas wheat	6.15	13.54	21.42	2.96	8.23	22.28	40.27	6.42	12	27.37	54	8.01	80.58	193.18	368.00	70.57
Lean hogs	9.85	17.88	25.71	3.64	17.04	31.43	51.42	8.25	18	34.73	68	9.86	132.41	268.12	439.31	63.32
Live cattle	8.80	16.29	24.35	3.51	15.88	30.52	46.96	6.97	19	34.81	71	10.00	218.79	365.20	515.80	68.29
Soybeans	7.74	12.69	18.79	2.32	8.49	18.74	32.16	5.45	21	44.11	81	11.68	364.62	789.26	1302.94	195.63
Soybeans oil	9.07	13.72	22.27	2.39	14.19	22.16	36.55	3.70	14	32.15	64	10.38	186.94	391.28	638.65	88.29
Sugar	8.13	16.28	22.23	2.86	10.05	23.40	36.26	5.22	20	38.73	64	7.59	604.29	970.75	1535.07	157.90

Note: Table 3 contains descriptive statistics for the employed measures of CIT activity, number of CITs active in the market, and the open interest. MS refers to the market share of CITs, NET is the net long position of CITs, # CIT denotes the number of CITs, and OI is the number of open contracts (long+short). The data is sourced from the weekly SCOT report published by the CFTC and spans the period from January 2006 to November 2019.

i in week t (OI):

$$MS_{i,t} = \frac{CITL_{i,t} + CITS_{i,t}}{2 \times OI_{i,t}}. \tag{5}$$

Furthermore, we consider the net long position of CITs:

$$NET_{i,t} = \frac{CITL_{i,t} - CITS_{i,t}}{OI_{i,t}}. \tag{6}$$

Table 3 reports descriptive statistics for the total open interest, the number of CITs, and the CIT activity measures for each commodity futures market covered by the SCOT report.

It can be seen that CITs hold between 9% and 21% of open interest on average (market share), with positions fluctuating over time. At the peak, for example, CITs have a market share of 28% in Chicago wheat and 11% at the minimum. In addition, it can be seen that CITs generally take net long positions, with the degree of net long positions varying greatly between commodities and

Table 4
Mean degree of market efficiency - Variance ratios.

	VR4			VR8			VR12			AVR		
	pre	post	Δ	pre	post	Δ	pre	post	Δ	pre	post	Δ
A. Index commodities												
Brent oil	0.08	0.10	0.02*	0.16	0.13	−0.03*	0.18	0.16	−0.02*	0.05	0.10	0.05*
Crude oil	0.07	0.09	0.02*	0.16	0.13	−0.03*	0.20	0.17	−0.04*	0.04	0.07	0.02*
Gas oil	0.06	0.12	0.06*	0.15	0.17	0.03*	0.20	0.20	0.01	0.06	0.08	0.02*
Heating oil	0.10	0.10	0	0.20	0.17	−0.03*	0.27	0.23	−0.04*	0.05	0.07	0.02*
Natural gas	0.11	0.08	−0.04*	0.10	0.10	0	0.13	0.14	0.01	0.07	0.09	0.02*
Chicago wheat	0.06	0.04	−0.02*	0.12	0.13	0.01	0.16	0.18	0.02*	0.04	0.05	0
Corn	0.07	0.06	−0.01*	0.10	0.12	0.02*	0.14	0.13	−0.01*	0.10	0.06	−0.04*
Kansas wheat	0.12	0.05	−0.07*	0.11	0.10	−0.01*	0.14	0.16	0.02*	0.15	0.05	−0.1*
Soybean oil	0.07	0.08	0.01*	0.16	0.12	−0.04*	0.20	0.15	−0.05*	0.07	0.06	−0.01*
Soybeans	0.05	0.09	0.04*	0.13	0.08	−0.05*	0.16	0.11	−0.05*	0.06	0.04	−0.02*
Cocoa	0.10	0.09	−0.02*	0.13	0.08	−0.06*	0.16	0.13	−0.04*	0.07	0.06	−0.01*
Coffee	0.17	0.10	−0.07*	0.27	0.12	−0.15*	0.36	0.17	−0.19*	0.09	0.09	0.01*
Cotton	0.11	0.13	0.02*	0.11	0.16	0.05*	0.13	0.17	0.04*	0.05	0.09	0.04*
Sugar	0.10	0.10	0.01*	0.09	0.16	0.06*	0.12	0.26	0.15*	0.05	0.04	−0.01*
Feeder cattle	0.16	0.11	−0.04*	0.18	0.11	−0.07*	0.21	0.13	−0.08*	0.11	0.17	0.06*
Lean hogs	0.17	0.11	−0.06*	0.22	0.15	−0.07*	0.24	0.19	−0.05*	0.11	0.08	−0.02*
Live cattle	0.12	0.08	−0.05*	0.16	0.14	−0.03*	0.21	0.15	−0.06*	0.06	0.04	−0.02*
Gold	0.08	0.07	−0.01*	0.18	0.12	−0.05*	0.26	0.17	−0.09*	0.08	0.04	−0.04*
Silver	0.16	0.11	−0.05*	0.19	0.12	−0.07*	0.24	0.17	−0.07*	0.18	0.13	−0.06*
Aluminium	0.09	0.09	0	0.14	0.19	0.06*	0.20	0.24	0.05*	0.05	0.05	0
Copper	0.12	0.14	0.02*	0.12	0.21	0.08*	0.16	0.24	0.07*	0.11	0.08	−0.03*
Lead	0.14	0.08	−0.05*	0.15	0.14	−0.01*	0.14	0.16	0.02*	0.08	0.03	−0.05*
Nickel	0.11	0.13	0.03*	0.19	0.22	0.03*	0.28	0.29	0.01*	0.06	0.08	0.02*
Zinc	0.11	0.12	0.01*	0.20	0.16	−0.04*	0.24	0.11	−0.13*	0.07	0.10	0.02*
Mean	**0.11**	**0.09**	**−0.01**	**0.16**	**0.14**	**−0.02**	**0.20**	**0.18**	**−0.02**	**0.08**	**0.07**	**−0.01**
B. Nonindex commodities												
Propane	0.21	0.25	0.04*	0.26	0.27	0.01	0.27	0.28	0.01	0.16	0.24	0.08*
Minneapolis wheat	0.16	0.08	−0.08*	0.23	0.13	−0.1*	0.32	0.17	−0.15*	0.17	0.08	−0.09*
Oats	0.15	0.10	−0.04*	0.18	0.17	0	0.22	0.20	−0.02*	0.17	0.03	−0.14*
Rice	0.10	0.10	0	0.18	0.15	−0.03*	0.20	0.19	−0.01*	0.04	0.05	0.01*
Lumber	0.13	0.05	−0.08*	0.18	0.07	−0.11*	0.20	0.09	−0.1*	0.10	0.05	−0.06*
Orange juice	0.14	0.05	−0.09*	0.20	0.14	−0.06*	0.23	0.18	−0.05*	0.06	0.04	−0.02*
Pork bellies	0.10	0.14	0.05*	0.15	0.20	0.05*	0.19	0.26	0.07*	0.06	0.12	0.06*
Platinum	0.07	0.12	0.05*	0.14	0.20	0.07*	0.20	0.26	0.06*	0.07	0.05	−0.02*
Palladium	0.08	0.12	0.04*	0.14	0.15	0.01*	0.21	0.21	0	0.12	0.11	0
Tin	0.12	0.23	0.12*	0.17	0.26	0.09*	0.12	0.30	0.18*	0.10	0.15	0.05*
Mean	**0.13**	**0.12**	**0.00**	**0.18**	**0.17**	**−0.01**	**0.22**	**0.21**	**0.00**	**0.11**	**0.09**	**−0.01**

