Systematic Market Efficiency and Excess Speculation Activity in Commodity Futures Markets: Too Much of a Good Thing?

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Abstract

Systematic market efficiency exists when price efficiency co-moves across stocks. We explore the existence of systematic market efficiency component in commodity futures markets featuring WTI crude oil, corn and soybean during both open outcry (1996-2006) and electronic market years (2006-2013). We find that systematic market efficiency component only exists during the electronic market years. Our results suggest that excess co-movement between oil prices and agricultural commodity prices since 2006 has been driven by the systematic variation in efficiency across commodity futures markets. Surprisingly, we find that hedgers, instead of speculators, play a key role in arbitrage, which enforces market efficiency. We also document that excess speculation activity increases return predictability and therefore deteriorates market efficiency in commodity futures markets.

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1. Introduction

Commodity prices tend to rise and fall together and those prices are in unison because it is a common belief that they are influenced by common macroeconomic factors such as inflation and exchange rates, among others. Thus, the interest in commodity prices is not a recent phenomenon. However, substantial increases in speculation activity accompanied by unprecedented large fluctuations and excess co-movement in commodity prices in recent years have renewed interest on the impact of excess trading on commodity prices. In addition, globalization and increased integration of world markets have accelerated the “financialization of commodities (Tang and Xiong, 2012)” and therefore players in global financial markets view commodity markets as alternative investment area for hedging and portfolio diversification purposes (Baffes and Haniotis, 2010). In other words, commodities are being regarded as financial assets. Thus, intuitively, commodity markets can be subject to similar dynamics as financial markets. Thus, since the boom and bust in oil and agricultural commodity prices during 2006-2008 timeframes, policy makers have raised concern over the impacts of excess speculation activity on commodity prices. In addition, while many economists believe that energy and agricultural markets have become closely linked as production of biofuels surged since 2006 given that ethanol (primarily from corn) and biodiesel (primarily from soybean) are substitutes for gasoline and diesel, some researchers state there is no causal link between oil and agricultural commodity prices and document that the recent dynamics of commodity prices is due to the “financialization of commodities (e.g. Gilbert, 2010)”.

In this paper, we therefore examine whether commodity futures markets are efficient. Market efficiency remains central study of financial markets and recent research by Rösch, Subrahmanyam and Van Dijk (2016) shows that price efficiency of stocks in U.S. stock markets co-move across stocks. Using several market efficiency measures, they also show that those efficiency measures co-move with each other. Rösch, Subrahmanyam and Van Dijk (2016) therefore provide evidence of the existence of systematic market efficiency component in U.S. stock markets. They also document that the systematic market efficiency component varies through time with aggregate funding liquidity, frictions that impede arbitrage, and variables that affect market-making efficacy.

Motivated by Rösch, Subrahmanyam, and Van Dijk, we extend their work to commodity futures markets. We first note that commodity futures markets are different from U.S. stock markets in several ways. First, one of the major differences is that while stocks are investment assets, commodity futures assets are consumption assets and therefore in commodity futures markets, traders are primarily hedging or speculating based on their line of business. Second, unlike U.S stock markets, commodity futures markets are not constrained by short-selling restriction. Hence, unlike U.S. stock markets, liquidity providers are likely to facilitate both purchases and sales. Third, low transaction costs accompanied by substantial increases in speculation activity and commodity investing (also known as financialization of commodity markets) in recent years make commodity futures markets far more liquid than equity markets (Fleming, Ostdiek and Whaley, 1996; Fan and Xu, 2011; Tang and Xiong, 2012).

The primary objective of this paper is to explore the existence of systematic market efficiency component in commodity futures markets. Given that excess co-movement between oil prices and agricultural commodity prices is a concern, in this paper, we focus on West Texas intermediate (WTI) crude oil, corn and soybean futures markets. The agricultural commodities we include in this study are energy-intensive products and used in production of biofuels. Further, given that both New York Mercantile Exchange (NYMEX), which is a major exchange for energy commodities and Chicago Board of Trade (CBOT), which is a major exchange for agricultural commodities, launched electronic platforms in 2006 and co-movement between oil and agricultural commodity prices has increased since 2006, we explore the existence of systematic market efficiency during both open outcry (1996- 2006) and electronic market years (2006-2013) using data from Thomson Reuters Tick History (TRTH) from 1996 to 2013 at daily level. We employ three efficiency measures, namely, return predictability, variance ratio and Hasbrouck pricing error to test this. While we find no evidence of the existence of systematic market efficiency component during open outcry market years, we find strong evidence that systematic market efficiency component exists during the electronic market years. Next, we then examine co-movement between efficiency measures. We find that these efficiency measures co-move with each other. Consistent with Rösch, Subrahmanyam and Van Dijk (2016), we confirm the existence of systematic market efficiency in commodity futures markets. Given that efficiency measures are all linked to arbitrage activity and co-move with each other, we only focus on results from return predictability.

Next, we perform robustness checks. Our results hold even after controlling for two market friction variables: market liquidity and volatility. In addition, surprisingly, we find that market liquidity is associated with deterioration in market efficiency in commodity futures market. This finding is an important new result.

To further explore whether the trading of speculators, who are generally viewed as informed traders in commodity futures markets, drives systematic market efficiency, we employ weekly data on trader positions for WTI crude oil, corn and soybean futures market from commitments of traders (COT) reports. Specifically, we replicate all of our daily regressions at the weekly level and our choice of weekly frequency is dictated the existence of information in the COT reports. However, at weekly level, we find that the systematic market efficiency component is insignificant. We then analyse the impact of trading activity of speculators and hedgers on efficiency of commodity futures markets. Surprisingly, contrary to our expectation, we find that increases in speculation activity is positively related to return predictability and hence is associated with deterioration in market efficiency. Thus, our results here explain earlier results that show market liquidity is associated with deterioration in market efficiency at daily level. We also find that increases in trading activity of hedgers is associated with improvements in market efficiency. More importantly, our results indicate hedgers play a key role in arbitrage.

