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Speculation and the Informational Efficiency of Commodity Futures Markets

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Abstract

The recent financialization in commodity futures markets has prompted many calls for restricting speculative activity due to its diametrical effect on market quality. One aspect of market quality is that new information is instantanously reflected in the price. This article studies how speculative activity affects informational efficiency of commodity futures markets. We document significant temporal and cross-sectional variation in market efficiency in 20 commodity futures markets based on a sample of weekly closing prices from 1986 to 2019. The fixed effects panel regression finds no evidence for a significant relation between speculative activity and the degree of informational efficiency after controlling for volatility and liqudity. The results are robust across different window sizes, sampling frequencies and levels of trader aggregation.

JEL Classification: G14, G15, C12

Keywords: Market efficiency, Variance ratio test, Commodity futures

1 Motivation

The past decade has seen in commodity markets a rapid increase in trading volumes in conjunction with unprecedented large fluctuations and excess co-movement. As a result, policy makers and scholars have renewed their interest in the study of commodity markets. The general perception is that this significant change in commodity price behaviour is primarily caused by a sharp increase in speculative activity in commodity futures markets. The debate prompted many calls for restrictions on trading positions in order to limit speculative activity. Nevertheless, the academic literature has so far not settled on the question whether speculators or macroeconomic fundamentals were mainly responsible for the severe fluctuations in commodity prices.

The issue of speculation has received considerable critical attention by the literature. Several attempts have been made to investigate the influence of speculative activity on price dynamics (Brunetti et al., 2016; Manera et al., 2016), excess co-movement (Le Pen and Sévi, 2018; Büyükşahin and Robe, 2014) or risk premia (Hamilton and Wu, 2014). Nevertheless, little is known about the influence of speculative trading on the efficiency of commodity futures markets. Market efficiency is one of the building blocks of modern financial theory, since more informative prices fasciliate more efficient and better-informed capital allocation decisions.

Two different mechanisms are conceivable that could link speculative activity to market efficiency. First, microstructure theory suggests that security prices react to information-motivated trading (e.g., Glosten and Milgrom, 1985; Kyle, 1985), and information-motivated trading in turn should fasciliate information efficiency. In case that speculators primarily act on proprietary information, then their trading behaviour should fasciliate market efficiency with prices moving closer to fundamental values. On the contrary, speculators may consist of poorly informed noise traders (e.g. De Long et al., 1990), whose order flow impedes information transmission. For instance, Grossman and Miller (1988) argue that feedback trading of noise trader entails positive return autocorrelation. Moreover, it is conceivable

1

that non-informed trading leads to negative return autocorrelation. Suppose that the non-informed trading of noise traders pushes prices far beyond their equilibrium level. When

30 fundamental information becomes available, noise traders' subsequent trading pushes prices back to their fundamentally justified level (Poterba and Summers, 1988). The commodity futures markets provide an interesting testing laboratory to investigate the influence of trading motivation (speculation or hedging) on market efficiency due to the identifiable diverging trading incentives.

35 Second, market efficiency is closely related to liquidity provision (Chordia et al., 2008) since deteriorating liquidity increases trading costs and makes arbitrage activity less attractive.[1] This in turn, leads presumably to less efficient markets. Consequently, security prices should reflect fundamental information more accurately in case market liquidiy is higher. One of the key features of speculative activity is liquidity provision in that speculators act as

40 counterparts for hedging needs fasciliting efficient risk allocation in financial markets. For instance, Sanders et al. (2010) and Chen and Chang (2015) show that speculative activity is positively related to liquidity. Therefore, we expect that from a liquidity provider perspective speculators should enhance market efficiency.

This paper investigates the impact of speculative and hedging activity on informational

45 efficiency in a sample of 20 major commodity futures markets spanning the period January 1986 to May 2019. Drawing upon recent improvements in the literature, we test for return predictability by utilizing the Choi (1999) automatic variance ratio test (AVR). Time-varying measures of market efficiency are derived through rolling-window estimations. Subsequently, the interrelation between trading motive and informational efficiency is examined. The

50 derived measure of market efficiency is regressed on selected variables that capture different aspects of speculative and hedging activity. We consider the total market share (in terms of open interest) of speculators and hedgers. Furthermore, we adopt the Working's (1960) T index to quantify the degree of excessive speculation. To construct the suggested measures of

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[1] Trading costs are related to liquidity in two ways. First, lower levels of liquidity widen generally the bid-ask spread. Second, trading activity in less liquid markets moves prices more adversely.

2

trading motive, we utilize information on trader positions that is provided by the Commodity Futures Trading Commission (CFTC).

In general, we find no evidence that speculators harm the informational efficiency of commodity futures markets. In most of the baseline regression models, we observe that speculators actually support the information incorporation process. However, regardless of the measure of speculation employed, the positive effect becomes insignificant after controlling for market volatility and different measures of market liquidity. In a similar vein, we cannot reject the null hypothesis that hedging activity is not related to the degree of market efficiency, even before controlling for different market state variables. This result may indicate that, if speculators are related to informational efficiency at all, they support market efficiency by providing liquidity to other market participants. This result holds across different window sizes, sampling frequencies and trader aggregation levels.

The remainder of the article proceeds as follows. Section 2 outlines the methodology and our main metric of informational efficiency. In Section 3, we introduce the data sample, while the analysis of return predictability variation and of the connection between market efficiency and speculation takes place in Section 4. Finally, Section 5 concludes.

2 Methodology

2.1 Market inefficiency and return autocorrelation

To date, the literature has highlighted various ways how to assess the elusive concept of market efficiency. This paper adopts the definition of Fama (1970), which builds on the idea that new information is instantanously and fully reflected in the price. For this reason, price increments should be unpredictable based on past information or, put another way, the return series should not exhibit any form of serial correlation. The presence of autocorrelation in the return process would indicate misreaction by investors to new information that is not conceivable with the concept of market efficiency. This notion is supported by different

theoretical models and frequently adopted in empirical studies.[2]

According to De Long et al. (1990), overreaction of market participants to new information may be associated to positive return autocorrelation. Conversely, Froot et al. (1995) argue that positive serial correlation arises due underreaction in the form of slow dissemination of market-wide information. Moreover, it is conceivable that systematic behavioural biases may affect traders to under- or overreaction to the arrival of new information (see, among others, Barberis et al., 1998). The presence of significant autocorrelation structures in the return process is further illustrated by the well documented profitability of contrarian (De Bondt and Thaler, 1985) and momentum trading strategies (Jegadeesh and Titman, 1993). Such trading strategies should not be rewarded with a significant positive return in informationally efficient markets.