Note: Table 4 reports the mean absolute deviation of the Automatic Variance Ratio (AVR) proposed by Choi (1999) and the original Variance Ratio of Lo and MacKinlay (1988) (VR4, VR8, and VR12) from unity. The metrics are computed for the sub-samples spanning the pre- and post-financialization period. Furthermore, Table 4 shows the difference in mean.
*Indicates statistical significance at the 5% level.

over time. Regarding the number of CITs active in the respective markets, a certain heterogeneity can also be observed. On average, between 24 (Feeder Cattle) and 47 (Corn) CITs are active.

2.3. Measures of informational efficiency

In the empirical analysis, we quantify the degree of price informativeness in different ways. The first measure that we adopt is closely related to the classic definition of market efficiency, initially proposed by Fama (1970). It states that prices reflect new information entirely and instantaneously if the market is efficient. From this definition it can be inferred that price changes follow a purely random process, and are thus not predictable on the basis of currently available information. This also precludes autocorrelation in the return process.[5]

To detect and quantify distinctive autocorrelation structure in the return process, we utilize variance ratios (VRs). Closely related to the VRs is the assumption that returns follow a random walk process, which is characterized by the absence of any serial correlation. Another feature of the random walk process is that the return variance over a holding period of q days should

[5] Although this definition serves as a basis for many theoretical and empirical studies, it is not without controversy. Opponents typically argue that return autocorrelation is not a distinct sign of market inefficiency. Rather, return autocorrelation can also emerge due to time-varying expected returns, market microstructural frictions or non-synchronous trading (see, among other, Conrad and Kaul, 1988; Conrad et al., 1991; Mech, 1993; Boudoukh et al., 1994). However, these objections can be overcome by using data at higher frequency. According to Ahn et al. (2002), in the case of daily returns, time-varying expected returns do not pose a problem as they are associated with low frequency changes in investment opportunities. Moreover, the objection that return autocorrelation arises due to microstructural frictions can be invalidated, because of highly liquid markets.

Table 5
Mean degree of market efficiency - Delay.

	Delay1			Delay2			Delay3		
	pre	post	Δ	pre	post	Δ	pre	post	Δ
A. Index commodities									
Brent oil	0.04	0.02	−0.02*	1.75	1.67	−0.08*	1.45	1.30	−0.15*
Crude oil	0.03	0.02	−0.01*	1.55	1.56	0.01	1.24	1.18	−0.06*
Gas oil	0.28	0.29	0	2.01	2.22	0.2*	1.82	1.90	0.08*
Heating oil	0.03	0.02	−0.01*	1.54	1.49	−0.06*	1.27	1.16	−0.11*
Natural gas	0.24	0.17	−0.07*	2.14	2.13	0	1.95	1.91	−0.04*
Chicago wheat	0.72	0.68	−0.04*	2.34	2.46	0.11*	2.27	2.35	0.08*
Corn	0.77	0.64	−0.13*	2.51	2.32	−0.19*	2.37	2.24	−0.13*
Kansas wheat	0.71	0.71	0	2.39	2.46	0.06*	2.29	2.32	0.03*
Soybean oil	0.83	0.48	−0.35*	2.45	2.24	−0.21*	2.47	2.16	−0.32*
Soybeans	0.80	0.56	−0.24*	2.43	2.23	−0.2*	2.42	2.16	−0.26*
Cocoa	0.81	0.70	−0.11*	2.49	2.19	−0.3*	2.45	2.32	−0.14*
Coffee	0.77	0.67	−0.1*	2.40	2.30	−0.11*	2.43	2.29	−0.15*
Cotton	0.80	0.71	−0.08*	2.51	2.47	−0.04*	2.51	2.42	−0.09*
Sugar	0.76	0.70	−0.06*	2.38	2.45	0.08*	2.43	2.42	−0.01
Feeder cattle	0.80	0.81	0.02*	2.53	2.42	−0.12*	2.48	2.47	0
Lean hogs	0.81	0.79	−0.01*	2.56	2.43	−0.13*	2.49	2.50	0.01
Live cattle	0.74	0.81	0.08*	2.54	2.60	0.05*	2.52	2.55	0.04*
Gold	0.44	0.24	−0.21*	2.04	1.85	−0.19*	2.17	1.98	−0.19*
Silver	0.59	0.32	−0.27*	2.33	1.95	−0.38*	2.38	2.11	−0.28*
Aluminium	0.84	0.85	0.01*	2.42	2.48	0.06*	2.42	2.50	0.08*
Copper	0.55	0.41	−0.14*	2.43	2.17	−0.26*	2.35	2.12	−0.24*
Lead	0.76	0.77	0.01	2.38	2.44	0.07*	2.42	2.50	0.08*
Nickel	0.78	0.73	−0.05*	2.45	2.31	−0.14*	2.37	2.26	−0.11*
Zinc	0.89	0.84	−0.04*	2.46	2.43	−0.02*	2.56	2.40	−0.16*
Mean	**0.62**	**0.54**	**−0.08**	**2.29**	**2.22**	**−0.07**	**2.23**	**2.15**	**−0.08**
B. Nonindex commodities									
Propane	0.27	0.37	0.1*	2.22	2.17	−0.05*	2.12	1.88	−0.24*
Minneapolis wheat	0.67	0.72	0.05*	2.43	2.51	0.08*	2.31	2.37	0.05*
Oats	0.78	0.75	−0.03*	2.38	2.40	0.02	2.29	2.37	0.08*
Rice	0.86	0.81	−0.05*	2.41	2.45	0.04*	2.46	2.46	0
Lumber	0.76	0.83	0.07*	2.44	2.48	0.04*	2.47	2.48	0
Orange juice	0.79	0.82	0.03*	2.43	2.56	0.13*	2.44	2.55	0.1*
Pork bellies	0.79	0.84	0.05*	2.48	2.73	0.25*	2.44	2.63	0.19*
Platinum	0.74	0.48	−0.26*	2.49	2.03	−0.45*	2.47	2.11	−0.36*
Palladium	0.81	0.50	−0.3*	2.47	2.17	−0.31*	2.38	2.16	−0.23*
Tin	0.84	0.79	−0.05*	2.45	2.37	−0.08*	2.50	2.41	−0.09*
Mean	**0.73**	**0.69**	**−0.04**	**2.42**	**2.39**	**−0.03**	**2.39**	**2.34**	**−0.05**