Finally, we examine the impacts of time-varying funding liquidity and frictions on intensity of speculation activity and trading activity of hedgers. Consistent with expectation, we find that decreases in VIX, which represents investor fear sentiment, is associated with increases in speculation activity, indicating that speculation activity increases when investor fear sentiment is lower, and decreases in ted spread, which represents funding liquidity, is associated with increases in speculation activity, indicating that speculation activity increases when funding liquidity is higher. On the other hand, we find that increases in trading activity of hedgers is associated with improvements in market liquidity, indicating trading activity of hedgers increases when market is liquid, and decreases in ted spread, which represents funding liquidity, is associated with increases in trading activity of hedgers, indicating that trading activity of hedgers increases when funding liquidity is higher. Surprisingly, we find that increases in market volatility is related to increases in trading activity of both speculators and hedgers.

This paper makes several new contributions to the literature. First, the previous literature focuses U.S. stock markets only and we are the first to explore the existence of systematic market efficiency component in commodity futures markets. Specifically, we explore the existence of systematic market efficiency component both open outcry and electronic market years. Second, contrary to the previous literature who only uses a proxy for arbitrage activity, we employ the actual data for speculators, who are generally viewed as informed traders in commodity futures market, to examine whether their trading actual improves market efficiency. Third, a considerable body of literature documents impacts of excess speculation activity on commodity futures markets but find no evidence that excess speculation activity is harmful to commodity futures markets. To our knowledge, we are the first to provide evidence that excess speculation activity is positively related to return predictability and hence, is associated with deterioration in market efficiency.

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

2.1 Prior studies

Our paper is most closely related to recent research by Rösch, Subrahmanyam and Van Dijk (2016) that documents systematic variation in market efficiency in U.S. stock markets. Using several market efficiency measures including return predictability, variance ratio, Hasbrouck pricing error and put-call parity, Rösch, Subrahmanyam and Van Dijk (2016) is the first to show that these efficiency measures co-move across stocks and with each other, providing evidence of the existence of systematic market efficiency component in U.S. stock markets. Their results indicate that arbitrage activity, which enforces market efficiency, happens across stocks at the same time systematically but not necessarily all the time. We extend their work to commodity futures markets.

In the context of commodity futures markets, our paper can be linked to the recent episode of excess co-movement in commodity prices. There is an abundant literature on the relationship between commodity markets, including oil, mainly focus on causal relationship between oil and other commodities. In particular, in recent years, oil prices and agricultural commodity prices tend to exhibit excess co-movement. The surge in agricultural prices after 2006 through 2008 goes hand in hand with the increases in the oil price. The episode has raised the question of whether oil markets have any explanatory power on the recent upward movements in agricultural commodity prices. Although many researchers indicate that increasing oil prices is the main driver behind the rising agricultural commodity prices (e.g. Rosegrant, Msangi and Sulser, 2008; Chang and Su, 2010), the large number of studies in this area, unfortunately, find no causal link (Yu, Bessler and Fuller, 2006; Gilbert, 2010; Zhang, Lohr, Escalante, Wetzstein, 2010; Nazlioglu and Soytas, 2011). For example, Yu, Bessler and Fuller (2006) examine the dynamic relationships between major traded edible oil prices and world crude oil prices from 1999 to 2006 but find no link between them. Gilbert (2010) states there is no direct causal relationship between oil prices and agricultural commodity prices and document that excess co-movement between them is due to financialization of commodity markets. Some studies, on the other hand, show varying results based on different time periods. For example, Campiche, Bryant, Richardson and Outlaw (2007) examine the co-movements between crude oil prices and agricultural commodity prices during the period 2003-2007 based on weekly data and using the analysis with cointegration test, they show that while there is no cointegrating relation among the variables in concern for the period 2003-2005, corn and soybean prices are cointegrated with crude oil prices during the 2006-2007 time frames. Furthermore, while many economists believe that energy and agricultural markets have become closely linked as production of biofuels surged since 2006 given that ethanol (primarily from corn) and biodiesel (primarily from soybean) are substitutes for gasoline and diesel, some researchers state there is no causal link between oil and agricultural commodity prices and document that the recent dynamics of commodity prices is due to the "financialization of commodities (e.g. Gilbert, 2010)". The existence of systematic market efficiency component in commodity futures market implies that arbitrage activity, which enforces market efficiency, happens across commodity futures market at the same time drives co-movement in commodity prices. Motivated by these studies, we focus on WTI crude oil and corn and soybean, which are used in the production of biofuels, to explore the existence of systematic market efficiency.

Our paper also is also related to a growing literature on limits to arbitrage. Shleifer and Vishny (1997) is the first to discuss the importance of limits to arbitrage. Both Shleifer and Vishny (1997) and Gromb and Vayanos (2002) focus on financial crisis and document that arbitrageurs face financial constraints and their ability to invest is constrained by their wealth. Financial constraints are more explicitly studied in more recent papers. Akbas, Armstrong, Sorescu, Subrahmanyam and Daniel (2012) emphasize that market efficiency requires that arbitrageurs are able to raise the capital needed to arbitrage away mispricing. Using U.S. stock data from 1979 to 2009, they show that when there is a reduction in the flow of funds, arbitrageurs are unable to fully implement arbitrage activity, allowing some level of inefficiency to persist. In particular, extending earlier papers, Rösch, Subrahmanyam and Van Dijk (2016) discuss the two sources of limits to arbitrage and using a proxy for arbitrageurs, they show that arbitrageurs face time-varying funding constraints as well as time-varying market frictions that affect market-marking efficacy. In line with Rösch, Subrahmanyam and Van Dijk (2016), Chordia, Roll and Subrahmanyam

(2008) already document a link between liquidity and market efficiency and show that liquidity stimulates arbitrage activity, which, in turn, enhances market efficiency. Rösch, Subrahmanyam and Van Dijk (2016) that use a proxy to study arbitrage activity in U.S stock markets. The drawback of using proxies is it may not reflect the actual behaviour of traders. On the contrary, we employ the actual data for speculators, who are generally viewed as informed traders in commodity futures markets, to study whether the trading of speculators plays a key role in arbitrage, which enforces market efficiency.

