Systematic Market Efficiency and Speculative Activity in the Crude oil and Agricultural Commodity Markets:

Evidence from the Commodity Futures Market

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Abstract

Over the past 10 years, oil and agricultural commodity prices have been rising and falling together. That raises two questions: does market efficiency co-move across the oil and agricultural commodity markets? If so then what drives the systematic variation in market efficiency? This paper explores the existence of the systematic variation in market efficiency in the oil and agricultural commodity markets over the regime of both the open outcry auction and electronic trading systems. We find the existence of systematic variation in market efficiency only in the regime of electronic trading system, which sees a substantial increase in speculative activity. More importantly, we find that an increase in speculative activity led to a decrease in market efficiency.

JEL classification: D40, G02, G14, Q11, Q41

Key words: Crude oil; Corn; Soybeans; Commodity; Market efficiency; Arbitrage; Liquidity; Speculator

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1. Introduction

One of the fundamental questions in the commodity market is whether the commodity market incorporates fundamentals of supply and demand efficiently. In particular, the market efficiency of the oil and agricultural commodity markets has become highly controversial since the well-synchronized boom and bust in the oil and agricultural commodity prices in recent years.[2] A broad conclusion of the most studies is that fundamentals were most likely behind the recent boom and bust in commodity prices.[3] However, there is a growing consensus among commercial traders and policy makers that speculation caused the well-synchronized boom and bust in the oil and agricultural commodity prices. [4]

Thus, the big question is whether speculative activity improves or worsens the market efficiency of the commodity market. In particular, the role of speculators in the commodity market has received considerable attention after a substantial increase in speculator participation over the past decade, a phenomenon which is called the financialization of the commodity market.[5] Economists generally view that speculators trade on fundamentals and trade in a way that eliminates mispricing.[6] Yet, there has been little research on the impact of speculative activity on market efficiency in the commodity market.[7] Hence, we attempt to fill that gap.

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[2] In June, 2008, then Opec president, Chakib Khelil, said "We are producing more than the market needs. We are annoyed because the price we see at this time shows a disconnect between price and fundamentals." A relevant article is available on the website: http://www.petroleum-economist.com/articles/markets/trends/2008/opec-on-the-attack

[3] Most of these papers including Campiche, Bryant, Richardson, and Outlaw (2007), Headey and Fan, (2008), Rosegrant, Zhu, Msangi, and Sulser (2008), and Chang and Su (2010), primarily focused on biofuel channel and suggested that rising oil prices and growing demand for biofuels were key factors that drove up both the oil and food prices.

[4] In February, 2012, dozens of congressional Democrats sent off a letter asking federal regulators to crack down on "fraud, abuse, and manipulation" in the oil markets, arguing that Wall Street is inflating gas prices. A relevant article is available on the website: https://www.washingtonpost.com/blogs/ezra-klein/post/are-speculators-to-blame-for-our-gas-price-woes/2012/03/05/gIQAqMS8sR_blog.html?noredirect=on&utm_term=.fa2886d6dd4e

[5] A dramatic increase in the popularity of commodity investing. See, for example, Tang and Xiong (2012).

[6] This standard view dates back to Friedman (1953).

[7] Several empirical papers including Büyükşahin and Harris (2011), Brunetti, Büyükşahin, and Harris (2016), and Bruno, Büyükşahin, and Robe (2016) examined the impact of speculative activity on the commodity market but found no evidence that speculators had destabilizing effects on the commodity market and concluded that fundamentals were most likely behind the 2006-2008 boom and bust in commodity prices. On the other hand, Fan and Xu (2011) explored the role of speculation in the boom and bust in oil prices in recent years and concluded that speculation became an important driver affecting oil price changes. However, these papers primarily focused on daily and weekly data when a

In this paper, we begin by studying the market efficiency of the commodity market. Specifically, we focus on dynamics of market efficiency. Traditional market efficiency research primarily focuses on a static concept of market efficiency, which does not consider the possibility that market efficiency could vary over time.[8] It is not until recently that empirical studies have begun to question determinants of market efficiency. The studies in this area considered some of the key market characteristics such as liquidity,[9] funding and algorithmic trading[10] given that these market characteristics vary over time. Notably, Chordia, Roll, and Subrahmanyam (2008) looked at the question of whether variations in liquidity are related to variations in market efficiency. Chordia et al. (2008) estimated the impact of liquidity on market efficiency using return predictability and found that an increase in market liquidity leads to an increase in market efficiency from the U.S. stock markets. Chordia et al. (2008) concluded that arbitrageurs have a tendency to submit their orders in more liquid periods to avoid higher trading costs. More recently, Rösch, Subrahmanyam, and Van Dijk (2016) found that market efficiency measures co-move across stocks and with each other, providing evidence that systematic variation in market efficiency exists in the U.S. stock markets. More importantly, Rosch et al. (2016) demonstrated that an increase in funding liquidity and an increase in the intensity of algorithmic trading, led to an increase in market efficiency using data for the U.S. stock markets over the period 1996 to 2010. Hence, the literature concludes that high liquidity and algorithmic trading have positive impacts on market efficiency.

Motivated by the above observations, we extend this line of the literature to the previously unexplored commodity market. Specifically, we focus on the commodity "futures" market. So far, there is only a small body of literature on the dynamics of market efficiency and the literature focused on the U.S. stock markets only. The commodity futures market is interesting markets to examine for several

dramatic increase in speculative activity happens on intraday intervals. Furthermore, to our knowledge, no work has examined the impact of speculative activity on market efficiency in the oil and agricultural commodity markets.

8 An early and influential paper, Fama (1970) emphasized the notion that efficiency implies a lack of return predictability. However, he did not consider the possibility that market efficiency may vary over time.

9 Liquidity, the ability to quickly and cheaply trade an asset at a fair price, is thought to be an important element that affects the value of securities.

10 Algorithmic trading are computers that monitor markets and manage the trading process at high frequency.

reasons. First, in the commodity futures market, traders are primarily hedging[11] or speculating[12] based on their line of business. Hedgers are usually producers such as farmers or oil producers, who demand liquidity from speculators to transfer price risk in the commodity futures market. On the other hand, speculators take the risk as investment opportunities for possible returns. Second, unlike the U.S stock markets, the commodity futures market is not constrained by short-selling restriction. Therefore, arbitrageurs are able to eliminate mispricing without being constrained by short-selling restriction. Third, low transaction costs make the commodity futures market far more liquid than equity markets.[13] Given that liquidity and speculative activity[14] are some of the key market characteristics that are commonly cited as sources of the variation in market efficiency in the recent studies, the commodity futures market therefore provides an ideal setting to study the impact of liquidity and speculative activity on market efficiency.