Note: Table 5 reports the delay measures suggested by Hou and Moskowitz (2005) (Delay1, Delay2, and Delay3). The metrics are computed for the sub-samples spanning the pre- and post-financialization period. Furthermore, Table 5 shows the difference in mean.
*Indicates statistical significance at the 5% level.

correspond to q times the return variance for a holding period of one day.[6] It is exactly this property that forms the basis of the VR of Lo and MacKinlay (1988) as follows:

$$VR(q) = \frac{Var[r_t(q)]}{qVar[r_t]}, \tag{7}$$

where $r_t(q) = r_t, r_{t-1}, \dots, r_{t-q+1}$. Given that the return time series follows a random walk, VR should take values near one. Eq. (7) can be restated to illustrate that market efficiency is associated with return serial correlation:

$$VR(q) = 1 + 2\sum_{k=1}^{q-1} \left(1 - \frac{k}{q}\right)\rho(k), \tag{8}$$

where $\rho(k)$ denotes the kth order autocorrelation coefficient of the return process $\{r_t\}$. VR can thus also be interpreted as a weighted average of return autocorrelation over different time horizons.

However, VR has the disadvantage that the holding period q must be determined in advance. Unfortunately, the selection is usually arbitrary without any statistical considerations. For this reason, Choi (1999) proposes a modification of VR, the automatic

[6] As we only have daily data, the variance is estimated using daily holding periods. However, one should keep in mind that estimates of the variance and thus the variance ratio based on high-frequency data are more precise Andersen et al. (2001). The sensitivity of the results with respect to this limitation needs to be analysed in future research.

Table 6
CIT regression.

	Panel A: CIT market share						
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
MS	−0.002*	−0.002**	−0.003	−0.004**	−0.016***	−0.009*	−0.010***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.005)	(0.003)
B	−0.044	−0.044	−0.029	−0.175	0.077	0.039	0.223
	(0.091)	(0.114)	(0.098)	(0.156)	(0.162)	(0.503)	(0.418)
IQ	0.001	0.001	−0.003	−0.003	−0.012***	0.003	−0.003
	(0.002)	(0.002)	(0.005)	(0.006)	(0.004)	(0.008)	(0.006)
Constant	0.129***	0.124***	0.171***	0.225***	0.853***	2.446***	2.429***
	(0.032)	(0.022)	(0.035)	(0.037)	(0.075)	(0.101)	(0.061)
	Panel B: CIT Net Long						
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
NET	−0.002***	−0.001***	−0.001*	−0.001	−0.006***	−0.003	−0.005***
	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
B	−0.015	−0.019	−0.015	−0.170	0.110	0.056	0.266
	(0.077)	(0.117)	(0.092)	(0.155)	(0.182)	(0.507)	(0.410)
IQ	0.001	0.001	−0.002	−0.003	−0.012***	0.003	−0.002
	(0.002)	(0.002)	(0.005)	(0.006)	(0.004)	(0.008)	(0.005)
Constant	0.130***	0.127***	0.157***	0.189***	0.708***	2.360***	2.362***
	(0.019)	(0.013)	(0.023)	(0.027)	(0.039)	(0.065)	(0.045)
Commdity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table 6 reports the pooled OLS regression results for Eq. (15). The dependent variable is the absolute deviation of the respective variance ratio from unity |VR-1| or the Delay measure for commodity market i in week t. The regression allows for clustering among observations of the same month and commodity futures market. Further, standard errors are reported in parentheses.

***Denote statistical significance at the 1% level.

**Denote statistical significance at the 5% level.

*Denote statistical significance at the 10% level.

variance ratio (AVR):

$$AVR(q) = 1 + 2\sum_{k=0}^{T-1} f(\frac{k}{q})\rho(k). \tag{9}$$

As weighting function $k(\cdot)$, Choi (1999) selects a quadratic spectral kernel that ensures positive but declining weights for the autocorrelation coefficients. Choi (1999) addresses the problem of arbitrary parameter values for q by adopting a method that originates from Andrews (1991) and postulates a data-dependent selection of q.[7]

We follow Boehmer and Kelley (2009) and use the absolute deviations of VR/AVR from one as a measure for the degree of market efficiency. Daily measures of informational efficiency are generated using a moving window approach with a window length of 250 trading days (approximately one calendar year).[8]

In addition to measures based on return autocorrelation, the literature (e.g., Busch and Obernberger, 2017; Griffin et al., 2010; Boehmer and Wu, 2013; Phillips, 2011) also uses metrics that measure the delay with which fundamental data are reflected in prices. The idea is that in efficient markets fundamental data are fully and immediately priced in when they become available. The greater the delay, the greater the deviation from the ideal state of absolute market efficiency. In quantifying the delay, we build on Mech (1993) and Hou and Moskowitz (2005). According to these studies, DL indicates how sensitive current returns react to past fundamentals. Similarly, we calculate DL as the deviation in R^2 between a model (10) which allows for delayed impact of (five daily lags) of fundamental data and a restricted model (11) without lags:

$$r_{i,t} = \alpha_i + \beta_i^0 * X_t + \sum_{n=1}^{5} \beta_i^n * X_{t-n} + \epsilon_{i,t} \tag{10}$$

$$r_{i,t} = \alpha_i + \beta_i^0 * X_t + \epsilon_{i,t}. \tag{11}$$

[7] Readers interested in the technical details of the selection process are referred to Choi (1999).

[8] An obvious question is whether a clear tendency towards positive or negative autocorrelation can be deduced from the time varying VRs. In a related study, Bohl et al. (2020) show that the AVR fluctuates around the value 1 without showing a clear trend. Interested readers are referred to Figure 2 in Bohl et al. (2020).

Table 7
CIT Decomposition Regression.