Our paper is also related to literature on commodity futures trading. Several studies document that the net position of speculators is related to positive trade return while the net position of hedgers is related to negative trade return in commodity futures markets (Sanders, Boris and Manfredo, 2004; Dewally, Ederington and Fernando, 2013). Therefore, speculators are therefore generally viewed as informed traders while hedgers are generally viewed as uninformed traders in commodity futures markets. In addition, Chen and Chang (2015) examine the impact of the trading positions of hedgers and speculators on agricultural, metal and energy futures markets. They show that hedgers' positions have negative impacts on price efficiency in commodity futures markets and suggest that hedgers are less likely to be information motivated. Our results in this paper indicate that arbitrage activity and information trading are not related.

Lastly, our paper adds to the ongoing debate on whether excess speculation activity destabilize commodity futures markets. The boom and bust in commodity prices during 2006- 2008 time frames accompanied by substantial increase in trading activity of speculators and commodity investing (i.e. also known as financialization of commodity markets) has led to a renewed interest in the potential effect of commodity futures trading. Although many researchers attempt to investigate whether speculation activity destabilizes commodity futures markets, to our knowledge, up until now, there is no work that actually shows that excess speculation activity is harmful to commodity futures markets. Sanders, Irwin and Merrin (2010) find that speculation rises merely as a response to a rise in hedging demand and speculation is not to be blamed for the boom and bust of 2008 in commodity futures price. Buyuksahin and Harris (2011) test whether speculators has destabilizing effect on commodity futures market and find little evidence that speculation has harmful impact. Chen and Chang (2015) also provide evidence that the net position of speculators have positive impact on price efficiency in commodity futures markets. However, the consensus view from this literature and the public perception is that speculation activity was behind the boom and bust in commodity prices in recent years but find little evidence for support their argument. In this study, we take up this task and attempt to contribute to filling this gap.

The consensus view from this literature is that speculators are informed traders because their trades are related to positive trade return and thus, their trades should positive impacts on price efficiency. However, we find that that is not the case and our results show that speculators positive return trading does not necessarily have positive impacts on price efficiency.

2.2 Theories

Contrary to market efficiency research that theoretically argues that arbitrage activity happens immediately when mispricing happens (Fama, 1970), the existence of systematic market efficiency components implies that the arbitrage activity, which enforces market efficiency, does not happen all the time. Rösch, Subrahmanyam and Van Dijk (2016) document systematic market efficiency component varies through time with aggregate funding liquidity, frictions that impede arbitrage, and variables that affect market-making efficacy. Rösch, Subrahmanyam and Van Dijk (2016) discuss three competing hypotheses to link between efficiency and market liquidity, namely, inventory-based model (Stoll, 1978). First, in inventory-based model, efficiency can be compromised if market makers have capital constraints or limited risk-bearing, inhibiting their ability to prevent prices moving away from fundamentals as a result of demand or supply shocks from liquidity traders. Second, alternatively, such shocks can also result in inefficiencies when market makers face cognitive limitations. Third, efficiency might be challenged as a result of informational differences. In this paper, we therefore focus on the first hypothesis given that in the electronic market context, cognitive limitation is less relevant. The third channel involves put-call parity efficiency measure which we do not employ in this paper. We therefore only focus on the first channel.

2.3. Hypothesis development

Our primary objective of this paper is to explore the existence of systematic market efficiency component in commodity futures markets. Rösch, Subrahmanyam and Van Dijk (2016) show that efficiency co-move across stocks in U.S. stock markets, thus, confirm the existence of systematic market efficiency in U.S. stock markets. We build our first hypothesis directly on evidence from Rösch, Subrahmanyam and Van Dijk (2016) and expect a positive relation between price efficiency of each commodity futures market and market-wide efficiency. Based on this objective, we formulate our first hypothesis.

Hypothesis 1 (H1). There is a positive relation between price efficiency of each commodity futures market and market-wide efficiency

Our next objective of this paper is to examine whether market frictions affect systematic market efficiency in commodity futures markets. First, we test the impact of bid-ask spread, which we use to proxy for market illiquidity, on systematic market efficiency. Chordia, Roll and Subrahmanyam (2008) document that liquidity stimulates arbitrage activity, which, in turn, enhances market efficiency and show that return predictability is diminished when bid-ask spreads are narrower. Building directly on evidence from Chordia, Roll and Subrahmanyam (2008), we formulate our second hypothesis.

Hypothesis 2 (H2). There is a positive relation between return predictability and market illiquidity.

Next, we test whether the impact of market volatility on systematic market efficiency. We use the standard deviation of the mid-quote returns based on one minute intervals to proxy for market volatility. Rösch, Subrahmanyam and Van Dijk

(2016) document that a positive shock to volatility, which affects the intensity of arbitrage activity, is associated with a deterioration in systematic market efficiency. In line with Rösch, Subrahmanyam and Van Dijk (2016), we hypothesize that a positive shock to volatility is associated with a deterioration in market efficiency.

Hypothesis 3 (H3). There is a positive relation between return predictability and market volatility.

Our last objective of this paper is to examine whether speculators play an important role in arbitrage activity in today's commodity futures markets. Sanders, Irwin and Merrin (2010) and Chen and Chang (2015) provide evidence that speculators are associated with greater liquidity and hence, more efficient pricing. Consequently, more speculation activity should facilitate arbitrage, which in turn, improves systematic market efficiency. We therefore hypothesize that increases in speculation activity is associated with improvements in systematic market efficiency. Based on this objective, we formulate the following hypothesis.