Our analysis proceeds in two steps. Following Rösch et al. (2016), we first explore whether systematic variation in market efficiency exists in the oil and agricultural commodity markets in the regime of both the open outcry auction and electronic trading systems. Specifically, our paper focuses on crude oil, corn and soy beans markets.[15] Given that WTI crude oil is the world's most traded commodity while corn and soybeans are the two mostly traded agricultural commodities,[16] developing a better understanding of key features of these markets may give us some clue on the general features of the commodity market. Our paper uses tick data for the crude oil, corn and soybeans markets from 1 February 1996 to 31 December 2015 and uses nearby contracts to focus on most active contracts. Specifically, we estimate whether there is co-movement in market efficiency across the oil and agricultural commodity markets and across market efficiency measures. We employ three market efficiency measures, namely, return predictability, variance

[11] Hedging is a transfer of risk.

[12] Speculating is buying or selling investments that are high risk, with the goal to make a very big profit.

[13] See, for example, Fleming, Ostdiek and Whaley (1996).

[14] Our indicating variable for algorithmic trading is speculative activity. Algorithmic trading is popular among speculators, who are financial institutions like large commercial banks and hedge funds.

[15] The agricultural commodity markets we include in this study are energy-intensive products and used in production of biofuels. Please refer to the footnote 3.

[16] The crude oil, corn and soy beans are among top five commodity markets. A relevant article is available on the website:https://www.investopedia.com/articles/active-trading/090215/analyzing-5-most-liquid-commodity-futures.asp

ratio and Hasbrouck pricing error. All three efficiency measures represent an inverse measure of informational efficiency, which means that lower values indicate greater efficiency. Our paper focuses on one minute-intervals. We only find significant co-movement in market efficiency across the oil and agricultural commodity markets and across the market efficiency measures in the regime of electronic trading system, which see the substantial increase in speculative activity. Hence, our empirical evidence confirms the existence of systematic variation in market efficiency in the oil and agricultural commodity markets.

In a second step, we then seek to determine what drives the systematic variation in market efficiency. Past work suggests that liquidity and algorithmic trading should have positive impacts on market efficiency. However, previous papers on this topic did not control for fixed effects (e.g. year, sector). Thus, it is not clear whether their results are robust. Furthermore, as shown in Table 1, the crude oil is the most liquid commodity in our sample in the regime of electronic trading system. Given that, the average return predictability for the crude oil suggests that the market efficiency of the crude oil is relatively higher compared to other commodities but that is not true for variance ratio and Hasbrouck. Therefore, the conclusion from the U.S. stock markets (Chordia et al., 2008) that high liquidity facilitates arbitrage activity, which in turn enhances market efficiency, is questionable. Our paper therefore improves upon the existing literature by including year fixed effects and sector fixed effects in our regression models to eliminate possible biases caused by omitted variables. The authors of previous articles also use a proxy for algorithmic trading to capture the behaviour of arbitrageurs.[17] However, the main concern with this proxy is that it is unclear how accurately the proxy captures the behaviour of arbitrageurs. Instead, we use the actual data for speculators as an indicating variable for arbitrageurs. First, we consider the impact of liquidity on market efficiency. Interestingly, after controlling for year fixed effects and sector fixed effects, the impact of liquidity on market efficiency is statistically insignificant. Having seen this, we then estimate the impact of speculative activity on market efficiency. For all three regressions based on the three market efficiency measures, we find that the impact of speculative activity on market efficiency is negative and two of them are statistically significant at 5 percent or less. Furthermore, given that our empirical

[17] See, for example, Rösch et al. (2016)

evidence only finds the systematic variation in market efficiency across the oil and agricultural commodity markets in the regime of electronic trading system, which sees the rise of algorithmic trading, it is likely that speculators drive the systematic variation in market efficiency across the oil and agricultural commodity markets using algorithmic trading. More worryingly, empirical evidence suggests that speculators have a tendency to buy when prices rise and sell when prices fall, which is consistent with positive feedback trading activity – that is, they are momentum traders and these traders tend to push prices away from fundamental values. This explains why the oil and agricultural commodity prices have been more volatile in the regime of electronic trading system than that of open outcry auction.

This paper makes several new contributions to the literature. First, to our knowledge, we are the first to provide evidence of the existence of systematic variation in market efficiency in the commodity market. Second, our empirical evidence lends no support for recent empirical views that high liquidity facilitates arbitrage activity which in turn enhances market efficiency. Third, our paper sheds light on the much-debated question of whether speculators improve or worsen market efficiency. We acknowledge that we focus on intraday one-minute intervals, and hence, short-term impacts. However, even these short-term findings are relevant because the magnitude of the negative impact of speculative activity is economically significant. Hence, it is concerning for investors, who see arbitrage opportunities in the commodity market. The substantial increase in speculative activity raises unexpected risks for these investors because it could lead to substantial losses for the investors who try to eliminate mispricing.[18] It is also concerning for policy makers because it may raise greater instability in the commodity market.[19]

The rest of the paper is organised as follows. Section 2 discusses the literature review and hypothesis development. Section 3 explains the data source

[18] SemGroup LP declared bankruptcy on Tuesday after $3.2 billion in oil trading losses torpedoed the formerly 12th-largest private U.S. company. A relevant article is available on the website: https://www.reuters.com/article/us-semgroup/huge-oil-trading-loss-sinks-energy-trader-semgroup-idUSN2227689520080722

[19] From the mid-1980s to early 2000, the inflation-adjusted price of a barrel of crude oil on NYMEX was generally under $25/barrel. By July 2008, oil prices peaked at $147.30 in, about 4.9 times expensive. Furthermore, corn prices rose 51 percent and soybean prices rose 74 percent, triggering a food crisis that particularly affected developing nations see, for example, Ivanic and Martin (2008), and Zezza, Davis, Azzarri, Covarrubias, Tasciotti, and Anriquez (2008).

and the selection of sample data. Section 4 presents the methodology. Section 5 presents empirical evidence. Section 6 concludes

2. Literature review and hypothesis development

In this section, we touch on some of the key market characteristics that are commonly cited and that appear to be most closely related to hypotheses that arise in the recent studies of market efficiency.