	Panel A: CIT Market Share						
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
#CIT	0.002	0.005***	0.001	−0.005	0.007	0.007	0.012
	(0.003)	(0.002)	(0.003)	(0.004)	(0.011)	(0.020)	(0.012)
CIT Expand	−0.003**	−0.003***	−0.003*	−0.003*	−0.020***	−0.012***	−0.013***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.002)
B	−0.037	−0.034	−0.023	−0.176	0.109	0.062	0.253
	(0.088)	(0.117)	(0.096)	(0.156)	(0.170)	(0.491)	(0.399)
IQ	0.002	0.002	−0.002	−0.003	−0.006*	0.008	0.003
	(0.002)	(0.002)	(0.005)	(0.005)	(0.003)	(0.008)	(0.005)
Constant	0.028	−0.018	0.092	0.245***	0.376*	2.106***	1.975***
	(0.060)	(0.039)	(0.072)	(0.086)	(0.222)	(0.411)	(0.234)
	Panel B: CIT Net Long						
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
#CIT	−0.002***	−0.002*	−0.001	−0.0004	−0.0004	0.008	0.004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.007)	(0.006)
CIT Expand	−0.002**	−0.001***	−0.001	−0.001	−0.007***	−0.005***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
B	−0.016	−0.021	−0.015	−0.168	0.129	0.094	0.295
	(0.075)	(0.117)	(0.095)	(0.155)	(0.173)	(0.506)	(0.409)
IQ	0.001	0.001	−0.002	−0.003	−0.012***	0.003	−0.002
	(0.002)	(0.002)	(0.005)	(0.006)	(0.004)	(0.007)	(0.005)
Constant	0.135***	0.151***	0.162***	0.164**	0.533***	2.009***	2.096***
	(0.019)	(0.036)	(0.057)	(0.065)	(0.145)	(0.218)	(0.170)
Commdity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table 7 reports the pooled OLS regression results for Eq. (17). The dependent variable is the absolute deviation of the respective variance ratio from unity |VR-1| or the delay measure for commodity market i in week t. The regression allows for clustering among observations of the same month and commodity futures market. Further, standard errors are reported in parentheses.

***Denote statistical significance at the 1% level.

**Denote statistical significance at the 5% level.

*Denote statistical significance at the 10% level.

Table 8
Difference-in-differences regression.

	Variance Ratio				Delay		
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
$D_{Index,2004}$	−0.016***	−0.022***	−0.021**	−0.026*	−0.077***	−0.047*	−0.076***
	(0.006)	(0.008)	(0.010)	(0.014)	(0.020)	(0.027)	(0.024)
Constant	0.062***	0.104***	0.176***	0.229***	0.887***	2.473***	2.499***
	(0.003)	(0.004)	(0.004)	(0.006)	(0.008)	(0.012)	(0.010)
Commdity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table 8 reports the pooled OLS regression results for Eq. (18). The dependent variable is the absolute deviation of the variance ratio from unity |VR-1| or one of the delay measures for commodity market i at time period t. The dummy $D_{Index,2004}$ takes on one if the commodity is index traded and $t \geq 2004$ and zero otherwise. The regression allows for clustering among observations of the same month and commodity futures market. Further, standard errors are reported in parentheses.

***Denote statistical significance at the 1% level.

**Denote statistical significance at the 5% level.

*Denote statistical significance at the 10% level.

Here, $r_{i,t}$ denotes the return of commodity futures contract i on trading day t, X_t is a vector containing the fundamental time series on trading day t. X_t consists of economic factors commonly associated with commodity futures returns: (1) The return on S&P 500 as a high-frequency measure of expectations about U.S. economic growth; (2) the return on MSCI Emerging Markets Asia Index as a high-frequency measure of expectations about emerging markets economic growth; (3) the return on trade weighted U.S. Dollar Index, since commodity futures contracts are usually settled in U.S. Dollar; (4) the percentage change in the VIX Index, because the

Table 9
Robustness - Different roll approach.

	Panel A: CIT Market Share						
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
MS	−0.002	−0.00005	−0.001	−0.003**	−0.018***	−0.007	−0.010**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.005)	(0.007)	(0.005)
B	−0.031	0.262	−0.093	−0.482	0.225	−1.298*	−0.987*
	(0.289)	(0.206)	(0.259)	(0.331)	(0.377)	(0.738)	(0.575)
IQ	0.001	0.001	−0.002	−0.001	−0.013***	0.004	−0.002
	(0.002)	(0.002)	(0.006)	(0.006)	(0.004)	(0.009)	(0.006)
Constant	0.106***	0.080***	0.139***	0.219***	0.889***	2.417***	2.432***
	(0.035)	(0.020)	(0.041)	(0.036)	(0.097)	(0.144)	(0.095)
	Panel B: CIT Net Long						
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
NET	−0.001*	−0.001**	−0.001	−0.001	−0.007***	−0.003	−0.005***
	(0.001)	(0.0004)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
B	0.010	0.297	−0.078	−0.472	0.350	−1.247*	−0.855
	(0.267)	(0.191)	(0.255)	(0.329)	(0.384)	(0.734)	(0.581)
IQ	0.002	0.001	−0.001	−0.001	−0.012***	0.004	−0.0001
	(0.002)	(0.002)	(0.006)	(0.007)	(0.004)	(0.008)	(0.006)
Constant	0.116***	0.108***	0.136***	0.180***	0.721***	2.348***	2.392***
	(0.024)	(0.014)	(0.025)	(0.028)	(0.051)	(0.077)	(0.057)
Commdity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table 9 reports the pooled OLS regression results for Eq. (15) based on futures continuous series rolled on the 10th calendar day of the pre-maturity month. The dependent variable is the absolute deviation of the respective variance ratio from unity |VR-1| or the Delay measure for commodity market i in week t. The regression allows for clustering among observations of the same month and commodity futures market. Further, standard errors are reported in parentheses.

***Denote statistical significance at the 1% level.

**Denote statistical significance at the 5% level.

*Denote statistical significance at the 10% level.

VIX represents a measure for uncertainty (Cheng et al., 2015); (5) the percentage change in Baltic Dry Index, which reflects the cost of transporting raw materials by sea, and is commonly employed as a measure for global economic conditions; (6) the return on GSCI Index as a proxy for general commodity market expectation.

Assuming efficient futures markets, new information should be instantaneously reflected in the futures price, and the regression coefficients for the lagged fundamental time series should not significantly deviate from zero. If the information incorporation is delayed, then we would assume coefficients for the lagged fundamental time series to deviate from zero, and consequently, the unrestricted model with lagged fundamentals to have a higher explanatory power than its restricted competitor.

The $DL1$ measure proposed by Hou and Moskowitz (2005) is as follows:

$$DL1 = 1 - \frac{R^2_{Restricted}}{R^2_{Unrestrictred}}. \tag{12}$$

The greater the explanatory power of the lagged fundamental information, the longer the delay until futures prices reflect new information. In other words, the higher the degree of informational efficiency, the smaller the difference between the two adjusted R^2. Since $R^2_{Unrestrictred}$ is by construction at least as large $R^2_{Restricted}$, $DL1$ takes values between 0 and 1. The higher the $DL1$ measure, the lower the degree of market efficiency.