Hypothesis 4 (H4). There is a negative relation between return predictability and speculation activity

Following Rösch, Subrahmanyam and Van Dijk (2016), we also examine the impacts of funding liquidity and investor fear sentiment affect market efficiency. Funding liquidity is important source of variation in arbitrage efficacy. We use ted-spread to proxy for funding liquidity. A negative coefficient on funding liquidity implies improved funding are associated with greater systematic market efficiency. Second, VIX, which represents investor fear sentiment, can deter arbitrage. A negative sign implies that decreases in investor fear sentiment is associated with improvements in systematic market efficiency

Hypothesis 5 (H5). There is a negative relation between return predictability and ted Spread

Hypothesis 6 (H6). There is a negative relation between return predictability and VIX

3. Data

We begin this section by describing our data and efficiency measures that we use in this study to our hypotheses in Section 2.3. We test our hypotheses using high frequency tick history data for West Texas light (WTI) crude oil futures traded on New York Mercantile Exchange (NYMEX), and corn and soybean agricultural futures traded on the Chicago Board of Trade (CBOT) from January 01, 1996 to December 31, 2013 and obtain the transaction data, including the bid and ask quotes, trade price, and trade volume from Thomson Reuters Tick History (TRTH). We begin in 1996 because the data is not available in earlier years in TRTH. All commodity futures prices are quoted in dollars and cents.

We split the sample into two subperiods: open outcry and electronic market years, since both CBOT and NYMEX launched electronic trading platforms in 2006. On August 1, 2006, the CBOT launched the electronic platform and NYMEX launched electronic platform on 5 September, 2006.

We use the nearest contract to delivery, but rollover to the next nearest contract on the first day of the delivery month to avoid thin trading and expiring effects. 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* – 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.

Our analysis in Section 5.1 and Section 5.2, we test for evidence of existence of systematic market efficiency component in commodity futures markets. To test our hypotheses, we need to construct a few variables including order flow and mid-quote return. For each interval, we aggregate all buys and all sells and compute the order flow. We follow the algorithm in Lee and Ready (1991) to assign a trade direction to each trade. 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. We compute order flow by taking the difference between buys and sells and divide it by the sum of buys and sells (OIB). The mid-quote return is associated with the last trade to the mid-quote of the last trade in the previous interval (to avoid the bid-ask bounce). In this paper we focus on one-minute interval and New York trading session and thus we use a total of 390 one-minute intervals. We discard trades that fall outside the New York continuous trading session (9:30 am till 4:00 pm EST).

For our robustness checks in Section 5.3, we employ two market frictions: market liquidity and market volatility, as our control variables. The first market friction is market liquidity. We compute quoted bid-ask spreads by taking the difference between the bid price and ask price and then divide it by the midpoint of the bid and ask prices. The second market friction is market volatility. We use midquote returns using the natural log function.

In our analysis in Section 5.4. we test whether the trading of speculators drives systematic market efficiency. We obtain weekly data on trader positions for WTI crude oil, corn and soybean futures market from COT reports. We then merge the weekly data with the data from TRTH. We also add VIX and ted spread which are proxies for investor fear sentiment and funding liquidity, respectively. We obtain data for ted spread from the FRED database of the Federal Reserve Bank of St. Louis and obtain data for VIX from Yahoo Finance.

Specifically, from Section 5.3 to Section 5.4, we restrict our analysis to data from the electronic market years given that we only find the existence of systematic market efficiency component during the electronic market years.

4. Methodology

The primary objective of this paper is to explore the existence of systematic market efficiency component in commodity futures markets. To test our hypotheses presented in Section 2.3, we require efficiency measures. Rösch, Subrahmanyam and Van Dijk (2016) employ four market efficiency measures including return predictability, variance ratio, Hasbrouck pricing error and put-call parity to examine the systematic variation in market efficiency. In this paper, we use three market efficiency measures used in Rösch, Subrahmanyam and Van Dijk for our empirical analysis in Section 5. However, we exclude put-call parity from our efficiency measures because we did not have access to the OptionMetrics database at the time when we commenced this study. All measures are inverse indicators of the degree of market efficiency, so that lower values indicate greater efficiency.

In Section 5.2, we employ return predictability, variance ratio and Hasbrouck pricing error to test whether these efficiency measures co-move with each other.

The first efficiency measure we employ in this study is intraday return predictability (Predictability): the predictability of returns from both order flow and past returns. The notion of efficient market (Fama, 1970) emphasizes a lack of return predictability as the criterion for efficiency. We therefore use Predictability as an inverse indicator of market efficiency. Several papers including Chordia, Roll and Subrahmanyam (2005) and Chordia, Roll and Subrahmanyam (2008) show evidence of return predictability from past returns or past order flows. In this paper, we focus on one-minute interval and estimate predictability of intraday return based on past returns and order flows as specified in equation (1). We use the mid-quote return to avoid the bid-ask bounce.

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

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

where the dependent variable $ret_{i,d,t}$ is the intraday return 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 return of commodity futures i in previous one-minute interval t – 1, $OIB_{i,d,t-1}$is the order flow in previous one-minute interval t – 1. We consider longer lags of returns and order flow to capture the magnitude and significance of lags of returns and order flow. In this paper, we regress mid-quote returns on five lags each of past returns and past order flow. The results for the regression model (1) is reported in Table 2.