2.2   Variance Ratio Test

The literature has proposed a variety of measures to quantify the degree of informational efficiency. Since the presence of serial correlation is closely related to the random walk model, we first recapitulate the random walk model to build the stage for our empirical approach. The random walk process assumes that the dynamics of the price series $\{P_t\}$ can be formulated as follows:

$$P_t = \mu + P_{t-1} + \epsilon_t \tag{1}$$

where μ denotes the constant drift term, capturing the expected price change, and ϵ_t is the error term with zero mean and variance σ^2. By utilizing recursive substitions of lagged P_t,

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[2]   While this notion of market efficiency is adopted in various theoretical and empirical studies, oponents argue that the presence of return autocorrelation itself does not necessary indicate market inefficiencies. For instance, serial return correlation is conceivable with rational information processing by market participants and not exploitable due to trading frictions (e.g. short sale restrictions, trading costs) (Jensen, 1978). A different strand of the literature argues that the serial return correlation may only reflect time-varying equilibrium expected returns.

mean and variance at time t, conditional on an initial value P_0, are given as follows:

$$E[P_t|P_0] = P_0 + t\mu$$
$$Var[P_t|P_0] = \sigma^2 t. \tag{2}$$

Evidently, conditional mean and variance of a random walk process depend on the time horizon t, which implies that a random walk is not stationary. An additional characteristic of the random walk model is that consecutive price increments are not forecastable based on the past history of $\{P_t\}$ and i.i.d. random variables:

$$P_t - P_{t-1} = \epsilon_t. \tag{3}$$

The variance ratio test (VR), that was initially proposed by Lo and MacKinlay (1988) and that we adopt to measure the degree of market efficiency, rests on the notion that, if price increments follow a random walk, then the return variance is a linear function of t. Hence, the q-period return variance should correspond to the return variance over one period multiplied with holding period q. In general, the VR is defined as:

$$VR(q) = \frac{Var[r_t(q)]}{qVar[r_t]}, \tag{4}$$

where $r_t(q) = r_t + r_{t-1} + \cdots + r_{t-q+1}$. In case the return process follows a random walk, then the VR should take values equal to unity. The VR is also closely related to the autocorrelation structure of the return process. This becomes apparent if we reformulate (4) as:

$$VR(q) = 1 + 2 \sum_{k=1}^{q-1} \left(1 - \frac{k}{q}\right)\rho(k), \tag{5}$$

where $\rho(k)$ denotes the kth order autocorrelation coefficient of $\{r_t\}$. Thus, the VR can be summarized as one plus a weighted average of the first $q-1$ autocorrelation coefficients $\{r_t\}$. Under the null hypothesis that the price follows a random walk process, $VR(q)$ takes values equal to unity, because price changes are serially uncorrelated.

5

A main advantage of the VR test over the frequently cited competing alternative Box-Pierce test is that it indicates the sign of serial correlation. A VR ratio below unity indicates that returns are overall negatively serially correlated, whereas a value above unity provides evidence for positive autocorrelation. As a metric for relative efficiency, the literature (Boehmer and Kelley, 2009; Rösch et al., 2017) employs the absolute deviation of the VR from unity, since relatively more efficient prices should exhibit less autocorrelation.

2.3 Automatic Variance Ratio

The adoption of the VR test requires the selection of a specific value for the holding period q. However, the choice of q is often made arbitrarily. Concerning this drawback, Choi (1999) suggests the automatic variance ratio (AVR) test, which rests on a fully data-dependent method for choosing q optimally:

$$VR(q) = 1 + 2 \sum_{i=0}^{T-1} k(\frac{i}{q}) \rho(i), \tag{6}$$

where $\rho(i)$ defines the autocorrelation coefficient of order i. For the weighting function $k(\cdot)$, which is characterized by positive and declining weights, Choi (1999) proposes the adoption of a quadratic spectral kernel:

$$k(x) = \frac{25}{12\pi^2\chi^2} \left[\frac{\sin\left(6\pi\chi\right)}{6\pi\chi/5} - \cos\left(\frac{6\pi\chi}{5}\right) \right]. \tag{7}$$

According to Choi (1999), the $AVR(k)$ is asymptotically equivalent to $2\pi f_Y(0)$, where $f_Y(0)$ denotes the normalized spectral density at zero frequency for return series $\{r_t\}$. Testing the null hypothesis that the VR is equal to unity requires choosing the value of holding period q. To circumvent the arbitrary choice of q, Choi (1999) adopts the data-dependent method of Andrews (1991). For the sake of brevity, we refer to Choi (1999) for a thorough description of the Andrews (1991) selection method. In the subsequent empirical analysis, we employ the absolute deviation of the $AVR(q)$ from unity as the dependent variable to assess

the influence of speculative activity on the degree of informational efficiency in commodity futures markets. This metric is an inverse measure, as higher values indicate lower degress of informational efficiency.

Time varying measures of market efficiency are derived by conducting moving-window analysis with a fixed length of 250 weekly observations, which corresponds to roughly five calendar years. However, we are aware of the possibility that our results may be driven by the choice of window size. Therefore, we conduct as a robustness check the empirical analysis with alternative window sizes of 100 and 400 weeks, which correspond to 2 and 8 years.

3 Data

3.1 Commodity Futures Data

For the purpose of this study, we construct a sample comprising twenty commodity futures markets. The choice of commodity markets is based on their coverage in the CFTC COT reports. Representative for the energy sector, we consider crude oil, natural gas and heating oil. The agricultural sector is represented by CBOT wheat, corn, KCBT wheat, soybeans, coffee, cocoa, cotton, sugar, feeder cattle, lean hogs and live hogs. For metals, we include gold, palladium, platinum, silver, and copper. Thus, our data include three energy products, five metals, and eleven agricultural commodities. The selected commodity futures contracts are traded at the Chicago Board of Trade (CBOT), the Kansas Board of Trade (KCBT), the Intercontinental Exchange (ICE), the New York Commodities Exchange (COMEX), and the New York Mercantile Exchange (NYMEX). All price series are retrieved from Datastream. Price quotations are in USD and represent daily closing prices. Continuous futures prices series are obtained by rolling over to the next nearby contract on the first trading day of the expiring month. The sample period spans from January 1986 to May 2019. The start date is confined by the availability of the COT report, which was initially introduced in January 1986 for selected commodities and extended in scope in the following years. We

utilize weekly data and compute tests on a weekly frequency.[3]

[FIGURE 1 about here]

Figure 1 depicts the evolution of futures market prices across the different markets and grouped by commodity sub-sector. For energy and metal commodities, the illustrated price process reflects inner-sectoral co-movement as well as pronounced spikes and crashes in the respective markets. While energy and metal prices were stable during the 1990s, they have risen sharply since then. The agricultural sub-sectors grain & oil seeds, livestock and softs exhibit compareable dynamics with substantial co-movement. However, in contrast to energy commodties, we observe no persistent increase in agricultural prices before 2005.