However, $DL1$ neither distinguishes between short and long lags, nor considers the precision of coefficient estimates. Therefore, Hou and Moskowitz (2005) suggest two alternative delay measures, $DL2$ and $DL3$:

$$DL2 = \frac{\sum_{n=1}^{5} n\beta^n}{\beta^0 + \sum_{n=1}^{5} \beta^n} \tag{13}$$

$$DL3 = \frac{\sum_{n=1}^{5} n\beta^n / se(beta^n)}{\beta^0/se(\beta^0) + \sum_{n=1}^{5} \beta^n/se(\beta^n)}, \tag{14}$$

where $se(\cdot)$ denotes the standard error of the estimated coefficient. Both measures are motivated by the work of Mech (1993) and Brennan et al. (1993), who employ similar measures. Higher estimates for $DL2$ and $DL3$ indicate lower degrees of price informativeness. In the construction of standard errors, we follow Hou and Moskowitz (2005) and use unadjusted OLS standard errors.

Table 10
Robustness - Only roll days.

	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
	Panel A: CIT Market Share						
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
MS	−0.002	0.00001	−0.001	−0.003*	−0.018***	−0.007	−0.010**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.007)	(0.005)
B	0.027	0.301	0.023	−0.341	−0.020	−1.248**	−1.018**
	(0.214)	(0.197)	(0.245)	(0.324)	(0.362)	(0.599)	(0.457)
IQ	0.002	0.002	−0.003	−0.003	−0.013**	0.009	0.001
	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.009)	(0.008)
Constant	0.108***	0.077***	0.133***	0.213***	0.890***	2.412***	2.440***
	(0.034)	(0.021)	(0.042)	(0.040)	(0.098)	(0.144)	(0.093)
	Panel B: CIT Net Long						
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
NET	−0.001*	−0.001**	−0.001	−0.001	−0.007***	−0.003	−0.005***
	(0.001)	(0.0005)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
B	0.054	0.328*	0.034	−0.341	0.027	−1.223**	−0.942**
	(0.201)	(0.190)	(0.239)	(0.322)	(0.396)	(0.602)	(0.480)
IQ	0.003	0.003	−0.003	−0.003	−0.012**	0.009	0.003
	(0.003)	(0.002)	(0.006)	(0.006)	(0.005)	(0.009)	(0.008)
Constant	0.117***	0.107***	0.137***	0.178***	0.720***	2.352***	2.404***
	(0.024)	(0.016)	(0.027)	(0.030)	(0.050)	(0.084)	(0.063)
Commdity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table 10 reports the pooled OLS regression results for Eq. (15) based sample covering only the first 10 calendar days of the pre-maturity month. The dependent variable is the absolute deviation of the respective variance ratio from unity |VR-1| or the delay measure for commodity market i in week t. The regression allows for clustering among observations of the same month and commodity futures market. Further, standard errors are reported in parentheses.

***Denote statistical significance at the 1% level.

**Denote statistical significance at the 5% level.

*Denote statistical significance at the 10% level.

The measures employed are widely used in the literature, but are not without criticism. For example, Lauter and Prokopczuk (2022) show that the correlation of price efficiency measures based on high-frequency data with their daily-frequency counterparts is low and that price efficiency is notoriously hard to capture with low-frequency (i.e. daily) data. One problem could be that pricing errors might be short-lived and hence difficult to be measured with daily settlement prices. However, Brogaard et al. (2022) show that their measure of market information reflected in the return process is strongly negatively associated with the delay measure of Hou and Moskowitz (2005). They also provide evidence that stocks that are inefficient in reflecting market-wide information tend to have noisier prices (i.e., the noise component is more relevant in driving returns). Consistently, they find that variance ratio measures are related to the incorporation of private and public information in the return process. In addition, Griffin et al. (2010) provide an in-depth discussion on limitations of commonly adopted measures of informational efficiency. For instance, empirical efficiency measures only test whether a specific information set is reflected in prices. This may be problematic for several reasons. On the one hand, empirical efficiency measures are based on incomplete information sets, which can account for very different shares of the total information set depending on the commodity market under consideration. This makes it difficult to draw conclusions about relative overall efficiency. On the other hand, all other things being equal, prices of commodities with little fundamental news are more likely to follow a random walk than those of a commodity with a high news flow if information absorption is not instantaneous.

To generate time-variable delay measures of market efficiency, we proceed as described for the VR measures. The regressions on which DL measures are based use a window of 250 trading days. DL measures are then computed based on the R^2, regression coefficients, and standard error estimates of these regression models.

To gain a first impression of whether financialization marks a structural change in the return process of indexed commodity futures, we subdivide the sample period in a pre-financialization period up to 2003, and a sub-sample covering the financialization period afterwards. Fig. 2 depicts the average degree of market efficiency before and after the assumed break in 2004 for index and non-index commodity futures markets, respectively.

As is apparent from Fig. 2, we fail to replicate the results reported by Brogaard et al. (2019) (see Figure 2 in their paper). On the contrary, Fig. 2 indicates that index commodities experienced a break towards better informational efficiency. For both groups of commodities a lower value for delay and variance ratio can be observed, whereas the difference is even more pronounced for indexed commodities.

Next, we report in Tables 4 and 5 for each sub-sample the mean of the market efficiency measures for each single commodity market. On closer inspection, we neither find evidence for a structural break that only affected indexed commodities, nor is a

Table 11
Robustness - Market environment.

	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
Panel A: Recession & CIT Market Share							
MS	−0.003*	−0.002*	−0.002	−0.003*	−0.016***	−0.009**	−0.010***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.005)	(0.003)
REC	−0.0002	0.001	−0.002	−0.002	−0.002	0.011	0.004
	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.008)	(0.005)
MS × REC	0.0001	−0.002	−0.002	−0.002	0.014***	0.013***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
Panel B: Recession & CIT Net Long							
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
NET	−0.002***	−0.001***	−0.001	−0.001	−0.006***	−0.003	−0.004***
	(0.001)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
REC	0.0003	0.001	−0.002	−0.002	−0.001	0.011	0.005
	(0.002)	(0.002)	(0.005)	(0.005)	(0.004)	(0.007)	(0.005)
NET × REC	0.0004	−0.001	−0.001	−0.002	0.008***	0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Panel C: Contango & CIT Market Share							
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
MS	−0.001	0.0004	−0.0003	−0.003*	−0.018***	−0.007	−0.010*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.007)	(0.005)
CONT	0.026	0.038*	0.069**	0.015	0.007	0.076	0.027
	(0.024)	(0.021)	(0.029)	(0.035)	(0.080)	(0.050)	(0.046)
MS × CONT	−0.002	−0.003**	−0.004*	0.0002	0.001	−0.004*	−0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.006)	(0.002)	(0.003)
Panel D: Contango & CIT Net Long							
	AVR	VR(4)	VR(8)	VR(12)	Delay1	Delay2	Delay3
NET	−0.001*	−0.001	−0.0001	−0.001	−0.007***	−0.002	−0.005***
	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
CONT	0.052***	0.040***	0.071***	0.035**	−0.054	0.085*	0.003
	(0.018)	(0.014)	(0.010)	(0.017)	(0.054)	(0.044)	(0.038)
NET × CONT	−0.002**	−0.002***	−0.003***	−0.001	0.004	−0.003*	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Commdity FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table 11 reports the pooled OLS regression results for Eq. (19). The dependent variable is the absolute deviation of the respective variance ratio from unity |VR-1| or the delay measure for commodity market i in week t. The regression allows for clustering among observations of the same month and commodity futures market. Further, standard errors are reported in parentheses.