The second market efficiency measure is variance ratio as introduced in 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 and variance ratio examines how closely the price of individual stocks adhere to a random benchmark. The variance ratio tends to unity as serial dependence in asset returns tend to zero. Thus, the greater deviations of the variance ratio from one signal lower price efficiency. We compute the variance ratio from mid-quote return. Following Rösch, Subrahmanyam and Van Dijk (2016), we estimate a daily variance ratio based on overlapping intraday returns and define the variance ratio as follows:

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

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

The third market efficiency measure we employ is Hasbrouck pricing errors (Hasbrouck, 1993). We estimate Hasbrouck pricing errors based on intraday data. 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. As in Rösch, Subrahmanyam and Van Dijk (2016), 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, in our previous study, Rösch, Subrahmanyam and Van Dijk were more interested in the magnitude of the pricing error rather than in its intraday variation. Following Rösch, Subrahmanyam and Van Dijk (2016), we also take the maximum of the absolute pricing errors of the trades in a commodity futures market on a given day as an inverse measure of the price efficiency for that asset on that day and label it the Hasbrouck measure. Since 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, only the return equation in Hasbrouck (1993) is used. 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.

Next, in Section 5.1, we estimate the degree of co-movement in efficiency across commodity futures markets to explore whether systematic market efficiency component exists in commodity futures markets. Following Rösch, Subrahmanyam and Van Dijk (2016), we run the time-series regressions of the efficiency of each futures market on contemporaneous, lead and lagged market-wide efficiency. In this analysis, we primarily focus on results from return predictability given that all three efficiency measures significantly co-move with each other as presented in Table 2.

For commodity future market i on day d, we estimate the following regression

$$Eff_{i,d} = \alpha_i + \beta_1 MktEff_{i,d} + \gamma_1 MktEff_{i,d-1} + \delta_1 MktEff_{i,d+1} + \varepsilon_{i,d} \quad (4)$$

where $Eff_{i,d}$is the price efficiency of commodity future market i, and $MktEff_{i,d}$ is the market-wide efficiency (defined as the value-weighted average efficiency across all futures market in our sample excluding commodity futures market i). β_1 is the focus of our analysis. A positive and significant coefficient confirms the existence of systematic market efficiency component in commodity futures markets.

In Section 5.3, we add two market frictions, namely, market liquidity and market volatility, and test whether our results in Table 1 hold even after controlling for these frictions.

For commodity future market i on day d and market friction j, we estimate the following regression

$$Eff_{i,d} = \alpha_i + \beta_1 MktEff_{i,d} + \gamma_1 MktEff_{i,d-1} + \delta_1 MktEff_{i,d+1} + \sum_{j}^{n} Frictions_{i,d}^{j} + \varepsilon_{i,d} \quad (5)$$

Where $Eff_{i,d}$is the efficiency of commodity future i on day , and $MktEff_{i,d}$ is the market-wide efficiency (defined as the value-weighted average efficiency across all futures in our sample excluding future i , $Frictions_{i,d}$ represents market frictions that can affect the intensity of arbitrage activity.

In section 5.4, once we finish exploring the existence of systematic market efficiency component in commodity future markets, we test whether the trading of speculators, who are generally viewed as informed traders, plays a key role in arbitrage, which enforces market efficiency and therefore drives systematic market efficiency. we replicate all of our daily regressions at the weekly level and our choice of weekly frequency is dictated the existence of information in the COT reports. We also add two variables, namely, funding liquidity and investor fear index, which can affect the intensity of arbitrage.

For commodity future market i in week t, trader position k , variables l and market friction j, we estimate the following regression

$$Eff_{i,t} = \alpha_i + \beta_1 MktEff_{i,t} + \beta_2 Trader\ position_{i,t}^{k} + \sum_{j}^{n} variables\ _{i,t}^{l} + \sum_{j}^{n} Frictions_{i,t}^{j} + \varepsilon_{i,t} \tag{6}$$

In Section 5.4, lastly, we also examine the impacts of funding liquidity, investor fear index and two market frictions on intensity of trading activity of speculators and hedgers.

For commodity future market i in week t trader position k and market friction j, we estimate the following regression

$$Trader\ position_{i,t}^{k} = \alpha_i + \beta_1 VIX_{i,t} + \beta_2 Ted\ Spread\ _{i,t} + \sum_{j}^{n} Frictions_{i,t}^{j} + \varepsilon_{i,t} \tag{7}$$

5. Empirical analysis

We begin our empirical analysis by exploring the existence of systematic market efficiency in commodity futures markets during open outcry futures market years and electronic market years using data for WTI crude oil, corn and soybean futures markets (Section 5.1). We then examine whether efficiency measures co-move with each other (Section 5.2) and perform robustness checks (Section 5.3). Further, we examine whether the trading of speculators, who are generally viewed as informed traders, drives systematic market efficiency and additionally, we analyse the impact of funding liquidity, VIX and frictions on intensity of trading activity of speculators and hedgers (Section 5.4).

5.1. Systematic market efficiency

In this section, we examine whether price efficiency co-move across WTI crude oil, corn and soybean futures markets during open outcry market years and electronic market years. As mentioned earlier, prior to 5 September, 2006, trading on WTI crude oil futures market was entirely in the open-outcry market while trading on corn and soybean futures markets was entirely in the open-outcry market prior to 1 August, 2006.

To estimate the degree of co-movement in efficiency across WTI crude oil, corn and soybean futures markets, we run the regression as specified in equation (4). We run our results with year-fixed effects and sector-fixed effects to control for changes in the year and sector. Table 1 presents the results. The table reports coefficients, the average R^2 as well as the adjusted R^2. The first column presents the results for the open outcry market years and the second column presents the results for the electronic market years. In this analysis, our main interest lies on the $MKTEff_d$, which represents the contemporaneous market-wide efficiency.

We first look at the results for the open outcry market years in the first column. Previously, Campiche, Bryant, Richardson and Outlaw (2007) show that there is no link between oil prices and agricultural commodity prices until 2005. The coefficient on $MKTEff_d$, which represents contemporaneous market-wide efficiency, is negative and statistically significant at 10 percent, which is the opposite to the prediction of the first hypothesis. The results also indicate there is no co-movement in commodity prices, supporting Campiche, Bryant, Richardson and Outlaw (2007). We therefore find no evidence of the existence of systematic market efficiency during open outcry market years.