Since computation of market efficiency measures relies on return figures, we derive weekly returns as the log difference of weekly prices as follows:

$$R_{i,w} = ln\left(\frac{p_{i,w}}{p_{i,w-1}}\right), \tag{8}$$

where $p_{i,w}$ denotes the price of market i in week w. Table 1 presents descriptive statistics of the weekly logarithmic futures returns. Roughly two thirds of all return series exhibit a negative skewness, suggesting that severe price drops are more common than large price increases. For all return series we observe kurtosis values well in excess of 3, which is the reference kurtosis value of the normal distribution. This implies that none of the series follow a normal distribution, but feature fat tails instead. Lastly, we examine the stationarity properties of each futures return series by conducting the ADF test. Our test results unequivocally indicate that commodity prices are stationarity in first differences.

[TABLE 1 about here]

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[3]   In a robustness exercise, we repeat the analysis employing daily return data. For each sub-sample, we derive the absolute deviation of the automatic variance ratio from unity and then move the window by one week. In this way, we derive a weekly measure of market efficiency based on daily autocorrelations.

3.2 Measures of speculation

The Commodity Futures Trading Commission (CFTC) provides trader position data in the Commitment of Traders (COT) report on a weekly basis. More specifically, the COT report includes information on end-of-day open interest on a specified trading day per week (usually Tuesday), itemised by direction (long or short) and commercial interest of the trading party. The different trader categories can be defined as follows:

1. Commercial trader: Frequently named as hedger. The commercial trader is assumed to have a physical interest in the underlying commodity spot market.

2. Non-commercial trader: Primarily defined as speculators with no inherent physical interest in the underlying spot market.

3. Non-reporting traders: Not obligated to disclose the nature of their trading to the CFTC since their holdings do not exceed the minimum reporting threshold defined by the CFTC.

In accordance with the literature (e.g., Bessembinder, 1992; De Roon et al., 2000), we refer to commercial and non-commercial traders as hedgers and speculators, respectively.

The literature offers a variety of measures to quantify the degree of speculation. Among others, Manera et al. (2016) suggest the percentage of open interest held by traders with assumed speculative intentions as a proxy for speculative intensity. The measure can be computed as follows:

$$S_t = \frac{NCL_t + NCS_t + \alpha \times (NRL_t + NRS_t)}{2 \times MOI_t} \times 100, \tag{9}$$

where NCL_t and NCS_t denote the long and short position held by non-commercial traders, respecively. Further, NRL_t and NRS_t are the long and short positions held by non-reporting traders, whereas α captures the share of non-reporting traders that are assumed to follow speculative intentions. However, the adequate choice of α is somehow arbitrary. Concerning

9

this matter, we follow Sanders et al. (2010) and assume the proportion of speculators among non-reporting traders to be equal to the porportions observed for reporting traders.

A measure, that is commonly applied in the literature to gauge excessive speculative activity, is the Working (1960) T index (herafter W_t):

$$W_t = \begin{cases} 1 + \frac{SS_t}{HS_t + HL_t}, & \text{if } HS_t \geq HL_t \\ 1 + \frac{SL_t}{HS_t + HL_t}, & \text{if } HS_t < HL_t, \end{cases} \tag{10}$$

where SL_t (HL_t) and SS_t (HS_t) denote the long and short open interest held by speculators (hedgers). The positions are computed as follows:

$$SL_t = NCL_t + \alpha \times NRL_t$$
$$SS_t = NCS_t + \alpha \times NRS_t$$
$$HL_t = CL_t + (1 - \alpha) \times NRL_t$$
$$HS_t = CS_t + (1 - \alpha) \times NRL_t. \tag{11}$$

The rational for the Working's T is that each hedging position is backed by a corresponding speculation position. In case long and short positions of hedgers do not offset each other ($HS_t \neq HL_t$), then speculators are required to meet excess hedging demand so that the market is cleared. In this context, excessive speculation is defined as the situation in which speculators take positions surpassing the inherent market inbalance. Increasing values for the Working's T indicate higher levels of excessive speculation.

While we are mainly interested in the effect of speculative activity on informational efficiency, we also derive two metrics of hedging intensity. The first measure is calculated as the total proportion of open interest held by market participants identified as commercial traders. Therefore, the total open interest share of traders identified as hedgers, H_t, can be derived as follows:

$$H_t = \frac{CL_t + CS_t + (1 - \alpha) \times (NRS_t + NRL_t)}{2 \times MOI_t} \times 100. \tag{12}$$

The second metric that we consider to measure the degree of hedging activity is hedging pressure. The net position held by hedgers is commonly regarded as hedging pressure. Following De Roon et al. (2000) and Acharya et al. (2013), we derive the hedging pressure as follows:

$$HP_t = \frac{CS_t + (1 - \alpha) \times NRS_t - CL_t - (1 - \alpha) \times NRL_t}{CS_t + (1 - \alpha) \times NRS_t + CL_t + (1 - \alpha) \times NRL_t}. \tag{13}$$

Complementing the COT report, the CFTC started in 2006 to release a weekly Commodity Index Trader (CIT) report for a smaller subset of thirteen agricultural commodities. This report provides insight into the trading positions of index trader who were debated vigorously in public and academic discussions. In a robustness exercise, we employ the CIT data and repeat the analysis for index and non-index speculators. To quantify the extent of index trader activity, we compute the total share of open interest held by index traders and split the group of non-reportable traders according to the procedure utilized for the overall sample.

4 Time-varying return predictability

In order to assess the relationship between speculation and market efficiency, the following regression model is estimated:

$$|AVR_{i,t} - 1| = \alpha + \gamma AR + \beta_1 TO_{i,t} + \beta_2 VOL_{i,t} + \beta_3 Illiq_{i,t} + \beta_4 Spec_{i,t} + \mu_t + \phi_i + \epsilon_{i,t}, \tag{14}$$

where $|AVR_{i,t} - 1|$ denotes the measure of informational efficiency for commodity futures contract i in week t, $TO_{i,t}$ is the turnover ratio scaled by open interest, and $VOL_{i,t}$ the market volatility based on the conditional volatility estimates of an AR(1)-GARCH(1,1) model. Furthermore, $Illiq_{i,t}$ is a measure for illiquidity proxied by the Amihud (2002) ratio, and $Spec_{i,t}$ denotes a proxy for speculative/hedging activity. Further, we control for common shocks in a given year by including year-specific dummies (μ_t) and for time invariant commodity specific heterogeinity (such as storability of the commodity or different market mechanism frameworks) by including time-invariant commodity-specific fixed effects

11

(ϕ_i). Lastly, $\epsilon_{i,t}$ is the error term. We allow for clustering among observations of the same commodity market and add the lagged dependent variable to the regression equation since deviations from unity are relatively persistent through time. By doing this, we want to ensure that the present autocorrelation does not bias the regression results.

[TABLE 2 about here]

4.1 Variation of informational efficiency

The dependent variable of (14) is the absolute deviation of the automatic variance ratio from unity. This measure quantifies the magnitude of the commodity futures price deviation from the random walk benchmark model. Table 2 reports descriptive statistics for the dependent and independent variables in (14).