***Denote statistical significance at the 1% level.

**Denote statistical significance at the 5% level.

*Denote statistical significance at the 10% level.

disparity between indexed and non-indexed commodities apparent. Taken together, the initial results do not support a conclusion that market efficiency in indexed commodities was harmed by the financialization. Conversely, the results indicate that information efficiency has improved. A comparison of average efficiency measures between pre- and post-financialization shows that, for the most part, there has been a reduction in average information inefficiency, i.e., commodity futures markets process and incorporate information better after 2004. This observation is at odds with the position advocated by Brogaard et al. (2019), among others, that financialization has led to a deterioration of information processing in commodity futures markets. This statement is not sensitive with respect to the efficiency measure under consideration. It should be noted, however, that this is primarily a descriptive observation that requires further econometric analysis.

3. Results

3.1. Index trading and informational efficiency

In this section, we test whether CIT activity is associated with informational efficiency in commodity futures markets. As mentioned earlier, for a subgroup of commodities (exclusively agricultural commodities), the CFTC publishes weekly figures for

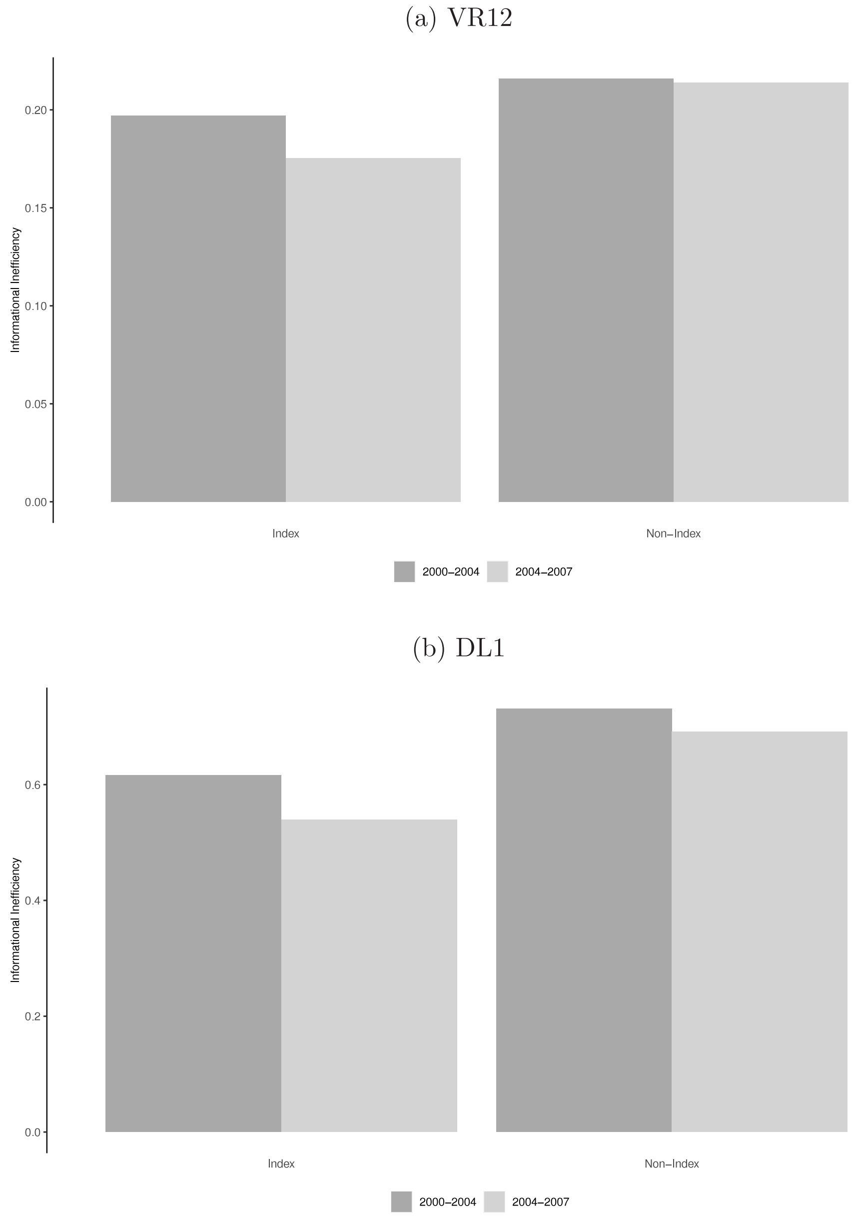

Fig. 2. Financialization and Informational Efficiency
Note: The graphs show the average degree of market inefficiency for index and non-index commodities in the pre- and post financialization period, respectively. DL1 refers to the delay measure proposed by Hou and Moskowitz (2005), whereas VR12 refers to the Variance Ratio measure developed by Lo and MacKinlay (1988) with a holding period of 12 days.

the open interest held by CITs. Based on this dataset, we investigate whether the relative presence of CITs affects the degree of market efficiency.

To test the null hypothesis that index trading has no effect on market efficiency, we estimate the following OLS regression model:

$$EF_{i,t} = \alpha + \beta_2 CIT_{i,t} + \beta_3 B_{i,t} + \beta_4 IQ_{i,t} + \mu_t + \phi_i + \varepsilon_{i,t} \ , \tag{15}$$

where the dependent variable $EF_{i,t}$ is either the absolute deviation of the selected variance ratio (VR or AVR), or one of the DL measures. For the original VR, we consider three holding periods, namely four, eight and twelve trading days. The independent variable $CIT_{i,t}$ refers to one of the adopted CIT activity measures. To match the weekly trader position data with our efficiency measure, we proceed as follows. We stick to the daily sampling frequency and assign for each reporting date the accompanying efficiency measure for the respective day (usually, Tuesday market close). To control for time-invariant unobserved heterogeneity among commodity futures, we include commodity fixed effects (ϕ_i). Lastly, the error term is denoted by $\varepsilon_{i,t}$. All standard errors are clustered at the commodity market and month level. By estimating model (15) we examine if the market activity of CITs has an influence on the degree of market efficiency. To the extent that the hypothesis of Brogaard et al. (2019) holds true, we would expect that an increase in the activity of CITs leads to a higher distortion of the information content in prices, i.e. to lower market efficiency. Results for regression model Eq. (15) are reported in Table 6.