Next, we look at the results for the electronic market years in the second column. Campiche, Bryant, Richardson and Outlaw (2007) show excess co-movement between oil prices and agricultural commodity prices since 2006. Coincidently, 2006 is when both exchanges NYMEX and CBOT launched the electronic platforms. Consistent with the first hypothesis, the coefficient on $MKTEff_d$ is positive and statistically at 1 percent. Consistent with Rösch, Subrahmanyam and Van Dijk (2016), the results confirm the existence of systematic market efficiency. We also obtain R^2 of 45 percent which is comparable to the R^2 of around 6 percent reported in Rösch, Subrahmanyam and Van Dijk (2016). The results also indicate co-movement in commodity prices and therefore support the literature that documents that commodity prices are correlated during 2006-2007 time frames. The results therefore suggest excess co-movement between oil prices and agricultural commodity prices since 2006 has been driven by the systematic variation in efficiency across commodity futures markets.

Next, the second column presents the results for the robustness check after controlling for any variation in market volatility. The inclusion of *Volatility* does not weaken the significance of the coefficient on $MKTEff_d$. We therefore confirm that our earlier results in the second column of Table 1 remain robust after controlling for any variation in market volatility. Next, we check the coefficient on *Volatility*. Rösch, Subrahmanyam and Van Dijk (2016) show that a positive shock to volatility is associated with a deterioration in systematic market efficiency. Less consistent with Rösch, Subrahmanyam and Van Dijk (2016), the coefficient is negative but statistically insignificant.

In summary, we find that systematic market efficiency only exists during electronic market years. Consistent with Rösch, Subrahmanyam, and Van Dijk (2016), we find that systematic market efficiency exists in commodity futures markets.

Table 1 co-movement regressions of daily, commodity futures market-level efficiency on market-wide efficiency

This table reports the results of the efficiency co-movement regressions from Equation (4). The first column presents the results for the open outcry market years and the second column presents the results for the electronic market years. The dependent variable $Eff_{i,d}$ is the efficiency of commodity futures market i on day d. The independent variable $MKTEff_d$, $MKTEff_{d-1}$ and $MKTEff_{d+1}$ represent contemporaneous, lead and lagged market-wide efficiency, respectively. Data are from TRTH.

Dependent variable : $Eff_{i,d}$		
Efficiency measures: *Return predictability*		
	Open Outcry market years 01 January 1996- 31 July 2006 (corn and soybean) 01 January 1996- 4 September 2006 (WTI crude oil)	Electronic market years 01 August 2006- 31 December 2013 (corn and soybean) 05 September 2006- 31 December 2013 (WTI crude oil)
$MKTEff_d$	-0.048*	0.427***
(*t*-stat)	(-1.910)	(17.780)
$MKTEff_{d-1}$	0.009	-0.042**
(*t*-stat)	(0.350)	(-2.000)
$MKTEff_{d+1}$	0.009	-0.048**
(*t*-stat)	(0.380)	-2.020
Year Fixed	Yes	Yes
Sector Fixed	Yes	Yes
R^2	0.148	0.455
Adj R^2	0.144	0.453
# regressions	3205	3592

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

5.2. Co-movement in efficiency across measures

Next, we examine whether efficiency measures co-move with each other. Rösch, Subrahmanyam and Van Dijk (2016) show that market efficiency measures co-move with each other.

In this section, we employ three market efficiency measures defined in Section 4, namely, return predictability, variance ratio and Hasbrouck pricing error to test whether these efficiency measures co-move. It is important to note that these efficiency measures are all inked to arbitrage activity which enforces market efficiency.

We present the Pearson and Spearman rank correlation between the three market-wide efficiency measures in Table 2. The first column presents results for WTI crude oil futures, the second column presents results for corn futures and the third column presents results for soybean futures market. All of nine correlations in Table 2 are positive and statistically significant at the 1 percent. Most of the correlations are both economically and statistically significant, which indicates that although the degree of price efficiency varies considerably across individual commodity futures markets, the different efficiency measures tend to provide a similar indication of the relative degree of price efficiency of individual commodity futures markets. Consistent with Rösch, Subrahmanyam and Van Dijk (2016), our results show that efficiency measures co-move with each other.

In summary, consistent with Rösch, Subrahmanyam and Van Dijk (2016), we find that efficiency measures co-move with each other.

In next sections, we primarily focus on results from return predictability given that all three efficiency measures are significantly positively correlated.

5.3. Robustness with market frictions

Next, in this section, we examine more closely how market frictions as discussed in Section 2 and in other empirical studies impact systematic market efficiency. We now focus on the electronic market years since only this period provides evidence of the existence of systematic market efficiency component in commodity futures markets. We add two market frictions, namely, market liquidity and market volatility, as robustness checks on our previous results in Table 1. First, we add a market liquidity variable and test the impact of market liquidity on systematic market efficiency. We use quoted bid-ask spreads to proxy for market illiquidity. Second, we add a market volatility variable. We use the standard deviation of the mid-quote returns based on one minute intervals to proxy for market volatility. We perform robustness checks by running the regression as specified in equation (5). Table 3 presents the results. The table reports coefficients, the average R^2 as well as the adjusted R^2.

The first column presents the results for the robustness check after controlling for any variation in market liquidity. Overall, the significance of all of the original

Table 2 Time-series correlations across daily, market-wide efficiency measures

This table reports Spearman rank correlations between three efficiency measures, namely, return predictability, variance ratio and Hasbrouck pricing error. The results are based on data from electronic market years. Data are from TRTH.