[FIGURE 2 about here]

To illustrate the evolution of informational efficiency, Figure 2 depicts the time series of the dependent variable over the sample period for each commodity market. Overall, most of the commodity futures markets show prolonged periods in which the AVR clearly deviates from unity. However, the results do not point to a clear trend across all commodities. Even at the commodity sub-group level (e.g. grains, livestock and softs) a common trend is hardly identifiable. To identify a structual break since the onset of the financialization period, Table 3 reports for each commodity market the mean absolute deviation of the AVR from unity for the total sample, a sub-sample spanning the pre-financialization period up to 2003 and a sub-sample covering the financialization period.[4] From Table 3, it becomes obvious that the dawn of the financialization period does not constitute a structural break in the degree of informational efficiency.

Taken together, the Figure 2 and Table 3 results stand in sharp contrast to common public

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[4] Among others, Hamilton and Wu (2015) claim that the finanacialization of commodity markets started during 2004-2005 period.

12

opinion that the financialization period and the accompanied emergence of commodities as an asset class did harm market quality in commodity futures markets.

[TABLE 3 about here]

4.2 Speculation and Informational Efficiency

Table 4 reports coefficient estimates for different specifications of (14). Column (1) shows the most parsimonious model with only a constant and the total percentage of open interest held by non-commercial investors as a proxy for speculative activity. The coefficient estimate is significant at the 10% level, and the negative sign suggests that speculators improve market efficiency. This relationship holds even after inlcuding the lagged dependent variable (at the 5% level). However, the observed effect vanishes after including time- and market-specific fixed-effects and control variables (see Column (3)).

[TABLE 4 about here]

Concerning the control variables, we observe that the turnover ratio is highly significant (at the 1%-level) with a negative sign. This observation is consistent with the literature that documents a significant negative relationship between trading activity and return auto-correlation (e.g. Campbell et al., 1993). Diminishing liquidity is related to increasing serial return correlation and hence less informationally efficient markets. For instance, Chordia et al. (2000) show that frequently traded securities react faster to the arrival of new information. Table 4 reports similar results for the alternative proxy of market liquidity based on the Amihud (2002) metric. An increase in the degree of liquidity (decrease of the Amihud (2002) ratio) is associated with a smaller deviation of the AVR from unity and hence greater informational efficiency.

The level of market volatility is positively associated with market inefficiency at the 1%-level. This observation contrasts the prediction of the Sentana and Wadhwani (1992) model.

13

However, the sign is justifiable from an economic perspective. According to Shiller (1981), noise rather than the arrival of new information is primarily responsible for excessive levels of return volatility. In the context of the Chan (1993) model, securities with noisy signals tend to incorporate new information more slowly. This is also consistent with McQueen et al. (1996), who document that market volatility is positively associated with a price delay measure.

Subsequently, we repeat the regression analysis but adopt the Working's T index as a measure for speculative activity. Columns (4)-(6) present the coefficient estimates for excessive speculation. The results are consistent with the estimates obtained for the total market share of speculators. In the baseline model, the coefficient estimate for the Working's T index is negative and highly significant. However, after the inclusion of fixed effects and control variables, the coefficient estimate turns insignificant. This illustrates, that even speculative activity beyond just providing liquidity for hedging needs of commercial traders is not related to the degree of informational efficiency after controlling for market state variables and unobserved time- and market-specific heterogeinity. However, this implies also that speculators do not harm the process of how markets respond to the arrival of new information.

[TABLE 5 about here]

The coefficient estimates concerning the influence of market participants with a commercial interest in the underlying commodity (hedger) on the informationally efficiency are reported in Table 5. In general, we find that hedging activity measured by the total share of open interest held by commercial traders is positive and significantly related to informational inefficiencies before controlling for market state variables. However, after controlling for liquidity, volatility and unobserved heterogeinity, the significant effect vanishes. This implies, that hedgers do not affect market efficiency beyond their association with market states. Conceivably, hedgers may decrease the general level of market liquidity due to the nature of their trading, which is demanding liquidity for hedging trades.

14

As mentioned before, the moving-subsample approach requires choosing a window size. In order to investige the robustness of our results, we repeat the analysis with alternative window lengths. Namely, we reestimate the regression models with window sizes of 100 and 400 weeks, which correspond to 2 and 8 years, respectively. Tables 6 and 7 show the coefficient estimates with alternative window sizes for speculative activity and Tables 8 and 9 for hedging intensity.

[TABLES 6 AND 7 about here]

In general, the results are robust across the different window lengths. Speculative activity (total & excessive) is not associated with the degree of infromational efficiency in commodity markets. However, the observed positive effect on informational efficiency before controlling for market states is only present in the 400 weeks window regression. The same applies to hedging activity, where the negative influence of total hedging activity turns insignificant in the baseline model with 400 weeks.

[TABLES 8 AND 9 about here]

A final concern may be the data frequency for that the autocorrelation structure is evaluated. Therefore, we repeat the earlier analysis and derive the AVR based on daily data. In order to match the daily series of AVR with the COT data, which is solely available on a weekly basis, we estimate the AVR for a sub-sample of 1000 days (which corresponds to our choice of 250 weeks) and after the AVR is estimated for the first sub-sample, the window is moved by one week.

[TABLES 10 AND 11 about here]

Again, the results for the influence of speculative and hedging activity on market efficiency remain robust (see Tables 10 and 11). In principle, speculative activity does neither harm

15

nor improve market efficiency, especially after controlling for market volatility and liquidity.

4.3 Index Trading, Speculation and Informational Efficiency

The discussions around the financialization of commodity markets focus mainly on the question whether long-only index investors diametrically affected market quality in commodity futures markets. In the preceding analysis, we considered speculators as a merely homogenous group. However, it may be conceivable for instance that index traders affect market efficiency differently than classic long-short speculators. Index trader may only react to the demand of investors to gain exposure to the commodity sector due to its diversifying ability, while long short speculators may actually trade on information.

[TABLE 12 about here]

Addressing this conceivable concern, we repeat the analysis employing the Supplemental Commitment of Traders (SCOT) report, which is published by the CFTC for a smaller subset of 13 agricultural commodities since 2006 on a weekly basis. While the cross-sectional and temporal dimension of the data set is rather limited compared to the one we employed in the earlier analysis, it may reveal some interesting insight concerning the suggested disparate trading effect of index and long-short speculators.

Table 12 reports the findings of repeating the analysis for the more disaggregated dataset. In general, we find that even after disaggregating the group of speculators in long-only index investors and long-short speculators, speculators are not associated with any variation in informational efficiency after controlling for market state variables.

Taken together, we cannot reject the null hypothesis that the mere trade motivation of market participant does not affect the informational efficiency of a commodity futures market. This finding remains robust over different trader categories (long-short speculators, index trader, hedger), sub-sample lengths and data frequencies.