Overall, we find no empirical evidence that CITs are detrimental to the degree of market efficiency. Most of the specifications of regression model (15) suggest that CITs could even be conducive to market efficiency. We find empirical evidence that CITs improve the degree of market efficiency for VR and DL. Both CIT market share and the net long position of CITs are associated with lower values for VR and DL. This result can be attributed to different economic mechanisms. For example, CITs can create a market environment in which it is easier for other, informed investors to trade on the basis of their information. In addition, CITs themselves could lead to information being better reflected in prices. For example, the coefficients on delay measures show that CIT activity is strongly related to less delayed processing of fundamental information in commodity futures markets.

The observed temporal and cross-sectional fluctuations in CIT activity may result from new CITs entering the market, or from existing CITs expanding their activity, or from both. Therefore, we follow Glosten et al. (2021), and study the relative importance of each channel on informational efficiency in commodity futures markets. We decompose CIT activity by regressing CIT activity ($CIT_{i,t}$, measured by MS or $NET_{i,t}$) on the number of CITs active in underlying futures market i ($\#CIT_{i,t}$):

$$CIT_{i,t} = \alpha_i + \beta_i \#CIT_{i,t} + \epsilon_{i,t}. \tag{16}$$

Next, we use the fitted values from Eq. (16) ($\#\widehat{CIT_{i,t}}$) as a proxy for CIT activity that results from new CITs entering the market and the residual (orthogonal) component ($CIT-Expand_{i,t} = \epsilon_{i,t}$) as a measure of CIT activity stemming from existing CITs expanding their market positions. In order to evaluate, which component drives the observed association between CIT activity and informational efficiency, we reestimate Eq. (15) by replacing $MS_{i,t}$ with its approximated components:

$$EF_{i,t} = \alpha + \beta_2 \#\widehat{CIT_{i,t}} + \beta_3 CITExp_{i,t} + \beta_4 B_{i,t} + \beta_5 IQ_{i,t} + \mu_t + \phi_i + \varepsilon_{i,t}\ . \tag{17}$$

In general, the results suggest that the positive effect of CIT activity on informational efficiency is mainly driven by CITs expanding portfolio holdings and not by new CITs entering the market. Most of the regression coefficients for $CITExp_{i,t}$ are negative and statistically significant, whereas most of the coefficients for $\#\widehat{CIT_{i,t}}$ are insignificant. From an economic point of view, it is worth noting that it is not the number of CITs but the market position that is relevant for the degree of information efficiency. Additional CITs do not seem to make any additional information contribution insofar as the volumes they hold are small. This also suggests that some scaling of trading activity is necessary to be able to influence the information efficiency environment.

3.2. *Difference-in-differences regression*

The OLS regression framework may suffer from an omitted variable basis. Therefore, it is not clear whether the observed association between index investing and informational efficiency can be interpreted as a causal relationship. In order to address this issue and confirm our earlier results based on single market efficiency measures, we adopt the difference-in-differences approach of Brogaard et al. (2019). The resulting regression model reads as follows:

$$EF_{i,t} = \alpha + \beta_1 D_{i,t} + \beta_3 \mu_t + \beta_4 \phi_i + \varepsilon_{i,t}. \tag{18}$$

To study the presence of a potential structural break in the return process, we include a dummy variable $D_{i,t}$ that indicates whether a market belongs to the treatment (indexed) or control (not indexed) group. Following Brogaard et al. (2019), the treatment group is defined as commodity futures market tracked by the S&P GSCI or the Bloomberg Commodity Index (former Dow Jones-UBS Commodity Index). The dummy takes on one, if the commodity under scrutiny is index traded and $t \geq 2004$, and zero, otherwise. By this means, we can identify whether the financialization period had a significant impact on the degree of market efficiency in commodity futures markets. Further, we control for time-invariant and market-specific unobserved heterogeneity among commodity futures by including month and commodity market fixed effects (μ_t and ϕ_i). Finally, we cluster standard errors at the commodity market and month level.

To reduce the effect of other potential forces as well as to ensure consistency, we adopt the same sample period as Brogaard et al. (2019) from January 2000 to December 2007. In case the financialization period reflects a structural break in market efficiency of indexed futures markets, we expect a significant coefficient for the financialization dummy variable.

Results are reported in Table 8. Our findings clearly contradict the results of Brogaard et al. (2019). We find evidence for a significant positive impact of the financialization period on informational efficiency in index commodity futures markets, as highlighted by the significant negative coefficient estimates, regardless of the utilized efficiency measure. In this context, a significant negative sign indicates that the financialization had a positive influence on the degree of information efficiency, i.e., the financialization period has contributed to the fact that indexed commodity futures markets process fundamental information more quickly after 2004. One reason for this could be that index investors contributed to higher liquidity, which in turn makes it easier for informed investors to trade on the basis of private information. Another reason could be that index investors trade on the basis of information and thus bring previously unpriced information into the respective futures market through their trading behaviour.

4. Robustness

4.1. Different roll approach

Although the approach used to construct the continuous futures price time series is the most common in the literature, the question arises whether it is the most adequate in the context of the issue considered in this study. In this context, it is necessary to clarify to what extent the results of the empirical analysis are affected by the rolling method. More specifically, the chosen roll method may not comprehensively capture the price impact of CITs. The background to this is that CITs could more closely track the rolling behaviour of the indices being replicated. For instance, the S&P GSCI rolls the underlying futures contract from the 5th to the 9th trading day of maturity months and the Bloomberg Commodity Index from the 6th to the 10th trading day of maturity months. In the robustness test, we follow Singleton (2014) and assumed CITs roll their futures positions on the 10th calendar day of the month. Since the index roll takes place typically between the 5th and 10th business day of the month, the adopted rolling method represents a reasonable compromise.

The results of the robustness test based on the alternative continuous futures price series are shown in Table 9. The efficiency measures are recalculated using the alternative continuous series and regression model (15) is re-estimated. Overall, it can be seen that the results of the original analysis still hold. There is no evidence that the presence of CITs in the commodity futures market is associated with a deterioration in market quality. This can be observed regardless of which efficiency measure and which form of quantification of the activity of CITs is considered. On the contrary, in some cases it can be observed that CIT activity and improvement in market quality are positively correlated.