	WTI crude oil			Corn			Soybean		
Efficiency measures	*Predictability*	*Variance Ratio*	*Hasbrouck*	*Predictability*	*Variance Ratio*	*Hasbrouck*	*Predictability*	*Variance Ratio*	*Hasbrouck*
Predictability		0.286*** (0.000)	0.293*** (0.000)		0.553*** (0.000)	0.251*** (0.000)		0.632*** (0.000)	0.278*** (0.000)
Variance Ratio			0.434*** (0.000)			0.151*** (0.000)			0.204** (0.000)
N observations	2429			982			1208		

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

Table 1 Robustness check with market liquidity and market volatility

This table reports the results of robustness from Equation (5) after controlling for market liquidity and market volatility, in the first column and the second column, respectively. The dependent variable $Eff_{i,d}$ is the efficiency of commodity futures market i on day d. The independent variable $MKTEff_d$, $MKTEff_{d-1}$ and $MKTEff_{d+1}$ represent contemporaneous, lead and lagged market-wide efficiency, respectively. *Illiquidity* and *Volatility* are control variables. Data are from TRTH.

Dependent variable : $Eff_{i,d}$		
Efficiency measures: *Return predictability*		
Electronic market years 01 August 2006- 31 December 2013 (corn and soybean) 05 September 2006- 31 December 2013 (WTI crude oil)		
MKTEffd	0.373***	0.372***
(*t*-stat)	(17.140)	(17.090)
$MKTEff_{d-1}$	-0.038*	-0.042**
(*t*-stat)	(-1.800)	(-2.000)
$MKTEff_{d+1}$	-0.049**	-0.049**
(*t*-stat)	(-2.050)	(-2.030)
Illiquidity	-5.042**	
(*t*-stat)	(-2.130)	
Volatility		-0.170
(*t*-stat)		(-0.200)
Year Fixed	Yes	Yes
Sector Fixed	Yes	Yes
R^2	0.456	0.455
Adj R^2	0.453	0.452
# regressions	3592	3592

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

coefficients presented in the second column of Table 1 remain unchanged. Thus, we confirm that our earlier results in the second column of Table 1 remain robust after controlling for any variation in market liquidity.

Next, we turn to check the coefficient on *Illiquidity*. Chordia, Roll and Subrahmanyam (2008) show that liquidity enhances market efficiency. Surprisingly, contrary to expectations as mentioned in Section 2.3, the coefficient is negative and statistically significant at 5percent. Inconsistent with Chordia, Roll and Subrahmanyam (2008), our results indicate that return predictability is positively related to market liquidity. In other words, market liquidity is associated with deterioration in market efficiency and this finding is an important new result.

In summary, our results hold even after controlling for market frictions. Surprisingly, we find that market liquidity is associated with deterioration in market efficiency.

5.4. Key drivers of systematic market efficiency

In this section, we examine whether the trading of speculators plays a key role in arbitrage which enforces market efficiency and therefore drives systematic market efficiency in commodity futures markets. In this analysis, we replicate all of our daily regressions at the weekly level and our choice of weekly frequency is dictated the existence of weekly data in the COT reports.

We test the fourth hypothesis by running the regression as specified in equation (6). The results are presented in Table 4.

The results in Table 4 show that coefficient on $MKTEff_d$ is again positive but statistically insignificant. We therefore find no evidence of the existence of systematic market efficiency at weekly level. Our results indicate that systematic market efficiency component is not strong at weekly level.

Next, we analysing the drivers of efficiency of commodity futures markets. Surprisingly, inconsistent with the fourth hypothesis, the coefficient on speculator positions is positive and statistically significant at 1 percent. Our results in Table 4 indicate that increases in speculation activity is positively related to return predictability. In other words, increases in speculation activity is associated with deterioration in market efficiency. Thus, our results in Table 4 explain earlier results in Table 3 that show market liquidity is associated with deterioration in market efficiency at daily level. On the other hand, the coefficient on hedger positions is negative and statistically significant at 1 percent. Our results indicate that increases in trading activity of hedgers is negatively related to return predictability. In other words, increases in trading activity of hedgers is associated with improvements in market efficiency. Contrary to our expectation, our results in Table 4 indicate that trading activity of hedgers play a key role in arbitrage.

We then examine factors and frictions that affect the intensity of trading activity of speculators and hedgers. In this analysis, we include VIX which presents investor fear sentiment, ted spread which represents funding liquidity and two frictions, namely, market liquidity and volatility. We estimate it by running the regression as specified in equation (7). The results are presented in Table 5.

The first column in Table 5 presents results for speculators. Panel A presents results after controlling for market liquidity. The coefficient on *VIX*, which represents investors fear sentiment, is negative and statistically significant at 1 percent, indicating that a negative relation between speculation activity and VIX. The results imply that increases in VIX is associated with deterioration in speculation activity.

The second column in Table 5 presents results for hedgers. The coefficient on market illiquidity is negative and statistically significant at 10 percent. The results imply that increases in trading activity of hedgers is associated with improvements in market liquidity.

Further, we examine the impact of funding liquidity and frictions on the intensity of speculation activity and trading activity of hedgers. Consistent with expectation, we find that decreases in VIX, which represents investor fear sentiment, is associated with increases in speculation activity, indicating that speculation activity increases when investor fear sentiment is lower, and decreases in ted spread, which represents funding liquidity, is associated with increases in speculation activity, indicating that speculation activity increases when funding liquidity is higher. On the other hand, we find that increases in trading activity of hedgers is associated with improvements in market liquidity, indicating trading activity of hedgers increases when market is liquid, and decreases in ted spread, which represents funding liquidity, is associated with increases in speculation activity, indicating that trading activity of hedgers increases when funding liquidity is higher. Surprisingly, we find that increases in market volatility is related to increases in trading activity of both speculators and hedgers.

In summary, we find that systematic market efficiency component is insignificant. When we examined whether the trading of speculators drives

Table 2 Results for co-movement regressions of efficiency on market-wide efficiency at weekly level.