16

5 Conclusion

A central topic in financial economics remains the study of market efficiency and the factors predominately driving its variation. However, little is known so far about how market efficiency in commodity futures markets varies over time and what role trading motivation plays in driving temporal and cross-sectional variation. This study adresses this gap in the literature by computing time-varying measures of informational efficiency and by analyzing the influence of speculative and hedging activity. We provide evidence for 20 major commodity futures markets over the period January 1986 to May 2019. First of all, we document significant variation in the degree of market efficiency across the markets and time periods. Noteworthy, we find that the financialization period, which is frequently associated with reduced levels of commodity market quality, shows no systematic variation in market efficiency. The fixed effect regressions reveal that speculative activity and heging activity are not significantly related to informational efficiency in commodity futures markets after controlling for other important determinants such as liquidity and volatility. This observation remains valid after considering alternative window lengths and sampling frequencies. Furthermore, a more granular trader categorization considering the heterogeinity among speculators does not alter the conclusion of this paper. Neither long-only index trader nor classic long-short speculators are significantly related to how markets react to the arrival of new information.

An essential implication emerging from the empirical analysis is that regulators should not waste their time discussing the possible diametrically effects of commodity futures market participants on the price formation process. More importantly, they should shift their attentions towards market liquidity and volatility for which we document a significant effect on the degree of informational efficiency. Instead of debating about suggested effects of the financialization period, regulators should focus on containing market volatility and policy reforms that increase trading activity. By doing this, policy makers may affect positively the informational efficiency of asset markets and hence capital allocation decision.

Future research should investigate, whether the documented effect is present in measures

17

of market efficiency which go beyond the autocorrelation structure in the return process by relying on high-frequency data. Furthermore, regulators are encouraged to provide scholars with more granular categories for the market participants so that future research may provide insights on which trader groups improve or harm market efficiency.

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Table 1: Descriptive Statistics Returns

Contract	Exchange	Min	Mean	Max	St.dev.	Skew.	Kurt.	ADF
Chicago Wheat	CBOT	-0.18	0.00	0.20	0.04	0.23	4.75	-32.77*
Cocoa	ICE	-0.17	-0.00	0.24	0.04	0.36	4.92	-33.59*
Coffee	ICE	-0.33	-0.00	0.28	0.05	0.10	6.23	-32.30*
Copper	COMEX	-0.22	0.00	0.19	0.03	-0.35	5.93	-26.56*
Corn	CBOT	-0.25	0.00	0.22	0.04	-0.04	6.84	-30.78*
Cotton	ICE	-0.75	-0.00	0.17	0.04	-3.24	55.82	-32.17*
Crude Oil	NYMEX	-0.28	0.00	0.31	0.05	-0.25	6.63	-32.07*
Feeder Cattle	CME	-0.17	0.00	0.12	0.02	-0.32	6.26	-34.81*
Gold	COMEX	-0.16	0.00	0.17	0.03	0.25	9.58	-33.68*
Heating Oil	NYMEX	-0.28	0.00	0.27	0.05	-0.28	7.02	-33.95*
Kansas Wheat	KBOT	-0.16	0.00	0.20	0.04	0.20	5.05	-32.87*
Lean Hogs	CME	-0.29	0.00	0.29	0.05	0.02	8.65	-30.89*
Live Cattle	CME	-0.17	0.00	0.11	0.02	-0.38	6.07	-34.06*
Natural Gas	NYMEX	-0.37	0.00	0.48	0.07	0.17	6.10	-27.84*
Palladium	NYMEX	-0.33	0.00	0.22	0.05	-0.43	7.37	-32.20*
Platinum	NYMEX	-0.26	0.00	0.21	0.04	-0.13	8.34	-32.23*
Silver	COMEX	-0.27	-0.00	0.23	0.04	-0.43	6.95	-32.06*
Soybeans	CBOT	-0.20	0.00	0.16	0.03	-0.42	5.78	-30.75*
Soybean Oil	CBOT	-0.19	0.00	0.16	0.03	0.05	4.48	-30.88*
Sugar	ICE	-0.24	-0.00	0.40	0.06	0.27	6.45	-33.25*

Note: The exchange abbreviations CBOT, CME, COMEX, ICE, KBOT and NYMEX refer to the Chicago Board of Trade, the Chicago Mercantile Exchange, the Intercontinental Exchange U.S. (New York), the Kansas Board of Trade and the New York Mercantile Exchange. * denotes statistical significance at the 5% level.

Table 2: Descriptive Statistics Regression

Contract	Min	Mean	Max	St.dev.	Skew.	Kurt.	ADF
|AVR-1|	0.00	0.08	0.47	0.08	1.33	4.70	-8.99*
Total Speculation	3.55	27.78	63.14	9.86	0.49	3.01	-4.57*
Working's T	0.99	1.17	1.89	0.12	1.59	5.72	-1.79*
Total Hedging	29.38	61.96	95.74	11.95	0.00	2.66	-2.33*
Hedging Pressure	-0.40	0.09	0.74	0.17	0.68	3.84	-17.57*
Volatility	0.00	0.00	0.04	0.00	4.83	57.86	-18.27*
Turnover	0.01	0.68	4.05	0.26	0.70	4.44	-14.49*
Illiquidity	0.00	0.01	4.42	0.06	28.66	1427.29	-50.00*

Note: * denotes statistical significance at the 5% level.

Table 3: Mean Deviation from Unity Benchmark

	|AVR-1|		
	total	pre 2003	post 2003
Chicago Wheat	0.050	0.052	0.049
Chicago Wheat	0.050	0.052	0.049
Cocoa	0.090	0.106	0.079
Coffee	0.078	0.091	0.069
Copper	0.102	0.105	0.100
Corn	0.064	0.063	0.065
Cotton	0.098	0.090	0.104
Crude Oil	0.156	0.254	0.092
Feeder Cattle	0.060	0.066	0.056
Gold	0.034	0.046	0.025
Heating Oil	0.114	0.182	0.067
Kansas Wheat	0.046	0.033	0.054
Lean Hogs	0.118	0.077	0.135
Live Cattle	0.042	0.028	0.052
Natural Gas	0.079	0.167	0.036
Palladium	0.093	0.059	0.113
Platinum	0.065	0.084	0.052
Silver	0.050	0.071	0.036
Soybeans	0.084	0.067	0.096
Soybean Oil	0.058	0.072	0.048
Sugar	0.106	0.141	0.082

Note: Table 3 reports the the mean absolute deviation of the Automatic Variance Ratio proposed by Choi (1999) from unity. The metric is computed for the total sample as well as for sub-samples spanning the pre- and post-financialization period.