2.1. Liquidity

Recent evidence indicates that liquidity varies over time.[20] Liquidity, the ability to quickly and cheaply trade an asset at a fair price, is thought to be an important element that affects the value of securities.[21] Motivated by these observations, Chordia et al. (2008) estimated the link between liquidity and market efficiency using data for the U.S. stock markets over the period 1993 to 2002 and find that an increase in liquidity leads to an increase in market efficiency. Their empirical finding indicates that liquidity stimulates arbitrage activity. Chordia et al. (2008) conclude that market makers, who have limited risk-bearing capacity, have a tendency to submit arbitrage orders in more liquid periods to avoid higher trading costs.[22] In other words, their findings imply that arbitrageurs are more likely to submit orders to profit from the temporary deviation of fundamental values when bid-ask spreads, a measure of illiquidity, are low. We thus hypothesize that an increase in liquidity enhances market efficiency.

2.2. Speculative activity

Speculators enter markets when temporary deviations of prices from fundamentals are greatest and trade in a way that eliminates mispricing. This reduces excessive price fluctuations and stabilizes prices and therefore speculators

[20] Chordia, Roll and Subrahmanyam (2000) found significant co-movement in liquidity across stocks and Chordia, Roll and Subrahmanyam (2001) demonstrated that liquidity declined significantly in down markets where transaction costs increased dramatically.
[21] Amihud (2002) shows that liquidity predicts expected stock returns.
[22] Trading costs are higher in illiquid periods.

play a key role in arbitrage. This standard view, which is called rational speculative stabilizing theory, dates back to Friedman (1953). The recent empirical findings in Rösch et al. (2016) support this view. Rösch et al. (2016) focused on algorithmic trading, which provides liquidity in the U.S. stock markets, and find that an increase in the intensity of algorithmic trading enhances market efficiency. Algorithmic trading is popular among speculators, who are financial institutions like large commercial banks and hedge funds.[23] Thus, it is reasonable to assume that speculative activity reflects algorithmic trading. Hence, we hypothesize that an increase in speculative activity enhances market efficiency.

It is worth note that the literature, however, distinguishes between two types of speculators, namely, rational speculators and "noise" traders.[24] Other studies including Black (1986) and De Long, Shleifer, Summers, and Waldmann (1990) recognize that speculative activity could sometimes be destabilizing if based on noise trading, which leads to temporary market inefficiency.

3. Data

Our data are drawn from Thomson Reuters Tick History (TRTH), commitments of traders (COT) reports from U.S. Commodity Futures Trading Commission (CFTC) and the FRED database of the Federal Reserve Bank of St. Louis. First, to explore the existence of systematic variation in market efficiency across the oil and agricultural commodity markets, we use tick history data for West Texas light (WTI) crude oil traded on New York Mercantile Exchange (NYMEX), and corn and soybean traded on the Chicago Board of Trade (CBOT) from 01 February, 1996 to 31 December, 2015. We begin in 1996 because the data for earlier years is not available in TRTH. We obtain the transaction data including the bid and ask quotes, trade price, and trade volume from TRTH. All commodity prices are quoted in dollars. To avoid thin trading and expiring effects, we use the nearest contracts to delivery.[25]

[23] Chaboud, Chiquoine, Hjalmarsson, and Vega (2014) review the source of algorithmic trading volume.

[24] Noise trading describe traders who do not possess fundamental information and trade on noise as if it were information.

[25] Following De Ville de Goyet, Dhaene, and Sercu (2008), we replace a contract that expires in month m with the next nearest-to-maturity contract on the last day of month m – 1. For example, March contract expires in February (month m) but its most actively traded period is January (month m

We employ three efficiency measures, namely, (return) predictability, variance ratio and Hasbrouck pricing error. To construct these measures, we are first required to construct order flow and mid-quote returns. We compute order flow by taking the difference between buys and sells and dividing it by the sum of buys and sells (OIB).[26] We follow the algorithm in Lee and Ready (1991) to assign a trade direction to each trade.[27] Mid-quote returns are based on the mid-quote associated with the last trade to the mid-quote of the last trade in the previous interval (to avoid the bid-ask bounce).

Our primary focus is on short-term market efficiency and our focus on the short-term aspect of informational efficiency is in the spirit of Chordia, Roll, and Subrahmanyam (2005) that find that price adjustments to new information occur substantially within thirty minutes in the U.S. stock markets. We build on this insight by focusing on intraday periods. Our paper focuses on one-minute intervals when such activity are likely to take place.[28] We discard trades that fall outside the New York continuous trading session (9:30 am till 4:00 pm EST).

Other variables are constructed as follows: Our indicating variable for market liquidity is quoted bid-ask spreads and we compute quoted bid-ask spreads by taking the difference between the bid price and ask price and then dividing it by the midpoint of the bid and ask prices. Our indicating variable for funding liquidity is TED spreads and we obtain the data from the FRED database of the Federal Reserve Bank of St. Louis. Our indicating variable for market volatility is the standard deviation of mid-quote returns. We compute mid-quote returns using the natural log function.

To analyse the impact of speculative activity on market efficiency, we use information on aggregate speculator crude oil, corn and positions to construct

– 1). Thus, we only consider quotes and trades from January (month m – 1) for the March contract. Specifically, on the last day of month m – 1, the last trade price is the last observation of the expiring contract (March contract) whereas on the first day of month m, the first trade price is the first observation of the new contract (April contract). This ensures roll-over of contracts.

[26] For each interval, we aggregate all buys and all sells and compute order flow.

[27] We assign a buy if the transaction price is above the bid-ask midpoint and a sell if the transaction price is below the bid-ask midpoint. The midpoint is defined as the average of the best bid and best ask prices. Trades executed exactly at the midpoint are classified as neither buyer nor seller initiated and considered as no trade.

[28] There are 390 one-minute intervals per trading day.

indicating variables for speculative activity.[29] We obtain the data from COT reports that are available on U.S. futures trading commissions.

4. Methodology

The primary goal of this paper is to estimate the impact of speculative activity on market efficiency. To study this, we first explore the existence of systematic variation in market efficiency at the daily level. We employ three market efficiency measures, namely, return predictability, variance ratio and Hasbrouck pricing error.[30] All three measures are inverse indicators of the degree of market efficiency, which means that lower values indicate greater efficiency. In this study, we assume that informationally efficient prices follow a random walk. According to the random walk theory, price changes are random and therefore cannot be predicted by past information. If prices changes can be predicted by past information and then the market is known to be inefficient.