This table reports the results from Equation (6) after controlling for market liquidity and market volatility, in the first column and the second column, respectively. The dependent variable $Eff_{i,t}$ is the efficiency of commodity futures market i in week t. The independent variable $MKTEff_t$, represent contemporaneous market-wide efficiency, respectively. *Illiquidity* and *Volatility* are control variables. *VIX* and *Ted Spread* represent investor fear sentiment and funding liquidity, respectively. Data are from COT reports and TRTH.

Dependent variable : $Eff_{i,d}$		
Efficiency measures: *Return predictability*		
Electronic market years 01 August 2006- 31 December 2013 (corn and soybean) 05 September 2006- 31 December 2013 (WTI crude oil)		
$MKTEff_t$	0.054	0.055
(*t*-stat)	(1.030)	(1.070)
Speculator positions	0.007***	0.006***
(*t*-stat)	(2.990)	(2.620)
Hedger positions	-0.005***	-0.005**
(*t*-stat)	(-2.600)	(-2.510)
VIX	0.000	0.000
(*t*-stat)	(0.190)	(-0.100)
Ted Spread	0.000	-0.001
(*t*-stat)	(0.050)	(-0.600)
Market illiquidity	1.656**	
(*t*-stat)	(2.160)	
Market volatility		1.648
(*t*-stat)		(5.430)
Year Fixed	Yes	Yes
Sector Fixed	Yes	Yes
R^2	0.456	0.455
Adj R^2	0.453	0.452
# regressions	1026	1026

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

systematic market efficiency, contrary to our expectation, we find that increases in speculation activity is associated with deterioration in market efficiency. Surprisingly, our results show that hedgers, who are generally viewed as uninformed traders, play a key role in arbitrage. Further, we find that decreases in VIX is associated with increases in speculation activity and decreases in ted spread is associated with increases in speculation activity. On the other hand, we find that

Table 3

Panel A Results After controlling for market liquidity

This table reports the results from Equation (7). The dependent variable *Trader position* $_{i,d}$ represents weekly aggregate position held by speculators and hedgers at commodity futures market i in week t. The independent variable $MKTEff_t$, represent contemporaneous market-wide efficiency, respectively. *Illiquidity* and *Volatility* are control variables. *VIX* and *Ted Spread* represent investor fear sentiment and funding liquidity, respectively. Data are from COT reports and TRTH.

Electronic market years
01 August 2006- 31 December 2013
(corn and soybean)
05 September 2006- 31 December 2013
(WTI crude oil)

	Dependent variable : *Speculator position* $_{i,d}$	Dependent variable : *Hedger position* $_{i,d}$
Market illiquidity	-31.197	-63.482*
(*t*-stat)	(-1.160)	(-1.860)
Market volatility		
(*t*-stat)		
VIX	-0.009***	-0.002
(*t*-stat)	(-3.330)	(-0.730)
Ted Spread	-0.067	-0.112
(*t*-stat)	(-0.980)	(-1.290)
Year Fixed	Yes	Yes
Sector Fixed	Yes	Yes
R^2	0.540	0.540
Adj R^2	0.530	0.530
# regressions	1026	1026

Panel B Results After controlling for market volatility

	Dependent variable : *Speculator position* $_{i,d}$	Dependent variable : *Hedger position* $_{i,d}$
Market volatility	43.025***	50.760
(*t*-stat)	(3.360)	(3.040)***
VIX	-0.009***	-0.001
(*t*-stat)	(-3.470)	(-0.460)
Ted Spread	-0.138**	-0.215***
(*t*-stat)	(-2.460)	(-2.950)
Year Fixed	Yes	Yes
Sector Fixed	Yes	Yes
R^2		
Adj R^2		
# regressions	1026	1026

***,**,* Means statistically significant at the 1 %, 5%, and 10% level respectively increases in trading activity of hedgers is associated with improvements in market liquidity and decreases in ted spread is associated with increases in trading activity of hedgers. Surprisingly, we find that increases in market volatility is related to increases in trading activity of both speculators and hedgers.

5. Conclusion

Market efficiency remains central the study of financial markets. Given that little is known about how market efficiency measures vary over time, recent research by Rösch, Subrahmanyam, and Van Dijk (2016) shows the systematic variation in market efficiency across across stocks in U.S. stock markets. We extend their work to commodity futures markets.

First, using data for WTI crude oil, corn and soybean futures market from 1996 to 2013, we explore the existence of systematic market efficiency in both open outcry and electronic market years. We employ three market efficiency measures, namely, return predictability, variance ratio and Hasbrouck pricing error to test the first hypothesis. We find that systematic market efficiency only exists during electronic market years. We also find that efficiency measures co-move with each other. Consistent with Rösch, Subrahmanyam, and Van Dijk (2016), we find the existence of systematic market efficiency in commodity futures markets.

Next, we perform robustness checks after controlling for two market frictions: market liquidity and market volatility. Our results hold even after controlling for market frictions. We then analyse the impact of these frictions on systematic market efficiency and surprisingly find that market liquidity is associated with deterioration in market efficiency.

Having explored the existence of systematic market efficiency component, we then examine whether the trading of speculators, who are generally viewed as informed traders, plays a key role in arbitrage, which enforce market efficiency, at weekly level using weekly data from COT reports. We find that systematic market efficiency component is insignificant. We then analyse the impact of speculators on efficiency of commodity futures market. Contrary to our expectation, our results show that increases in speculation activity is associated with deterioration in market efficiency. Surprisingly, our results show that hedgers, who are generally viewed as uninformed traders, play a key role in arbitrage.

Further, we examine the impact of funding liquidity and frictions on the intensity of speculation activity and trading activity of hedgers. We find that decreases in VIX is associated with increases in speculation activity and decreases in ted spread is associated with increases in speculation activity. On the other hand, we find that increases in trading activity of hedgers is associated with improvements in market liquidity and decreases in ted spread is associated with increases in trading activity of hedgers. Surprisingly, we find that increases in market volatility is related to increases in trading activity of both speculators and hedgers.

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