Table 4: Regression Speculative Activity - Window Size 250 Weeks

	Total Speculation			Excess Speculation		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag		0.989***	0.986***		0.989***	0.986***
		(0.001)	(0.001)		(0.001)	(0.001)
Speculation	−0.001*	−0.00002**	0.00002			
	(0.001)	(0.00001)	(0.00001)			
Volatility			0.409***			0.405***
			(0.129)			(0.129)
Turnover			−0.001***			−0.001***
			(0.0003)			(0.0003)
Illiquidity			0.004***			0.004***
			(0.001)			(0.001)
Workings T				−0.083**	−0.001	0.001
				(0.040)	(0.001)	(0.001)
Constant	0.115***	0.001***	0.004	0.177***	0.002**	0.003
	(0.022)	(0.0002)	(0.006)	(0.051)	(0.001)	(0.006)
Commdity FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.026	0.979	0.979	0.017	0.979	0.979

Note: Table 4 reports the pooled OLS regression results for Equation 14. The dependent variable is the absolute deviation of the AVR from unity |AVR-1| for commodity market i at time period t. The regression allows for clustering among observations of the same commodity futures market and standard errors are reported in parantheses. ***,** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The window size for the moving-subsample is 250 weeks.

Table 5: Regression Hedging Activity - Window Size 250 Weeks

	Total Hedging			Hedging Pressure		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag		0.988***	0.986***		0.989***	0.986***
		(0.001)	(0.001)		(0.001)	(0.001)
Hedging Total	0.002**	0.00002**	0.00001			
	(0.001)	(0.00001)	(0.00002)			
Volatility			0.393***			0.398***
			(0.123)			(0.127)
Turnover			−0.001***			−0.001***
			(0.0003)			(0.0003)
Illiquidity			0.004***			0.004***
			(0.001)			(0.001)
Hedging Pressure				−0.019	−0.001	0.0002
				(0.028)	(0.0004)	(0.001)
Constant	−0.020	−0.0004	0.004	0.081***	0.001***	0.005
	(0.037)	(0.001)	(0.006)	(0.008)	(0.0001)	(0.006)
Commdity FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.06	0.979	0.979	0.002	0.979	0.979

Note: Table 5 reports the pooled OLS regression results for Equation 14. The dependent variable is the absolute deviation of the AVR from unity |AVR-1| for commodity market i at time period t. The regression allows for clustering among observations of the same commodity futures market and standard errors are reported in parantheses. ***,** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The window size for the moving-subsample is 250 weeks.

Table 6: Regression Speculative Activity - Window Size 100 Weeks

	Total Speculation			Excess Speculation		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag		0.969***	0.965***		0.969***	0.965***
		(0.002)	(0.002)		(0.002)	(0.002)
Speculation	−0.0003	−0.00001	0.0001			
	(0.0004)	(0.00001)	(0.00003)			
Volatility			0.754***			0.735***
			(0.186)			(0.181)
Turnover			−0.003***			−0.003***
			(0.001)			(0.001)
Illiquidity			0.014***			0.013***
			(0.003)			(0.003)
Workings T				−0.029	−0.0005	0.001
				(0.033)	(0.001)	(0.003)
Constant	0.110***	0.003***	0.002	0.137***	0.004***	0.002
	(0.010)	(0.0005)	(0.011)	(0.039)	(0.001)	(0.010)
Commdity FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.001	0.939	0.939	0.001	0.939	0.939

Note: Table 6 reports the pooled OLS regression results for Equation 14. The dependent variable is the absolute deviation of the AVR from unity |AVR-1| for commodity market i at time period t. The regression allows for clustering among observations of the same commodity futures market and standard errors are reported in parantheses. ***,** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The window size for the moving-subsample is 100 weeks.

Table 7: Regression Speculative Activity - Window Size 400 Weeks

	Total Speculation			Excess Speculation		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag		0.994***	0.991***		0.994***	0.991***
		(0.001)	(0.001)		(0.001)	(0.001)
Speculation	−0.002*	−0.00001	0.00001			
	(0.001)	(0.00001)	(0.00001)			
Volatility			0.146***			0.144***
			(0.051)			(0.049)
Turnover			−0.001***			−0.001***
			(0.0002)			(0.0002)
Illiquidity			0.0001			0.00004
			(0.001)			(0.001)
Workings T				−0.091*	−0.0004	0.001
				(0.049)	(0.0004)	(0.001)
Constant	0.117***	0.001***	−0.006	0.177***	0.001**	−0.006
	(0.030)	(0.0002)	(0.007)	(0.064)	(0.0004)	(0.008)
Commdity FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.054	0.988	0.988	0.026	0.988	0.988

Note: Table 7 reports the pooled OLS regression results for Equation 14. The dependent variable is the absolute deviation of the AVR from unity |AVR-1| for commodity market i at time period t. The regression allows for clustering among observations of the same commodity futures market and standard errors are reported in parantheses. ***,** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The window size for the moving-subsample is 400 weeks.

Table 8: Regression Hedging Activity - Window Size 100 Weeks

	Total Hedging			Hedging Pressure		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag		0.969***	0.965***		0.969***	0.965***
		(0.002)	(0.002)		(0.002)	(0.002)
Hedging Total	0.001**	0.00003**	0.00002			
	(0.0004)	(0.00001)	(0.00002)			
Volatility			0.718***			0.728***
			(0.185)			(0.181)
Turnover			−0.002***			−0.003***
			(0.001)			(0.001)
Illiquidity			0.013***			0.014***
			(0.003)			(0.003)
Hedging Pressure				−0.010	−0.001	0.001
				(0.023)	(0.001)	(0.001)
Constant	0.054**	0.001*	0.002	0.104***	0.003***	0.003
	(0.026)	(0.001)	(0.012)	(0.005)	(0.0003)	(0.011)
Commdity FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.008	0.939	0.939	0.001	0.939	0.939

Note: Table 8 reports the pooled OLS regression results for Equation 14. The dependent variable is the absolute deviation of the AVR from unity |AVR-1| for commodity market i at time period t. The regression allows for clustering among observations of the same commodity futures market and standard errors are reported in parantheses. ***,** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The window size for the moving-subsample is 100 weeks.

Table 9: Regression Hedging Activity - Window Size 400 Weeks

	Total Hedging			Hedging Pressure		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag		0.993***	0.991***		0.994***	0.991***
		(0.001)	(0.001)		(0.001)	(0.001)
Hedging Total	0.002**	0.00001*	0.00000			
	(0.001)	(0.00001)	(0.00001)			
Volatility			0.138***			0.141***
			(0.052)			(0.049)
Turnover			−0.001***			−0.001***
			(0.0002)			(0.0002)
Illiquidity			−0.00003			0.00002
			(0.001)			(0.0005)
Hedging Pressure				−0.028	−0.0002	−0.00001
				(0.026)	(0.0002)	(0.0004)
Constant	−0.035	−0.0002	−0.006	0.073***	0.0004***	−0.006
	(0.043)	(0.0003)	(0.007)	(0.010)	(0.0001)	(0.007)
Commdity FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.083	0.988	0.988	0.005	0.988	0.988

Note: Table 7 reports the pooled OLS regression results for Equation 14. The dependent variable is the absolute deviation of the AVR from unity |AVR-1| for commodity market i at time period t. The regression allows for clustering among observations of the same commodity futures market and standard errors are reported in parantheses. ***,** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The window size for the moving-subsample is 400 weeks.

Table 10: Regression Speculative Activity - Window Size 1000 Days

	Total Speculation			Excess Speculation		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag		0.993***	0.991***		0.993***	0.991***
		(0.001)	(0.001)		(0.001)	(0.001)
Speculation	0.001	0.00001*	0.00000			
	(0.001)	(0.00000)	(0.00001)			
Volatility			−0.029***			−0.029***
			(0.001)			(0.001)
Turnover			0.001			0.001
			(0.001)			(0.001)
Illiquidity			3.169***			3.013***
			(0.750)			(0.692)
Workings T				0.094	0.001	−0.0004
				(0.077)	(0.0004)	(0.001)
Constant	0.028	0.0002	0.001	−0.048	−0.0003	0.001
	(0.022)	(0.0001)	(0.001)	(0.089)	(0.0005)	(0.001)
Commdity FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Adjusted R²	0.037	0.987	0.987	0.036	0.987	0.987

Note: Table 10 reports the pooled OLS regression results for Equation 14. The dependent variable is the absolute deviation of the AVR from unity |AVR-1| for commodity market i at time period t. The regression allows for clustering among observations of the same commodity futures market and standard errors are reported in parantheses. ***,** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The window size for the moving-subsample is 1000 days.

Table 11: Regression Hedging Activity - Window Size 1000 Days

|	Total Hedging			Hedging Pressure		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag		0.993***	0.991***		0.993***	0.991***
		(0.001)	(0.001)		(0.001)	(0.001)
Hedging Total	−0.001	−0.00000	0.00000			
	(0.001)	(0.00000)	(0.00001)			
Volatility			−0.029***			−0.029***
			(0.001)			(0.001)
Turnover			0.001			0.001
			(0.001)			(0.001)
Illiquidity			2.968***			3.214***
			(0.699)			(0.931)
Hedging Pressure				0.018	0.00002	0.0001
				(0.021)	(0.0003)	(0.0004)
Constant	0.109**	0.001**	0.0004	0.062***	0.0004***	0.001
	(0.050)	(0.0003)	(0.001)	(0.009)	(0.0001)	(0.001)
Commdity FE	No	No	Yes	No	No	Yes
Year FE	No	No	Yes	No	No	Yes
Adjusted R^2	0.018	0.987	0.987	0.002	0.987	0.987

Note: Table 11 reports the pooled OLS regression results for Equation 14. The dependent variable is the absolute deviation of the AVR from unity |AVR-1| for commodity market i at time period t. The regression allows for clustering among observations of the same commodity futures market and standard errors are reported in parantheses. ***,** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The window size for the moving-subsample is 1000 days.

Table 12: Regression Index Investor Activity - Window Size 250 Weeks

	Index Investor		
	(1)	(2)	(3)
Lag		0.986***	0.984***
		(0.002)	(0.003)
Index Investor	−0.007	0.0001	0.0002
	(0.005)	(0.0001)	(0.0002)
Volatility			−0.120
			(1.307)
Turnover			−0.010*
			(0.005)
Illiquidity			−0.922
			(0.676)
Constant	0.749***	0.006*	0.005
	(0.120)	(0.003)	(0.010)
Commdity FE	No	No	Yes
Year FE	No	No	Yes
Adjusted R^2	0.968	0.982	0.968

Note: Table 12 reports the pooled OLS regression results for Equation 14. The dependent variable is the absolute deviation of the AVR from unity |AVR-1| for commodity market i at time period t. The regression allows for clustering among observations of the same commodity futures market and standard errors are reported in parantheses. ***,** and * denote statistical significance at the 1%, 5% and 10% level, respectively. The window size for the moving-subsample is 250 weeks.
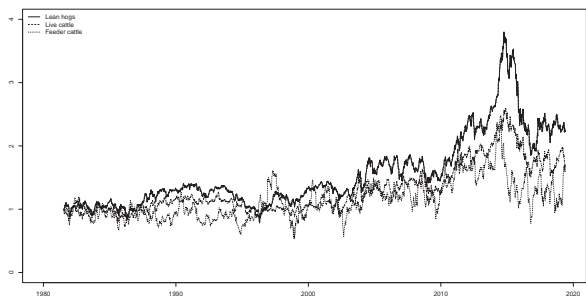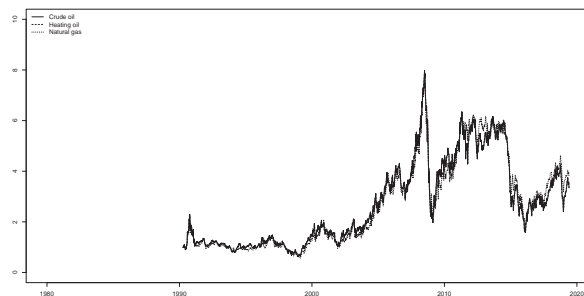
(a) Grain & Oil Seeds
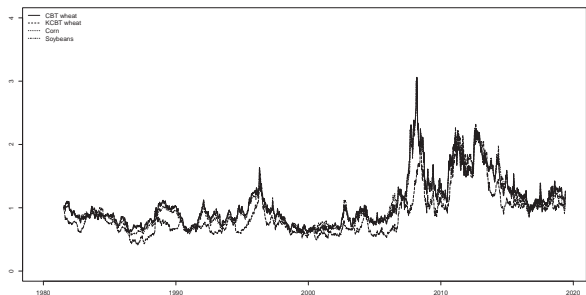
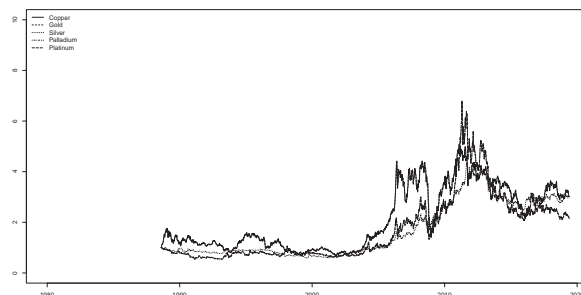(b) Softs
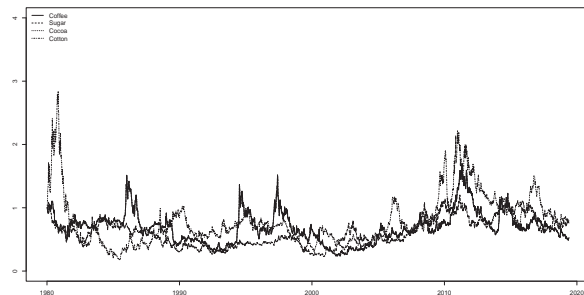
(c) Meat

(d) Energy

(e) Metals

Figure 1: Time-Series

Note: The graphs show the time-varying absolute deviation from the random walk benchmark process of each futures contract. Values above unity indicate that a positive autocorrelation is present, whereas values below unity suggest the opposite.

34

(a) Chicago Wheat - CBOT

(b) Cocoa - ICE

(c) Coffee - ICE

(d) Copper - COMEX

(e) Corn - CBOT

(f) Cotton - ICE

(g) Crude Oil - NYMEX

(h) Feeder Cattle - CME

(i) Gold - COMEX

(j) Heating Oil - NYMEX

(k) Kansas Wheat - KBOT

(l) Lean Hogs - CME

(m) Live Cattle - CME

(n) Natural Gas - NYMEX
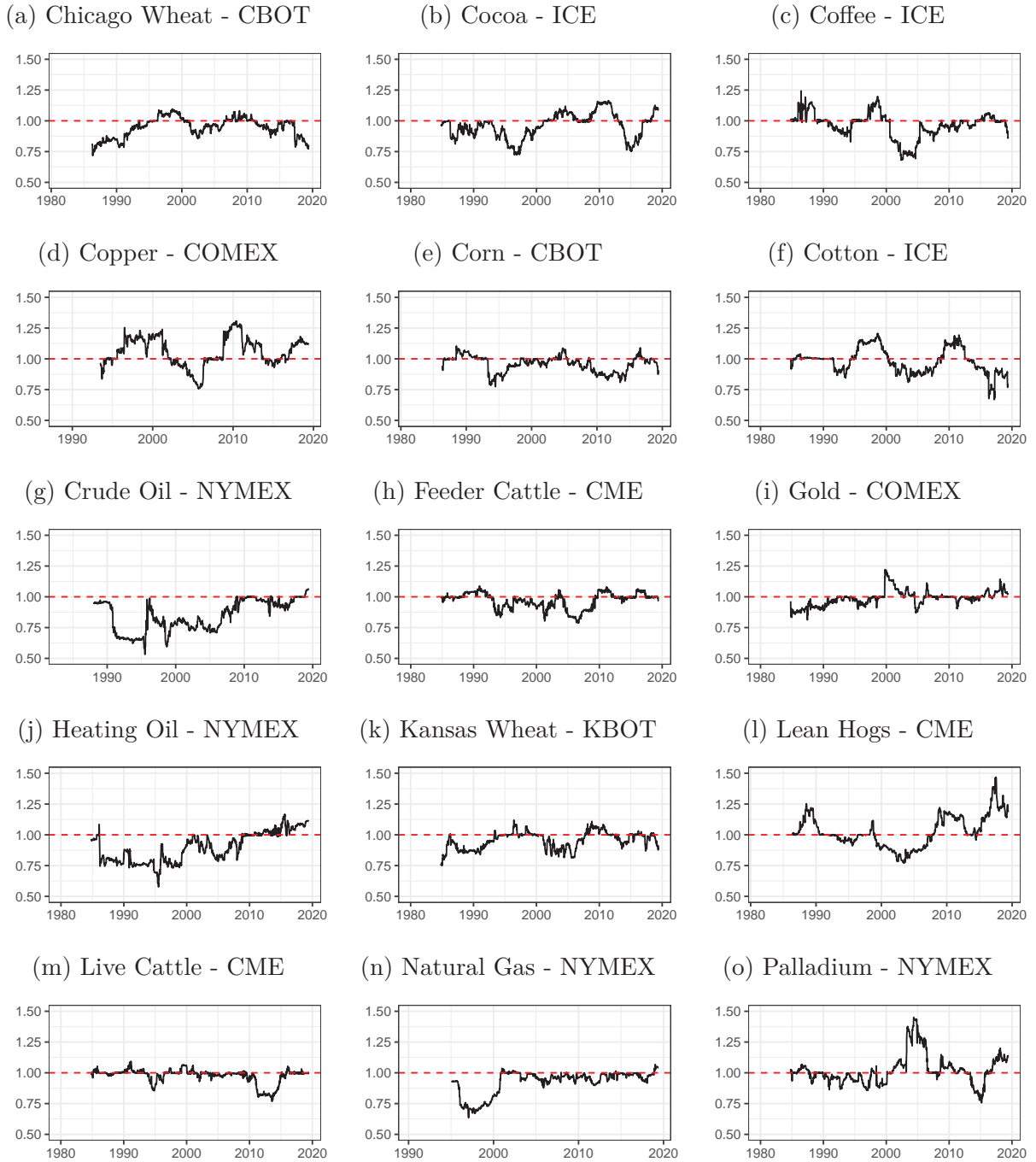
(o) Palladium - NYMEX

Figure 2: Time-Varying Degree of Informational Efficiency

Note: The graphs show the time-varying absolute deviation from the random walk benchmark process of each futures contract. Values above unity indicate that a positive autocorrelation is present, whereas values below unity suggest the opposite.

(a) Platinum - NYMEX (b) Silver - COMEX (c) Soybean Oil - CBOT
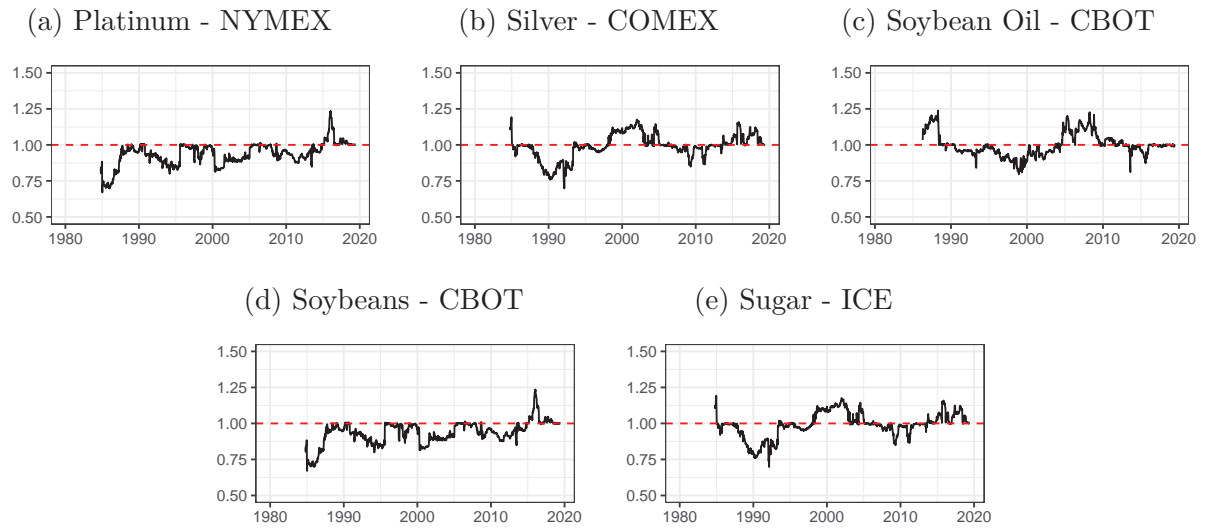
(d) Soybeans - CBOT (e) Sugar - ICE

Figure 2: Time-Varying Degree of Informational Efficiency