Our first efficiency measure is intraday return predictability (*Predictability*): the predictability of returns from both order flow and past returns. The notion of efficient market in Fama (1970) emphasizes a lack of return predictability as the criterion for efficiency. Several empirical papers including Chordia et al. (2005) and Chordia et al. (2008) show empirical evidence of return predictability from past returns or past order flows in short-term intervals. Our paper estimates the predictability of intraday returns based on past returns and order flows as specified in equation (1). We use the mid-quote returns to avoid the bid-ask bounce. For each day, we have a total of 390 one-minute intervals. We consider longer lags of returns and order flow to capture the magnitude and significance of lags of returns and order flow and therefore regress mid-quote returns on first five lags of past returns and past order flow.

For futures market i, day d and interval *t*, we estimate the following regression:

[29] We transform aggregate speculator positions into the natural logarithm to reduce the influence of large positively skewed data.
[30] Rösch et al. (2016) employed four market-wide efficiency measures namely, return predictability, variance ratio, Hasbrouck pricing error and put-call parity to explore the existence of a systematic market efficiency component in the U.S. stock markets. We exclude put-call parity from our study because we did not have an access to the OptionMetrics database at the time when we commenced this study.

$$ret_{i,d,t} = \alpha_{1,d}ret_{i,d,t-1} + \cdots + \alpha_{5,d}ret_{i,d,t-5} + b_{1,d}OIB_{i,d,t-1} + \cdots + b_{5,d}OIB_{i,d,t-5} + \varepsilon_{i,d,t} \quad (1)$$

where the dependent variable $ret_{i,d,t}$ is the intraday returns based on the mid-quote associated with the last trade to the mid-quote of the last trade in the previous interval, $ret_{i,d,t-1}$is the intraday returns in the previous interval $t-1$, $OIB_{i,d,t-1}$is the order flow in previous interval $t-1$.

Our second market efficiency measure is *Variance ratio* (Lo and MacKinlay, 1989). Since the seminal work of Lo and MacKinlay (1989), the variance ratio test has been widely used for testing market efficiency. Variance ratio examines how closely the price of individual stocks adhere to a random benchmark and tends to unity as serial dependence in asset returns tend to zero. Thus, the greater deviations of the variance ratio from one indicate lower market efficiency. Since the daily level estimates of the variance ratio exhibit several large outliers, we use the logarithmic transformation to mitigate their influence. We compute the variance ratio from mid-quote return. Following Rösch et al. (2016), we estimate a daily variance ratio based on overlapping intraday returns and define the variance ratio as follows:

$$VR\ (q) = |1 - \frac{30\ Var\ (1min)}{Var\ (30min)}\ | \quad (2)$$

Where $Var\ (1min)$ is the return variance estimated from one-minute mid-quote returns within a day and $Var\ (30min)$ is the return variance estimated from 30-minute mid-quote returns within a day

Our third market efficiency measure is *Hasbrouck* (Hasbrouck, 1993). In the model, the overall market quality is measured by the variance of pricing error. A lower variance suggests greater pricing efficiency and higher market quality. We estimate a five-lag vector autoregression (VAR) model based on intraday data. In the original model in Hasbrouck (1993), the author uses the standard deviation of the intraday pricing errors as an inverse measure of informational efficiency. However, as in Rösch, et al (2016), we are more interested in the magnitude of the pricing error rather than in its intraday variation. Following Rösch et al. (2016), we also take the maximum of the absolute pricing errors of the trades on a given day as an inverse measure of the price efficiency for that day. Since the daily level estimates of the maximum intraday pricing error exhibit several large outliers, we use the logarithmic transformation of Hasbrouck to mitigate their influence.

To calculate the pricing error, we only use the return equation in Hasbrouck (1993). The pricing error can be expressed as:

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + \alpha_2 v_{1,t-2} + \ldots + b_0 v_{2,t} + b_1 v_{2,t-1} + b_2 v_{2,t-2} + \ldots \tag{3}$$

where the pricing error s_t represents the deviation from the efficient price. We estimate α_j and b_j using the impulse response function.

$$\alpha_j = -\sum_{k=j+1}^{n} a_k^*$$

$$b_j = -\sum_{k=j+1}^{n} b_k^*$$

The sum of α_j and the sum of b_j represent the impact of an unexpected trade and impact of an unexpected return on returns after n transactions. It is driven by market frictions and noise trading. Intuitively, the pricing error is driven by temporary impacts of innovations in returns and trades, as well as by lagged adjustment to information. The variance of pricing error is a natural measure of transitory volatility.

Following Rösch et al. (2016), we then estimate co-movement in market efficiency across the oil and agricultural commodity markets and across market efficiency measures. This analysis yields the important result that systematic variation in market efficiency exists in the oil and agricultural commodity markets.

First, to estimate co-movement in market efficiency across the oil and agricultural commodity markets, we run the model specified in equation (4). The regression model also includes fixed effects for sector (e.g. oil, agriculture) and year to eliminate possible biases caused by omitted variables.

For futures market i on day d, year t, sector f, we estimate the following regression:

$$Eff_{i,d} = \lambda_f + \delta_t + \beta_m MktEff_{i,d} + \varepsilon_{i,d}$$

(4)

The dependent variable $Eff_{i,t}$is an indicating variable for the market efficiency of futures market i on day d.

Here, λ_f are sector fixed effects, δ_t are year fixed effects and ε is an error term. $MktEff_{i,d}$ is the aggregate market-wide efficiency (defined as the value-weighted average efficiency across the oil and agricultural commodity markets excluding the futures market i). The coefficient of interest β_m , captures co-movement in market efficiency across the oil and agricultural commodity markets.
$\beta_m > 0$ implies that there is co-movement in market efficiency across the oil and agricultural commodity markets. We run three regressions based on the three market efficiency measures. Table 2 reports the regression results.

We then estimate co-movement in market efficiency across the three market efficiency measures using Pearson and Spearman rank correlation.

Once we established the existence of systematic variation in market efficiency, we then seek to determine the key factors that drive the systematic variation in market efficiency. Our paper focuses on the impact of liquidity, speculative activity and funding liquidity on market efficiency.

First, we estimate the impact of liquidity on systematic variation in market efficiency. The regression model specified in equation (5) allows us to examine the impact of liquidity on market efficiency.