4.2. Only roll weeks/days

As described earlier, CITs roll their positions in the futures market on pre-specified days in line with the commodity index to be replicated. Accordingly, CIT activity is concentrated on individual days at the beginning of a roll month. Accordingly, it is conceivable that the possible effect of CIT trading behaviour on the information efficiency of the underlying markets is also limited to this period. Therefore, in a further robustness analysis, we check to what extent our results hold even if we only consider observations on roll days. In this context, we estimate regression model (15) and use only observations of the first 10 days of a calendar month. This choice of observations is motivated by the fact that the dominant indexes roll their positions on the first 10 working days of the month.

Table 10 shows the results of the empirical analysis using only potential rolling days. It can be seen that the results from the original analysis still hold. If anything, CITs have a positive impact on information efficiency in commodity futures markets.

4.3. Market environment

Another aspect that requires a deeper analysis is the influence of the market environment on the transmission effect of CIT activity on information efficiency in commodity futures markets. More precisely, it is of interest whether CITs have a stronger or weaker influence on the pricing of new information in commodity futures markets, for example in recessions or in specific market phases (e.g. in contango periods). To study the effect of market environment on the transmission of index trading on market efficiency, we extend model (15) as follows:

$$EF_{i,t} = \alpha + \beta_1 CIT_{i,t} + \beta_2 CIT_{i,t} * d_1 + d_1 + \text{Controls} + \mu_t + \phi_i + \varepsilon_{i,t} \ , \tag{19}$$

where the additional variable $d_1 \in [\text{CONT}, \text{REC}]$ denotes a binary variable and Controls refers to the basis and illiquidity measures already employed in (15). We consider two different approaches to study the effect of market environment. First, CIT activity may impact markets in recessions differently than in expansions. This could be due to the lack of arbitrage capital in economic downturns. Hence, d_1 is equal to one if the observation is from a recession period and zero otherwise. We refer to this market state variable as REC. Second, the state of the commodity market itself may affect the transmission process of CIT activity. More specifically, CIT activity might rise when prices are expected to rise (e.g., in periods of backwardation) and drop when prices are expected to drop (e.g., in periods of contango). Consequently, the influence of e.g., backwardation and contango should be controlled for in order to analyse the impact of CIT activity on informational efficiency. This market environment variable is referred to as CONT. Table 11 shows the results of estimating Eq. (15) for the different measures of information efficiency, CIT activity, and market environment. For the sake of brevity, only the coefficient estimates for CIT activity, the market state indicator d_1 and the interaction term are reported.

Based on Panel A and B in Table 11, it can be stated that CIT activity continues to have a negative and mostly significant influence on information inefficiency if one differentiates between economic expansions and recessions. The interaction term is insignificant for variance ratio measures. For delay, regardless of the measure considered, CIT activity has a weaker influence in recessions, which is represented by a positive interaction term. This can be interpreted as meaning that CIT makes a positive contribution to the information efficiency of markets in growth phases, but that this contribution is almost completely lost in recessionary environments. One reason for this could be that, insofar as CITs provide a liquid market environment for informed traders, they are unable to exploit inefficiencies even in crisis phases due to the limited availability of arbitrage capital and, accordingly, the market liquidity provided by CITs does not provide any benefit. However, this observation requires deeper analysis in future research.

Considering whether a futures market is in contango or backwardation is presented in Panel C and D of Table 11. In general, the regression coefficients for CIT activity remain negative, but in some cases lose statistical significance. Regarding the interaction term, it is found that CIT activity in contango phases improves the degree of information efficiency even more, which is reflected by a negative sign of the interaction term. However, the degree of statistical significance varies depending on the measure of information efficiency and CIT activity considered. In conclusion, the specific market environment appears to have an impact on whether and how CITs can contribute to higher market quality. However, this important finding requires further investigation to better understand the underlying economic mechanisms.

5. Conclusion

The substantial financial inflows into index funds that track commodity price indices have triggered an intense debate about the extent to which this change in the composition of market participants affects the quality of the underlying futures markets. A key determinant of market quality is the ability of a securities market to process new information accurately and promptly, often referred to as market efficiency. The aim of this paper is to investigate a possible relationship between commodity index trader (CIT) investments and the degree of market efficiency. The starting point is the recently published paper by Brogaard et al. (2019), which shows that companies whose business activities are connected to indexed commodities are negatively affected by selected indicators. The authors attribute this to, among other things, a lower quality of information on the futures markets, which in turn leads to suboptimal decision-making by the companies concerned. We investigate this claim based on a sample covering the time period from 1999 to 2019.

To quantify the degree of market efficiency, we use different variants of the variance ratio and the delay measures suggested by Hou and Moskowitz (2005). Basically, informational efficiency in commodity futures markets varies considerably in the cross-section and over time. However, using a limited sample (only agricultural commodities covered by the CFTC in its SCOT report), we examine whether the level of index activity measured by the market share of identified index investors is related to variations in market efficiency. We find no results that would suggest that index investor activity could harm the information processing of commodity futures markets. On the contrary, the results indicate that if there is a significant relationship between indexation and market efficiency, it appears to be positive.

Next, using a difference-in-differences approach, we do not find any results that support the findings of Brogaard et al. (2019). In general, we find no significant deterioration in market efficiency that can be observed exclusively for indexed commodities. Conversely, the empirical evidence suggests that indexed commodities experienced an improvement in informational efficiency after 2004. This indicates that fundamental information has been priced in faster during financialization than in the period before financialization has started.

Robustness tests show that the results of the original analysis still hold when only roll days of CITs or continuous futures price series that replicate a roll scheme similar to that of key commodity indices are considered. In addition, the first evidence was presented that the impact of CITs on market quality depends on the market environment. In particular, the positive influence of CITs on information efficiency weakens during recessions. Overall, this observation requires further investigation to better understand the underlying economic process.

A key implication of our work is that the assertion of a negative impact of commodity index investors on market quality, measured here by market efficiency, is not reflected in the data. In order to ensure market efficiency, regulators and policy makers should rather pay attention to fundamental market variables such as liquidity and volatility, for which there is evidence, based on an extensive literature, that these are crucial to ensure information processing. In addition, more extensive access to the temporally disaggregated CIT position data available from the U.S. Commodity Futures Trading Commission (CFTC) would help to further resolve this important research question.

CRediT authorship contribution statement

Martin T. Bohl: Conceptualization, Writing – original draft, Writing – review & editing, Formal analysis. **Scott H. Irwin:** Conceptualization, Writing – original draft, Writing – review & editing. **Alexander Pütz:** Software, Formal analysis. **Christoph Sulewski:** Software, Formal analysis.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Scott Irwin, Agricultural Markets Advisory Council, CME Group, Inc.

Data availability

The authors do not have permission to share data.

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