For futures market i on day d, year t, sector f, we estimate the following regression

$$Eff_{i,d} = \lambda_f + \delta_t + \beta_m MktEff_{i,d} + \beta_l Illiquidity_{i,d} + \varepsilon_{i,d}$$

(5)

Here, $Illiquidity_{i,d}$ is an indicator variable for liquidity and our proxy for $Illiquidity$ is quoted bid-ask spreads. Low quoted bid-ask spreads indicate high liquidity and vice versa. The coefficient of interest β_l , captures the impact of liquidity on systematic variation in market efficiency. $\beta_l > 0$ implies that an increase in liquidity enhances market efficiency. We run three regressions based on the three market efficiency measures. Table 4 reports the regression results.

Next, we estimate the impact of speculative activity and funding liquidity on market efficiency. We replicate all of our daily regressions at the weekly level and our choice of weekly frequency is determined by the existence of information in weekly COT reports.

For futures market i on week w, year j , sector k, we estimate the following regression

$$Eff_{i,w} = \lambda_f + \delta_t + \beta_m MktEff_{i,w} + \beta_{sp}\log(speculator)_{i,w} + \varepsilon_{i,w} \tag{6}$$

Here, $\log(speculator)_{i,w}$ is an indicator variable for speculative activity. The coefficient of interest β_{sp} , captures the impact of speculative activity on systematic variation in market efficiency. $\beta_{sp} < 0$ implies that an increase in speculative activity enhances market efficiency. We run three regressions based on the three market efficiency measures. Table 5 reports the regression results.

Table 1 presents the summary statistics on the three efficiency measures and quoted bid-ask spreads at the daily level.

Please insert Table 1 around here.

Table 1 provides a static picture. Panel A of Table 1 presents the summary statistics for quoted bid-ask spreads, which are our indicating variables for liquidity. Panel A shows that the average quoted bid-ask spreads are substantially narrower in the regime of electronic trading system than that of open outcry auction. This suggests an increase in liquidity over the regime of electronic trading system. Consistent with this view, Figures 1-3 show the substantial increase in speculator aggregate positions across the oil and agricultural commodity markets since 2006 when the regime of electronic trading system begun. Notably, in the regime of electronic trading system, the average quoted bid-ask spreads are substantially lower for crude oil, suggesting that the crude oil is the most liquid commodity in our sample. In particular, the average predictability for the crude oil suggests that the market efficiency of the crude oil is relatively higher compared to other commodity markets but that is not true for variance ratio and Hasbrouck. Therefore, the conclusion from the U.S. stock markets (Chordia et al., 2008) that high liquidity facilitates arbitrage activity, which in turn enhances market efficiency, is questionable as Chordia et al. (2008) only focused on market efficiency based on return predictability.

5. Empirical analysis

We begin by examining co-movement in market efficiency across the oil and agricultural markets and across market efficiency measures.

5.1. Co-movement in efficiency across the oil and agricultural commodity markets

Please insert Table 2 around here.

In Table 2, we report results where we examine whether there is co-movement in market efficiency across the oil and agricultural commodity markets using the model specified in equation (4). Hence, the outcome of interest is β_m , which captures the co-movement in market efficiency across the oil and agricultural commodity markets ($\beta_m > 0$). The baseline model includes year fixed effects and sector fixed effects. Table 2 reports results for *Predictability, Variance ratio and Hasbrouck* in columns 1 – 3, respectively.

Panel A reports the β_m estimates for the regime of open outcry auction. For all three regressions, the coefficient of β_m is insignificant. Hence, it is clear there is no co-movement in market efficiency across the oil and agricultural commodity markets in the regime of open outcry auction where human involvement is greater.

Panel B reports the β_m estimates for the regime of electronic trading system. For all three regressions, the coefficient of β_m is positive and two of the three regressions are statistically significant at the 1 percent. Consistent with the findings from U.S. stock markets (Rösch et al., 2016), our results in Panel B indicate that there is significant co-movement in market efficiency across the oil and agricultural commodity markets in the regime of electronic trading system where we see the substantial increase in speculative activity. This confirms that systematic variation in market efficiency exists across oil and agricultural commodity markets in the regime of electronic trading system, which sees the substantial increase in speculative activity. As mentioned earlier, it is worth note that algorithmic trading is popular among speculators, who are financial institutions like large commercial banks and hedge funds. Thus, it is reasonable to assume that speculative activity reflects algorithmic trading.

5.2. Co-movement in efficiency across market efficiency measures

Please insert Table 3 around here.

In Table 3, we report results where we examine whether there is co-movement across market efficiency measures. Table 3 reports these correlations for WTI crude oil, corn and soybean in columns 1 – 3, respectively.

Once again, consistent with the findings from U.S. stock markets (Rösch et al., 2016), all nine-correlations are positive and statistically significant at the 5 percent or less. Most of the correlations are economically substantial, ranging from 0.052 to 0.293. Hence, our results in Table 3 indicate that there is an economically significant co-movement in market efficiency across market efficiency measures. This confirms that systematic variation in market efficiency exists across market efficiency measures.

5.3. The impact of liquidity

Please insert Table 4 around here.

Having seen that systematic variation in market efficiency exists across the oil and agricultural commodity markets and across market efficiency measures, the next question that arises is: what drives the systematic variation in market efficiency?

First, we examine whether high liquidity enhances market efficiency using the model specified in equation (5). Our findings are reported in Table 4 where we estimate the impact of liquidity on market efficiency.

The coefficient of interest is β_l,which captures the impact of liquidity on market efficiency. If we see a positive impact ($\beta_l > 0$), this would indicate that arbitrageurs have a tendency to submit their orders in more liquid periods to avoid higher trading costs. For all three regressions, β_l estimates are statistically insignificant. Hence, our results lend no support for the conclusion from Chordia et al. (2008) that high liquidity facilitates arbitrage activity which in turn enhances market efficiency.

5.4. The impact of speculative activity

Please insert Table 5 around here.

We next turn to the primary contribution of this paper: whether speculative activity improves or worsens market efficiency.[31] Our hypothesis suggests a positive impact of speculative activity ($\beta_{sp} < 0$) if speculators actually trade on fundamentals and trade in a way that eliminates mispricing. Hence, we expect speculators to play a key role in arbitrage, which enforces market efficiency.

We report results in Table 5 where we examine the impact of speculative activity using the model specified in equation (6). Having seen that systematic variation in market efficiency exists across the oil and agricultural commodity markets and across market efficiency measures in Tables 2 to 4, we now restrict our

[31] It is worth note again that algorithmic trading is popular among speculators, who are financial institutions like large commercial banks and hedge funds. Therefore, it is reasonable to assume that speculative activity reflects algorithmic trading.

attention to the impact of speculative activity on the systematic variation in market efficiency. We find some important cautionary results.

If speculators actually trade on fundamentals and trade in a way that eliminates mispricing, we should see a positive impact ($\beta_{sp} < 0$). Hence, the outcome of interest is β_{sp} , which captures the impact of speculative activity on market efficiency. Furthermore, given that our empirical evidence only finds the systematic variation in market efficiency across the oil and agricultural commodity markets in the regime of electronic trading system, which sees the rise of algorithmic trading, it is likely that speculators drive the systematic variation in market efficiency across the oil and agricultural commodity markets using algorithmic trading.

In fact, Table 5 reveals that an increase in speculative activity could dramatically decrease market efficiency. For all three regressions, the coefficient of β_{sp} is positive and two of the three regressions are significant at 5 percent or less. Thus, our results indicate that an increase in speculative activity leads to a decrease in market efficiency. The magnitude of the negative impact of speculative activity is also economically significant, ranging from 0.004 for predictability to 0.367 for Hasbrouck. More worryingly, the evidence suggests that speculators have a tendency to buy when prices rise and sell when prices fall, which is consistent with positive feedback trading activity – that is, they are momentum traders and these traders tend to push prices away from fundamental values.[32] As a result, they destabilize prices. This explains why the oil and agricultural commodity prices have

[32] Momentum traders are considered as a special case of noise traders as they make trade decisions based on past returns and past trades

been more volatile in the regime of electronic trading system than that of open outcry auction.[33]

Overall, the results in Table 5 go against our hypothesis that speculative activity has a positive impact on market efficiency. On the one hand, we acknowledge that we focus on intraday one-minute intervals, and hence, short-term impacts of speculative activity on market efficiency. But on the other hand, even these short-term findings are relevant because the magnitude of the negative impact of speculative activity is economically significant.

5.4.1. Robustness Checks

Please insert Table 6 around here.

To ensure our results in Table 5 are robust, we next perform robustness checks. Two market characteristic that may affect the intensity of speculative activity is funding liquidity[34] and market volatility and thus we control for any variation in funding liquidity (*funding*) and market volatility (*volatility*). We control for these variables separately and Table 6 reports the results.

First, we check the sensitivity of our results after controlling for any variation in funding liquidity. Our proxy for funding liquidity is TED spreads and we add it to the model specified in equation (6). The results are reported in Panel A of Table 6. Overall, the results in Panel A of Table 6 are just as strong as in Table 5. This confirms that our results are robust to any variation in funding liquidity.

Next, we check the sensitivity of our results after controlling for any variation in market volatility. Our proxy for market volatility is the standard deviation of price returns and we add it to the model specified in Equation (6). The results are reported

[33] After many years of stability, both the oil and food prices surged upward at unprecedented rates from 2006 to 2008. From the mid-1980s to early 2000, the inflation-adjusted price of a barrel of crude oil on NYMEX was generally under $25/barrel.

[34] Arbitrageurs may face capital constraints, which prevent speculators from taking advantage of arbitrage opportunities. See, for example, Shleifer and Vishny, (1997), Brunnermeier and Pedersen (2009), and Rosch et al. (2016).

Panel B of Table 6. The results in Panel B of Table 6 are just as strong as in Table 5. The inclusion of the market volatility does not weaken our earlier results and confirms that our results remain robust to any variation in market volatility.

6. Conclusion and implications

This paper explores the existence of systematic variation in market efficiency in the oil and agricultural commodity markets over the regime of both the open outcry auction and electronic trading systems. Our paper employs three market efficiency measures. We find evidence that the systematic variation in market efficiency exists only in the regime of electronic trading system, which sees the substantial increase in speculative activity. We then try to determine what drives the systematic variation in market efficiency. Specifically, our paper focuses on the impact of liquidity and speculative activity on market efficiency. It turns out that the impact of speculative activity on market efficiency is negative while the impact of liquidity is insignificant. More worryingly, our empirical evidence suggests that speculators engage in positive feedback trading, which destabilise prices. This explains why the oil and agricultural commodity prices have been more volatile in the regime of electronic trading system than that of open outcry auction.

Hence, this paper provides some important cautionary results. Although we acknowledge that we focus on intraday one-minute intervals, and hence, short-term impacts, even these short-term findings are relevant because the magnitude of the negative impact of speculative activity is economically significant. Thus, the substantial increase in speculative activity raises unexpected risks for investors who see arbitrage opportunities because it could lead to substantial losses for the investors who try to eliminate mispricing. It is also concerning for policy makers because it may raise greater instability in the commodity market.

Finally, while not a focus of this study, it is also natural to wonder why speculators, who trade on noise (e.g. past returns), have a tendency to drive up (or down) commodity prices. Although the key role of speculators in the oil and agricultural commodity futures markets is providing liquidity to hedgers, they take the risk as investment opportunities for future positive returns. Hence, they have to drive up (or down) commodity prices to achieve expected returns. This should be true especially if speculators have borrowed in the present.

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Figures and Tables

Table 1 Summary statistics on the quoted bid-ask spreads and three efficiency measures, namely, predictability, variance ratio and Hasbrouck

Panel A: Quoted bid-ask spreads (Units are presented in basis points)

	Crude oil	Corn	Soybeans
Exchange	NYMEX	CBOT	CBOT
Open Outcry Auction			
Mean	35.80	33.90	33.00
St.Dev.	47.80	32.60	38.50
Min	1.35	5.40	2.95
Max	660.40	289.30	352.10
Observations	2,405	983	981
Electronic Trading System			
Mean	2.73	7.42	5.73
St.Dev.	7.15	10.10	16.00
Min	0.88	3.03	1.58
Max	144.50	266.70	406.90
Observations	2,429	982	1,208

Table 1 (continued)

Panel B: Predictability

	Crude oil	Corn	Soybeans
Exchange	NYMEX	CBOT	CBOT
	Open Outcry Auction		
Mean	0.046	0.025	0.067
St.Dev.	0.069	0.097	0.138
Min	0.003 ɐ	0.007 ɐ	0.004 ɐ
Max	0.963	0.972	0.995
Observations	2,399	969	1,473
Mean/obs	0.002	0.003	0.005
	Electronic Trading System		
Mean	0.025	0.048	0.043
St.Dev.	0.016	0.037	0.058
Min	0.033 ɐ	0.044 ɐ	0.033 ɐ
Max	0.131	0.539	0.972
Observations	2,429	979	1,204
Mean/obs	0.001	0.005	0.004

ɐ Units are presented in 10^3 .

Table 1 (continued)

Panel C: Variance Ratio

	Crude oil	Corn	Soybeans
Exchange	NYMEX	CBOT	CBOT
	Open Outcry Auction		
Mean	-1.757	-1.396	-1.036
St.Dev.	2.702	8.681	7.403
Min	-34.339	-33.336	-29.799
Max	73.242	74.103	74.735
Observations	2,404	981	1,493
Mean/obs	-0.073	-0.142	-0.069
	Electronic Trading System		
Mean	-1.639	-1.215	-1.342
St.Dev.	1.199	1.355	1.340
Min	-14.329	-7.857	-8.488
Max	1.055	6.526	4.379
Observations	2,429	982	1,208
Mean/obs	-0.067γ	-0.124γ	-0.111γ

γ are presented in percentage.

Table 1 (continued)

Panel D: Hasbrouck

	Crude oil	Corn	Soybeans
Exchange	NYMEX	CBOT	CBOT
	Open Outcry Auction		
Mean	-7.042	-9.603	-7.913
St.Dev.	1.111	5.228	1.780
Min	-12.608	-43.401	-39.812
Max	2.571	-4.655	-0.931
Observations	2,298	246	1,001
Mean/obs	- 0.003	- 0.039	-0.008
	Electronic Trading System		
Mean	-7.425	-7.058	-7.376
St.Dev.	0.683	0.653	0.679
Min	-10.684	-8.702	-9.109
Max	-4.906	-4.527	-3.715
Observations	2,211	974	1,190
Mean/obs	-0.003	-0.007	-0.006

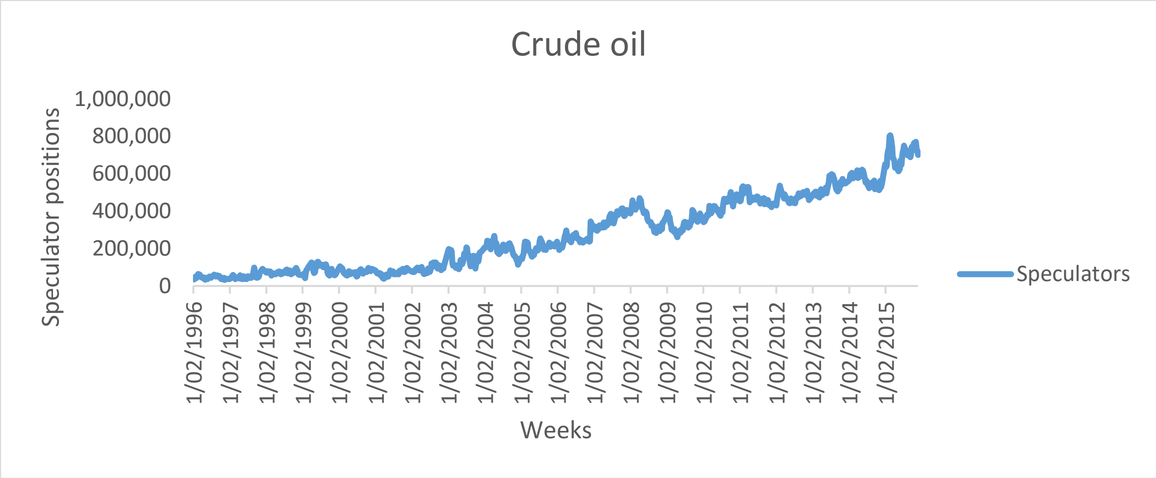

Figure 1 Aggregate speculator crude oil positions from 1996 to 2015

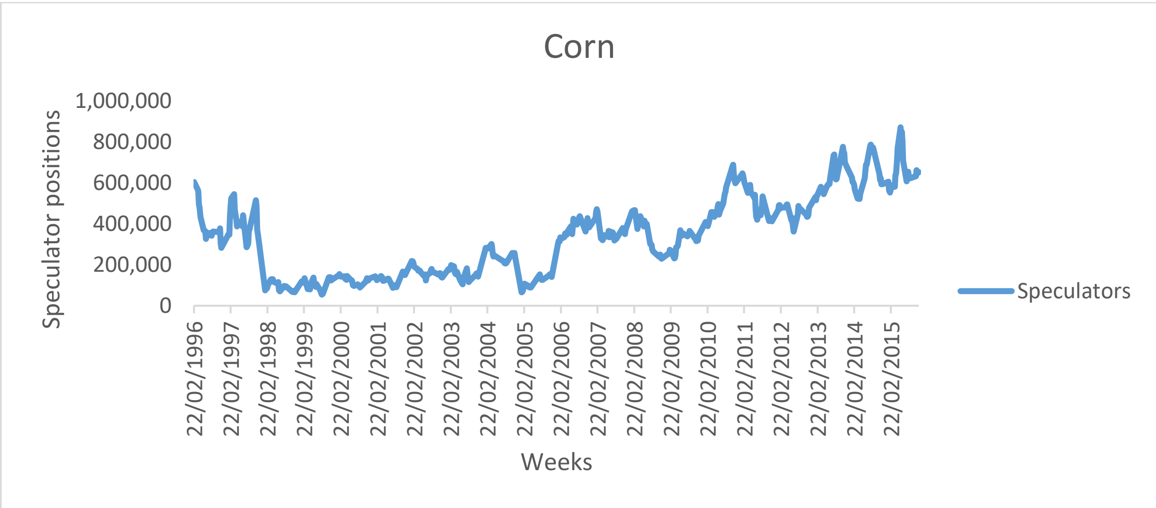

Figure 2 Aggregate speculator corn positions from 1996 to 2015

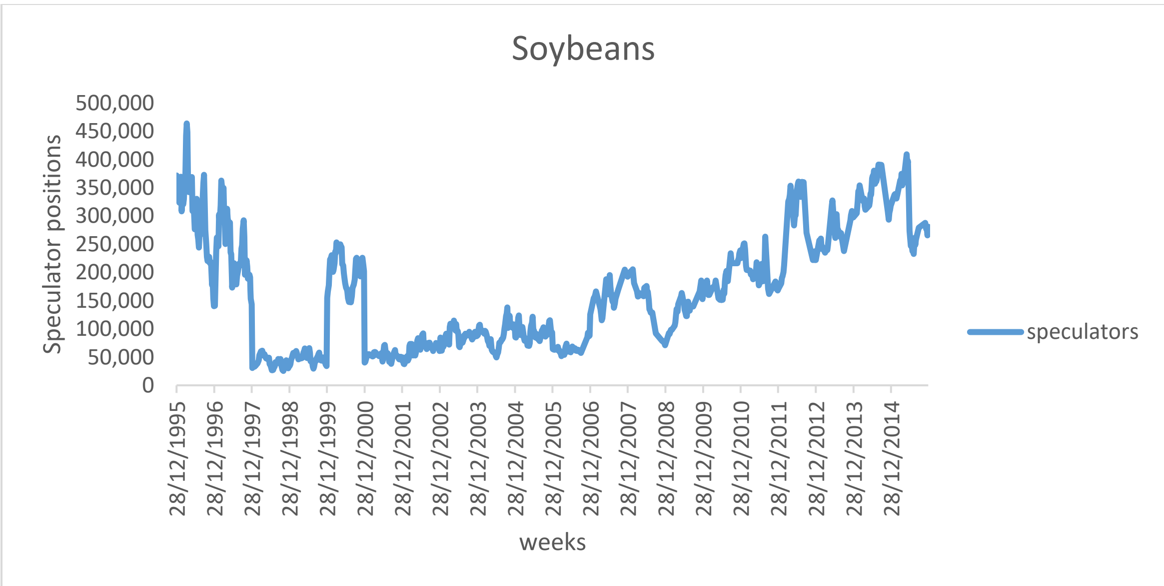

Figure 3 Aggregate speculator soybeans positions from 1996 to 2015

Table 2 co-movement in market efficiency across the oil and agricultural commodity markets

This table reports the results of regressions specified in equation (4). The dependent variable $Eff_{i,d}$ is the market efficiency of the commodity futures market i on day d. We employ three efficiency measures, namely, return predictability, variance ratio and Hasbrouck pricing error. Each regression includes year fixed effects and sector fixed effects. $MKTEff_d$ represents the aggregate market efficiency and is an indicating variable for whether there is co-movement in market efficiency across the foreign exchange and bond markets. Panel A reports the results for the regime of open outcry auction and Panel B reports the results for the regime of electronic trading system. Data are from TRTH.

Panel A: the regime of open outcry auction

	Dependent variable : $Eff_{i,d}$		
Efficiency measures	*Predictability*	*Variance Ratio*	*Hasbrouck*
$MKTEff_d$	0.016	-0.012	-0.056
(*t*-stat)	(0.790)	(-0.590)	(-1.440)
Year Fixed	Yes	Yes	Yes
Sector Fixed	Yes	Yes	Yes
R^2	0.181	0.061	0.912
Adj R^2	0.178	0.058	0.911
# regressions	3,882	3,957	3,545

Panel B: the regime of electronic trading system

Efficiency measures	*Predictability*	*Variance Ratio*	*Hasbrouck*
$MKTEff_d$	0.085***	0.036	0.106***
(*t*-stat)	(3.600)	(1.620)	(5.020)
Year Fixed	Yes	Yes	Yes
Sector Fixed	Yes	Yes	Yes
R^2	0.497	0.524	0.993
Adj R^2	0.494	0.522	0.993
# regressions	3,168	3,183	3,384

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

Table 3 estimates co-movement in market efficiency across market efficiency measures

This table reports Pearson and Spearman rank correlations between the three efficiency measures in the regime of electronic trading system.

	Crude oil			Corn			Soybeans		
Efficiency measures	*Predictability*	*Variance ratio*	*Hasbrouck*	*Predictability*	*Variance ratio*	*Hasbrouck*	*Predictability*	*Variance ratio*	*Hasbrouck*
Predictability		0.236*** (0.000)	0.293*** (0.000)		0.203*** (0.000)	0.251*** (0.000)		0.254*** (0.000)	0.278*** (0.000)
Variance Ratio			0.052** (0.014)			0.111*** (0.000)			0.142** (0.000)

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

Table 4 estimates the impact of liquidity on market efficiency

This table reports the results of regressions specified in equation (5) in the regime of electronic trading system. *Illiquidity* is an indicating variable for market liquidity.

Efficiency measures	*Predictability*	*Variance Ratio*	*Hasbrouck*
$MKTEff_d$	0.086***	0.038*	0.104***
(*t*-stat)	(3.670)	(1.710)	(4.910)
Illiquidity	-2.609	-55.034	34.219
(*t*-stat)	(-1.390)	(-1.380)	(1.100)
Year Fixed	Yes	Yes	Yes
Sector Fixed	Yes	Yes	Yes
R^2	0.497	0.524	0.993
Adj R^2	0.494	0.522	0.993
# regressions	3,168	3,183	3,384

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively

Table 5 estimates of the impact of speculative activity on market efficiency

This table reports the results of regressions specified in equation (6). Log(Speculator) is an indicating variable for speculative activity.

Efficiency measures	*Predictability*	*Variance Ratio*	*Hasbrouck*
Log (speculator)	0.004**	0.131	0.367***
(*t*-stat)	(2.400)	(1.180)	(6.940)
Year Fixed	Yes	Yes	Yes
Sector Fixed	Yes	Yes	Yes
R^2	0.297	0.758	0.993
Adj R^2	0.286	0.754	0.993
# regressions	963	838	838

Table 6 Robustness checks

Panel A reports the results of regressions specified in equation (6) after controlling for funding liquidity. Funding is an indicating variable for Funding liquidity. Panel B reports the results of regressions specified in equation (6) after controlling for market volatility. Volatility is an indicating variable for market volatility.

Panel A Robustness checks after controlling for funding liquidity

Efficiency measures	*Predictability*	*Variance Ratio*	*Hasbrouck*
Log (speculator)	0.004*	0.090	0.370***
(*t*-stat)	(1.900)	(0.790)	(6.800)
Funding	-0.002	-0.054	0.048
(*t*-stat)	(-0.610)	(-0.370)	(0.690)
Year Fixed	Yes	Yes	Yes
Sector Fixed	Yes	Yes	Yes
R^2	0.284	0.761	0.993
Adj R^2	0.271	0.757	0.993
# regressions	963	838	838

Panel B Robustness checks after controlling for market volatility

Efficiency measures	*Predictability*	*Variance Ratio*	*Hasbrouck*
Log (speculator)	0.005**	0.186*	0.362***
(*t*-stat)	(2.490)	(1.680)	(6.800)
Volatility	-0.496	-141.686***	14.482
(*t*-stat)	(-0.940)	(-4.620)	(1.000)
Year Fixed	Yes	Yes	Yes
Sector Fixed	Yes	Yes	Yes
R^2	0.297	0.765	0.993
Adj R^2	0.286	0.760	0.993
# regressions	963	838	838

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively