Is the tracking error time varying? Evidence from agricultural ETCs

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Abstract

This study argues that the high volatility of agricultural commodity prices creates a challenge for exchange-traded commodity (ETC) managers to track the underlying index. Furthermore, previous studies find exchange-traded products replicated synthetically report a high tracking error (TE). Accordingly, this study examines the level and persistence of the TE in agricultural ETCs. In particular, we examine whether the TE of ETCs varies over time depending on agricultural commodity price volatility. According to our findings, agricultural ETC fund managers do not drift from their investment style depending on commodity price volatility. However, investors in agricultural ETCs are exposed to high TE during periods of high volatility, although it is not persistent over time. Therefore, this study also adds evidence to the argument that synthetic replication leads to high TE in ETCs.

Keywords: Agricultural Commodity Market, Event Study Methodology, Exchange-Traded Commodities, Markov Switching Regression, Tracking Error

JEL Classification: C24, G14, G23, Q14

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1. Introduction

Exchange-traded commodities (ETCs) have evolved over the last decade to be highly attractive investment instruments due to their characteristics, such as accessibility, liquidity, transparency and cost effectiveness. ETCs are designed to provide exposure either to a single-commodity or a basket of commodities. The role of the fund manager is to passively replicate the return of the underlying commodity index.

The popularity of commodities as an investment asset class arises from their negative or zero correlation structure with traditional investment assets (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006). However, recent studies find a gradual change in this correlation structure because of the rise of index investing in commodities (Silvennoinen and Thorp, 2013; Tang and Xiong, 2010).

Investigating the performance of ETCs will essentially provide relevant findings to support investors in their decision-making process. For any passively managed ETCs, the quality of the ETC will depend on its ability to replicate the underlying index as closely as possible. The tracking difference may indicate either the inability of fund managers to replicate the index or an intentional style drift by the managers. Hence, the information about the tracking performance of an ETC helps investors decide whether they can achieve their investment objective by investing in these funds.

Previous studies have analyzed how the return of an exchange-traded product (ETP) differs from the return of its underlying index. These studies have concluded that ETPs tracking equity, debt, sector, domestic and international indices do not replicate the underlying index precisely.[1] Given the limited empirical studies related to commodity-based ETPs, this study aims at adding more evidence by analyzing the tracking performance of 84 agricultural ETCs.[2]

A priori, we expect agricultural ETCs to have a high level of tracking error (TE) for three reasons. First, agricultural commodity markets are now becoming vertically integrated by reducing the number of buyers and sellers in the market. Adjemian, Saitone, and Sexton (2016), MacDonald et al. (2004) and Peterson (2005) reveal that the US agricultural market is becoming highly concentrated due to the increased coordination between farmers and processors. This high concentration leads to the creation of thinly traded agricultural commodity markets.[3] The concern related to a thinly traded market is that it creates excess volatility in prices, and hence may be more prone to price manipulation (Peterson, 2005). Furthermore, these manipulated prices might inspire ETC fund managers to either overinvest or underinvest in certain commodities, leading them to deviate from their investment style.

Second, agricultural commodity markets have experienced drastic price increases in the 2007/2008, 2010/2011 and 2012/2013 periods. Liu, Filler and Odenning (2013) and Masters (2008) argue that this speculative bubble in commodity prices is driven by the large volume of index investments in commodities. ETC fund managers face a challenge in tracking the underlying index return when the agricultural commodity prices are highly volatile. Therefore, we expect fund managers to drift in their investment style depending on the time-varying characteristics of the commodity prices. As a result, there is a tendency for agricultural ETCs to report a high level of TE during periods of high volatility compared with periods of low volatility in agricultural commodity prices.

[1] Blitz and Huij (2012), Chu (2011), Drenovak, Urosevic and Jelic (2014), Jares and Lavin (2004), Johnson (2009), Milonas and Rompotis (2006), Rompotis (2009) and Shin and Soydemir (2010) find that ETFs either underperform or overperform the underlying index.

[2] To the best of our knowledge, only Aroskar and Ogden (2012), Dorfleitner, Gerl and Gerer (2018), Guo and Leung (2015) and Rompotis (2016) investigate the tracking performance of ETCs.

[3] Anderson et al. (2007) define a thinly traded market as a market in which the number of transactions over a given period is insufficient to ensure efficient price discovery. Adjemian et al. (2016) define a thinly traded market as a market with few buyers, low trading volume and low liquidity.

Third, agricultural ETCs create exposure to commodity markets by using derivatives such as futures contracts or swap contracts on commodities. According to Rompotis (2016), commodity exchange-traded funds (ETFs) using futures-based replication report a higher level of TE than physically replicated commodity ETFs. Naumenko and Chystiakova (2015) find that equity ETFs using swap-based replication lead to a higher TE compared with physically replicated ETFs. Accordingly, it is reasonable to expect agricultural ETCs also to report a high level of TE, since all the ETCs in our sample are replicated synthetically.

Therefore, this study first examines whether fund managers of agricultural ETCs show an investment style drift when the agricultural commodity markets are volatile. Second, we assess whether the tracking performance of these ETCs is significantly different between high- and low-volatility periods of agricultural commodity prices. Finally, we test whether the TE is persistent over time.

According to the results, fund managers do not systematically drift from being passive investors. They do not intentionally overinvest or underinvest depending on the commodity price cycles. Further, the results reveal that agricultural ETCs have a high level of TE, though not persistent, during high-volatility periods compared with low-volatility periods of commodity prices. This deviation in tracking performance may reflect the challenge confronted by fund managers in tracking the underlying index when commodity prices are highly volatile.

The remainder of this paper is organized as follows. In Section 2, we provide an overview of the previous related literature. Section 3 describes the data and summarizes the descriptive statistics of commodity returns and TEs. Section 4 discusses the methodologies adopted to identify the commodity price cycles and presents the findings thereof. Section 5 presents the empirical results on the tracking performance of agricultural ETCs. Section 6 discusses the results on the persistence of TE. Finally, Section 7 summarizes and concludes the paper.

2. Literature Review

There are numerous empirical studies contributing to the argument about whether ETPs have the ability to track the underlying index precisely, and these studies find inconclusive results. There is empirical evidence for the existence of TE in American, Asian and European ETFs (Shin and Soydemir, 2010), Hong Kong ETFs (Chu, 2011; Johnson, 2009), Malaysian and Taiwanese ETFs (Johnson, 2009), German ETFs (Osterhoff and Kaserer, 2016), Swiss ETFs (Milonas and Rompotis, 2006) and ETFs on emerging market indices (Rompotis, 2015).

In contrast, Gallagher and Segara (2006) conclude that Australian ETFs track their benchmark indices better compared with off-market index managed funds; Harper, Madura and Schnusenberg (2006) find uniformly negative but not significant TE in ETFs on foreign markets; and Buetow and Henderson (2012) reveal no significant TE on 845 ETFs on equity, fixed income, preferred stocks, real estate and diversified sectors.

With respect to commodities, there are only a limited number of empirical studies available. Guo and Leung (2015) analyze the performance of 23 leveraged ETFs investing in gold, silver, oil and building materials and find that the majority of these funds underperform their underlying index. However, Aroskar and Ogden (2012) conclude that commodity-based iPath exchange-traded notes perform well in tracking the underlying index. According to Dorfleitner, Gerl and Gerer (2018), ETCs traded on the German market, on average, are more likely to trade at a premium from their net asset values. This limited attention from researchers on the tracking performance of ETCs also motivated us to conduct this study.

Furthermore, the literature describes factors that affect the magnitude of this TE: management fees (Elton, Gruber, Comer and Li, 2002; Rompotis, 2006; 2011), changes in index composition (Frino, Gallagher, Neubert and Oetomo, 2004), return volatility of the underlying index (Rompotis, 2006), bearish and bullish equity market conditions (Qadan and

Yagil, 2012; Wong and Shum, 2010) and replication strategy (Drenovak and Urosevic, 2010; Fassas, 2014; Guedj, Li and McCann, 2011; Naumenko and Chystiakova, 2015; Rompotis, 2016). According to Chen (2015), the TE of commodity ETFs also differs depending on the bullish and bearish conditions in the equity market.

Accordingly, this study explores whether the TEs of agricultural ETCs vary over time depending on the volatility of agricultural commodity markets. We also intend to contribute to the argument that synthetically replicated ETPs have a high level of TE compared with physically replicated ETPs. An ETP using a futures contract may experience a high level of TE due to the rolling costs associated with futures contracts. An ETP using a swap contract may experience a high level of TE due to added swap counterparty risk. We expect these agricultural ETCs to report a high level of tracking deviation because they are synthetically replicated using either futures contracts or fully funded collateralized swap contracts.

3. Data

This section describes the data and summarizes the descriptive statistics of returns and TEs categorized by commodity. We construct a database of daily prices of 84 agricultural ETCs, with at least five years of price history, and the daily prices of underlying indices. We collect the data from the Bloomberg database. The price data of ETCs cover the period from the inception date of each fund until November 2016. The price data of commodity indices cover the period from January 2006 to November 2016.

The sample consists of 50 ETCs issued by UBS, Switzerland and 34 ETCs issued by ETFS Commodity Securities Limited, UK. There are 60 funds investing in a single-commodity index and 24 funds investing in a multi-commodities index. There are 52 funds primarily traded in the London market and 32 funds primarily traded in the Swiss market. The ETCs in this sample invest in coffee, cotton, corn, cocoa, lean hogs, live cattle, orange juice, rough rice, soybeans, soybean meal, soybean oil, sugar and wheat. Table 1 lists the single-commodity indices used to identify the price cycle of each commodity.

[Insert Table 1 about here]

We use the Bloomberg Agriculture Total Return Index (AgriTR Index) as the benchmark index to represent the aggregate return on the agricultural market. The AgriTR Index enables investors to gain exposure to a total return investment in a comprehensive basket of agricultural commodity futures contracts on coffee, corn, cotton, soybean, soybean oil, soybean meal, sugar and wheat. This index reflects the return on fully collateralized futures positions. Figure 1 displays the composition of the AgriTR Index as at 2nd August, 2017.

[Insert Figure 1 about here]

Table 2 presents the annualized mean returns, volatilities of returns, mean TEs, volatilities of TEs and their distribution by the commodity. ETC returns are calculated using daily ETC prices. During the period of analysis, all commodities report negative annualized mean returns, except soybean meal. The lowest mean return is -25.16% for wheat and the highest mean return is 13.91% for soybean meal. ETCs investing in multi-commodity indices also report a negative mean return of 6.09%. The annualized volatility of the daily commodity returns is, on average, 34.55%. The volatility of returns is at the highest (42.51%) for corn and at the lowest (20.12%) for rough rice.

[Insert Table 2 about here]

We calculate the TE of an ETC as the difference between the fund return and the underlying index return in Table 2. The mean TE is negative for all the commodities. This is an indication of the average underperformance of agricultural ETCs compared with their underlying index. The highest TE of -2.49% is reported for wheat and the lowest TE of - 16.6% is reported for soybeans. The volatility of the TE is highest for cotton (48.21%) and lowest for rough rice (19.71%).

We test the significance of the null hypothesis that the mean TE of an ETC equals to zero. The objective of this test is to examine whether the TE for the entire period is significant or not. The last column in Table 2 presents the distribution of the TE. According to the results, the mean TE is not significant for all the funds, when we do not take into account the price volatilities of agricultural commodities.

4. Identifying Commodity Price Cycles

To examine the time-varying nature of the ETC tracking performance, first we need to identify the periods in which commodity prices have experienced significant booms and busts. We adopt two approaches to identify commodity price cycles, namely, the Markov switching (MS) regression model and the event study method. The following sub-sections discuss each method and present the findings.

4.1. Markov Switching Regression Model

Theoretically, supply-and-demand forces determine the commodity prices in the market. Schwartz and Smith (2000) decompose commodity spot prices into short-term deviations and long-term dynamics.[4] We model short-term random shocks of commodity returns using the MS regression model. First, we assume that the commodity prices would shift only between two states, that is, high- or low-volatility states. Second, the transition process between these states is assumed to follow a Markov process. Finally, we assume the today's return of a single-commodity index is correlated with the previous day return of the benchmark agricultural commodity index (i.e. AgriTR Index). This study calculates a state-dependent intercept term, slope coefficient and standard deviation using the following model.

[4] The short-term deviations in prices are temporary changes that arise from unexpected shocks to supply-and-demand forces, whereas long-term dynamics are fundamental changes that arise due to changes in supply-and-demand forces and would persist.

$$r_{it} = \mu_{St} + \beta_{St} r_{ag,t-1} + \varepsilon_{St}, \quad (1)$$

where r_{it} is the return on commodity index i on day t, μ_{St} is the state-dependent intercept/ mean, β_{St} is the state-dependent slope coefficient, $r_{ag,t-1}$ is the return of AgriTR Index on day t-1, ε_{St} is the state-dependent error term on day t and s_t is State 1 or 2 when t=1 or t=2, respectively. This model estimates the state each commodity is in on each day based on the daily transitional probabilities. If the probability of continuing in the same state (i.e., either P11 or P22) is greater than or equals to 0.85, then the commodity is considered to be in that state on that given date.

For each single-commodity fund and multi-commodity fund, we calculate the daily TE from the inception of the fund until November 2016. We initially calculate the TE as the difference between the ETC return and the underlying index return. In addition, we calculate the TE using three alternative definitions that will be discussed in a subsequent section.

For single-commodity ETCs, we test the significance of the difference of the mean TE between State 1 and State 2 of the underlying commodity prices. For multi-commodity funds, we test the significance of the difference of the mean TE based on the states of each commodity in the fund. Our objective is to analyze whether a multi-commodity ETC tracks the underlying index closely during the states of each commodity in which the underlying index has invested. For example, consider a multi-commodity fund investing in Bloomberg Grains Total Return Index, which includes corn, soybeans and wheat. We examine the significance of the tracking deviation of each fund between the states of each commodity, that is, of corn, soybeans and wheat separately.

Accordingly, the null hypothesis is that the difference between the mean TE of State 1 and State 2 is equal to zero, and the alternative hypothesis is that this difference is not equal to zero. If we fail to reject the null hypothesis, the fund managers may indicate an ability to replicate the underlying commodity index precisely, irrespective of the state of the agricultural commodity market.

4.2. Results of the Markov Switching Regression Model

Table 3 demonstrates the results of the MS regression model given in equation (1) above. It presents the values of the state-dependent intercept (i.e. μ) and the standard deviation of each commodity. Further, it summarizes the average duration (in days) of being in each state and the average transition probabilities between states for each commodity. P11 and P22 represent the probabilities of being in either State 1 or 2 on the previous day and continuing to be in the same state today. P12 and P21 represent the probabilities of being in either State 1 or 2 on the previous day and shifting into State 2 or 1, respectively, today. The higher the probabilities of P11 and P22, the more likely commodity prices would remain in the same state that they were on the previous day. Though this table provides an average probability, we also estimate the daily transition probabilities for each commodity and based on that identify the state of the commodity on each day.

[Insert Table 3 about here]

The results in Table 3 show that commodities report a lower mean return in State 1 in comparison with State 2. All the commodities report a standard deviation between 1.65% and 3.09% during State 1 and a standard deviation between 0.84% and 1.5% during State 2, except coffee (the coffee returns show an unusual pattern and report an unexpectedly large standard deviation in State 1). Accordingly, State 1 is the high-volatility period and State 2 is the low-volatility period of agricultural commodity returns. The higher average duration in State 2 than in State 1 reveals that all commodities (except coffee, rough rice and sugar) spend the majority of the days in State 2. Finally, we calculate the daily transition probabilities of P11 and P22 and identify the days on which either of these probabilities is equal to or above the cut-off level of 0.85. We could identify the daily states of each commodity except for coffee and orange juice for which there were no days reporting daily transitional probabilities that meet the cut-off criteria.

4.3. Event Study Method

The event study methodology is widely adopted in studies related to both equity markets[5] and commodity markets.[6] With regard to ETPs, Chen (2015) and Rompotis (2016) examine how the bearish and bullish days in the stock market affect the prices of commodity ETFs. Both these authors identify bearish and bullish days in the stock market by calculating the daily excess returns on the equity market.

Our objective of using the event study method is to test the robustness of the findings of the MS regression model. We identify the days on which each commodity listed in Table 1 has significantly outperformed the return on a benchmark agricultural commodity index (i.e., AgriTR Index). We use the following market-adjusted model to calculate the daily abnormal return of a commodity index.

$$AR_{i,t} = r_{i,t} - r_{ag,t}, \tag{2}$$

where $AR_{i,t}$ is the abnormal return on a commodity index i on day t, $r_{i,t}$ is the return on a commodity index i on day t and $r_{ag,t}$ is the return on the AgriTR Index on day t. We test the null hypothesis that an abnormal return on a commodity index i on day t equals to zero. We use the standard t statistic of the abnormal return in the event study method.

[5] Fama, Fisher, Jensen and Roll (1969), Asquith (1983), Ritter (1991), Loughran and Ritter (1995), Lakonishok and Vermaelen (1990) and Ikenberry, Lakonishok and Vermaelen (1995) are some studies using the even study method to study the equity market.

[6] Milonas (1987) and Lehecka (2014) analyze the informational value of the Crop Progress Report on the cash prices and futures prices of agricultural commodities, respectively. Robenstein and Thurman (1996) study the response of meat futures prices to adverse health information. McKenzie and Thomsen (2001) and Lusk and Schroeder (2002) examine the effect of meat recalls on meat and livestock futures prices.

After identifying significant abnormal return days (both positive and negative), we examine the significance of the tracking performance difference of each ETC between abnormal return days and non-abnormal return days. We test the null hypothesis that the difference of the mean TE between abnormal return days and non-abnormal return days is equal to zero. Failure to reject the null hypothesis implies that commodity ETCs track the underlying index closely during abnormal return days on the commodity as well.

For multi-commodity ETCs, our objective is to test whether these funds display a difference in tracking performance between abnormal return and non-abnormal return days of each underlying commodity. For example, as mentioned above, consider a multi-commodity fund investing in Bloomberg Grains Total Return Index, which includes corn, soybeans and wheat. We analyze whether the difference of the mean TE is significant between the abnormal and non-abnormal return days of each commodity, that is, for corn, soybeans and wheat separately. Failure to reject the null hypothesis implies that multi-commodity ETCs track the underlying index closely during abnormal return days of each of the underlying commodities in the index.

4.4. Results of the Event Study Method

Table 4 summarizes the abnormal return days and non-abnormal return days of each commodity index listed in Table 1 using equation 2 above. Regardless of our expectation of observing frequent booms and busts in commodity prices, the results reveal that, on average, there are only 74 and 73 days of significant positive and negative abnormal returns, respectively. This is only a small fraction of the total number of days in the sample period (i.e., 2.75% positive abnormal return days and 2.73% negative abnormal return days). Soybean meal reports the highest number of positive abnormal return days (i.e., 90 days) and rough rice reports the lowest number of positive abnormal returns days (i.e., 52 days). Lean hogs and orange juice have the largest number of negative abnormal return days (i.e., 85 days) and soybean oil has the lowest number of negative abnormal return days (i.e., 58 days).

[Insert Table 4 about here]

In the following sections, we will examine the ability of ETC fund managers to track the underlying index during these states and abnormal and non-abnormal return days and the tracking performance of ETCs during these periods as well.

5. Performance Measurement

5.1. Performance Measurement Method

The traditional method of measuring the tracking performance of an ETP is to calculate the TE of the fund. TE is the difference between the fund return and the underlying index return. However, there are alternative definitions of TE used in previous studies.[7] Following these previous papers, this study also measures the tracking performance of agricultural ETCs using four widely adopted definitions as follows. TE1 denotes the difference between the fund return and the underlying index return, TE2 the absolute value of the difference between the fund return and the underlying index return, TE3 the standard error of the regression of fund returns on the underlying index returns and TE4 the standard deviation of the difference between the fund return and the underlying index return. We calculate daily TEs using these four definitions and thereafter test the significance of the difference of the mean TE between State 1 and State 2 and between abnormal and non-abnormal return days of the underlying commodity.

[7] Charupath and Miu (2012), Drenovak et al. (2014), Frino et al., (2004), Gallagher and Segara (2006), Milonas and Rompotis (2006), Rompotis (2016) and Shin and Soydemir (2010) provide different definitions for tracking error.

5.2. Results of the Performance Measurement

First, we present the findings of the test of whether fund managers overinvest or underinvest in an underlying commodity depending on the price cycle of that commodity. The positive (negative) values of TE1 represent overinvestment (underinvestment) in commodities by the ETC fund manager. Table 5 summarizes the difference of the tracking performance of ETCs and its distribution under states and abnormal and non-abnormal return days. Panel A shows the results for single-commodity ETCs and Panel B shows the results for multi-commodity ETCs.

[Insert Table 5 about here]

Under states, none of the single-commodity ETCs reports a significant difference in the tracking performance. However, only one multi-commodity ETC (positive difference) and two multi-commodity ETCs (negative difference) report significant tracking difference under the states of sugar. Further, we find a significant positive (negative) tracking difference for three (one) single-commodity ETCs and four (none) multi-commodity ETCs under abnormal return days. In accordance with these findings, we conclude that agricultural ETC fund managers do not systematically overinvest or underinvest in underlying commodities depending on their price characteristics. Thus, we can identify the decisions of these fund managers as free from being intentionally biased.

Thereafter, we test the tracking performance of ETCs using the other three alternative definitions of TE. Shin and Soydemir (2010) and Rompotis (2016) argue that the TE measured as the difference between the fund return and the underlying index return may (i.e., TE1) underestimate the error because positive and negative differences in daily returns may cancel out each other. We conduct a sign test[8] to analyze the equality of the signs between fund return

[8] A sign test is a non-parametric test used to test whether or not two variables are equally signed. The null hypothesis is that the median of the differences is zero. We have conducted the sign test to analyze whether fund returns and underlying index returns have an equal number of positive and negative signs during State 1

and underlying index return. According to this test, ETC returns are equally distributed between positive and negative signs. Therefore, we attribute the lack of evidence for significant over- or underinvestment by the ETC fund managers to this characteristic of the distribution of returns.

Table 6 demonstrates the TE (TE2, TE3 and TE4), difference between the TE and its distribution for single-commodity ETCs. Panel A presents the results between State 1 and State 2, whereas Panel B presents the results between abnormal return days and non-abnormal return days.

[Insert Table 6 about here]

According to these findings, single-commodity ETCs report, on average, 1.13% higher TE in State 1 than in State 2 and 1.25% higher TE during abnormal return days than in non-abnormal return days for all the commodities. Further, a majority of these single-commodity ETCs report a significant positive TE. In summary, it suggests that single-commodity ETCs do not track the underlying index closely during high-volatility periods compared with low-volatility periods of agricultural commodity prices.

Table 7 shows the results of multi-commodity ETCs under alternative definitions of TE. We test whether a multi-commodity ETC performs differently when at least one commodity in which it has invested undergoes booms and busts in commodity prices. The majority of multi-commodity ETCs report positive and significant TEs under the price cycle of each commodity. On average, the difference in TE of multi-commodity funds is 0.46% between states and 0.35% between abnormal and non-abnormal return days. This indicates that even multi-commodity ETCs do not track the underlying commodity index closely during high-volatility periods of agricultural commodity prices. However, multi-commodity ETCs show a

and 2 and during abnormal and non-abnormal return days. We find that the signs of these returns are equally distributed. We do not present the findings of this test in this paper, but the results are available upon request.

better ability in tracking the underlying index during high-volatility periods than single commodities. A possible explanation for this improved tracking performance of multi-commodity ETCs could be the diversification effect.

[Insert Table 7 about here]

6. Persistence of Tracking Error

6.1. Measuring the Persistence of Tracking Error

After confirming the existence of significant TE for agricultural ETCs using the empirical results presented above, we now investigate the persistence of this TE in the short run. The hypothesis of persistence assumes that ETCs reporting a TE in the previous two days will continue to have a TE today as well. Previous studies adopt different methods to test the persistence of TE. Shin and Soydemir (2010) employ a serial correlation test and to assess the persistence of TE. They find significant serial correlation coefficients, on average, up to six days in Asian markets, up to five days in European markets and only one day in US markets. Rompotis (2016) uses an autoregressive model to test the persistence, finds negative coefficients and concludes that the TE of commodity ETFs has a mean-reverting behavior.

This study also follows Rompotis (2016) and adopts the following autoregressive model to test the persistence of TE in agricultural ETCs. We test the persistence using the absolute value definition (i.e., TE2) and use daily TEs calculated for the entire sample period.

$$TE2_{i,t} = \alpha_i + \beta_{1,i} TE2_{i,t-1} + \beta_{2,i} TE2_{i,t-2} + \varepsilon_{i,t}, \qquad (3)$$

where $TE2_{i,t}$, $TE2_{i,t-1}$ and $TE2_{i,t-2}$ are TEs of ETC *i* on day *t*, on day *t-1* and on day *t-2,* respectively. This model assumes that the TE today depends on the previous two days' TE, that is, on day *t-1* and *t-2*. We model the error variance of this regression with a generalized autoregressive conditional heteroskedasticity (GARCH) (1,1) process.

The persistence of the TE is determined based on the significance of the β coefficients. TE is persistent if β coefficients are positive and significant. This implies that if an ETC has a TE in the previous two days, it will have a TE today as well. Negative and significant β coefficients show a mean-reverting behavior of TE. If β coefficients are not significant, it suggests that TE is not persistent. If α_i coefficients are significant, it reflects a fixed percentage of TE that cannot be explained by the lagged values of the TE. Hence, in this analysis, we test the significance of $\alpha_i, \beta_{1,i}$ and $\beta_{2,i}$ separately.

6.2. Results of the Persistence of Tracking Error

Table 8 presents the results of the persistence test of single-commodity ETCs and multi-commodity ETCs. This table summarizes α_i, $\beta_{1,i}$ and $\beta_{2,i}$ coefficients and their distributions, respectively. According to the results, there are only 15 ETCs (out of 84 funds) in the sample reporting a positive and significant $\beta_{1,i}$ coefficient and only 9 ETCs reporting a positive and significant $\beta_{2,i}$ coefficient. We do not find sufficient results to conclude that today's TE is independent of the past two days' TE. We find only one ETC reporting negative and significant $\beta_{1,i}$ and $\beta_{2,i}$ coefficients and this reflects a mean-reverting behavior in TE. In conclusion, though agricultural ETCs report a significant level of TE, there is no strong evidence for its persistence.

[Insert Table 8 about here]

In addition, for all 84 funds, we find positive and significant α_i coefficients. In summary, there is a significant portion of TE that is not explained by the past two days' TE of an agricultural ETC.

7. Conclusion

This study examines the tracking performance of agricultural ETCs using a sample of 60 single-commodity funds and 24 multi-commodity funds. First, we study whether ETC fund managers overinvest or underinvest systematically in underlying commodities depending on the commodity price cycle. Then, we test the significance of the TE difference between high- and low-volatility periods of the underlying commodity. Finally, we test the persistence of this TE. In fact, we discuss how the characteristics of agricultural commodity prices affect the tracking performance of agricultural ETCs.

We adopt two methods, the Markov switching regression model and the event study method, to identify high- and low-volatility periods of agricultural commodity prices. We calculate the daily TE of each ETC and test the significance of the difference of the mean TE between State 1 and 2 or between abnormal return days and non-abnormal return days.

First, the results show that fund managers do not systematically drift away from their investment style depending on the commodity price cycle. Then, under alternative definitions of TE, agricultural ETCs report a high level of TE when the agricultural commodity prices are highly volatile. The single-commodity ETCs, on average, report 1% more TE and multi-commodity ETCs on average report 0.5% more TE in high-volatility periods than in low-volatility periods. This is an indication of the challenge faced by agricultural ETCs in tracking the underlying index better during the commodity price cycle. Finally, according to the results of the majority of ETCs, the current TE is independent of the previous TE. Hence, this study does not find strong evidence of the persistence of this significant TE.

The implications of this study are important and tangible. First, agricultural ETC fund managers' decisions are free from bias and do not depend on the commodity price cycle. Second, investors should pay attention to the level of the TE of agricultural ETCs, as these funds expose investors to a high level of time-varying TE. However, the lack of persistence in

TE shows that there is no systematic problem in how ETCs operate. Third, this study approves the argument that synthetic replication leads to high TE which requires the attention of fund managers.

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Appendix A

Figure 1
Composition of AgriTR Index as at 2nd August 2017

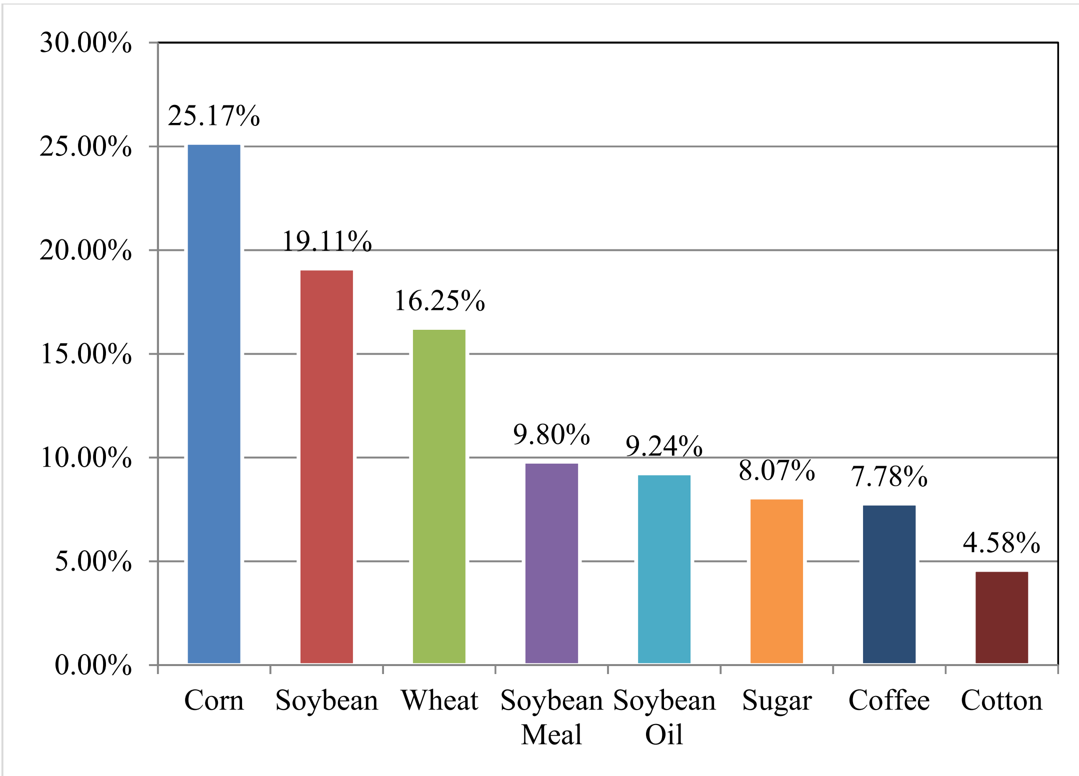

Table 1
List of commodities and their respective indices

This table lists the agricultural commodities and their respective commodity index in which the sample of 84 ETCs selected in this study has invested. The historical daily price data for all these indices are obtained from the Bloomberg database for the period from January 2006 to November 2016.

Commodity	Index	Index Ticker
Cocoa	Bloomberg Cocoa Sub Index Total Return	BCOMCCTR
Coffee	Bloomberg Coffee Sub Index Total Return	BCOMKCTR
Corn	Bloomberg Corn Sub Index Total Return	BCOMCNTR
Cotton	Bloomberg Cotton Sub Index Total Return	BCOMCTTR
Lean Hogs	Bloomberg Lean Hogs Total Return Index	BCOMLHTR
Live Cattle	Bloomberg Live Cattle Total Return Index	BCOMLCTR
Orange Juice	Bloomberg Orange Juice Sub Index Total Return	BCOMOJT
Rough Rice	UBS Bloomberg CMCI Rough Rice Total Return Index	CTRRTR
Soybeans	Bloomberg Soybeans Sub Index Total Return	BCOMSYTR
Soybean Meal	Bloomberg Soybean Meal Sub Index Total Return	BCOMSMT
Soybean Oil	Bloomberg Soybean Oil Sub Index Total Return	BCOMBOTR
Sugar	Bloomberg Sugar Sub Index Total Return	BCOMSBTR
Wheat	Bloomberg Wheat Sub Index Total Return	BCOMWHTR

Table 2
Descriptive Statistics

This table reports descriptive statistics of the 84 funds in our sample. The single-commodity funds are categorized based on their underlying commodity and the 24 multi-commodity ETCs are reported separately. The data cover the period from the inception of a fund until November 2016. All mean returns, standard deviations and tracking errors are annualized. The last column reports the distribution of the TE: the number of positive and significant funds (+), the number of insignificant funds (0) and the number of negative and significant funds (-).

Commodity	No of Funds	Mean Return	SD of Return	Mean TE	SD of TE	TE Distribution +/0/-
Cocoa	9	-6.68%	31.12%	-4.14%	28.87%	0/9/0
Coffee	6	-19.49%	40.91%	-6.91%	41.59%	0/6/0
Corn	8	-12.59%	42.51%	-7.23%	45.93%	0/8/0
Cotton	6	-8.61%	39.26%	-13.46%	48.21%	0/6/0
Rough Rice	3	-18.95%	20.12%	-3.19%	19.71%	0/3/0
Soybeans	5	-11.09%	37.73%	-16.60%	36.21%	0/5/0
Soybean Meal	1	13.91%	26.16%	-4.64%	24.77%	0/1/0
Soybean Oil	4	-13.12%	32.59%	-3.81%	33.01%	0/4/0
Sugar	9	-7.95%	38.53%	-5.28%	39.84%	0/9/0
Wheat	9	-25.16%	42.25%	-2.49%	41.75%	0/9/0
Multi-Commodities	24	-6.09%	28.88%	-4.85%	26.59%	0/24/0

Table 3
Markov Switching Regression Results

This table summarizes the results of the Markov switching regression model for State 1 and State 2. We report the state dependent μ and the standard deviation. State 1 is the high-volatility period and State 2 is the low-volatility period of each commodity. This table also provides the average duration of each commodity being in each state and average transition probabilities. P11 and P22 represent the probabilities of being in State 1 or 2 on the previous day and continuing to be in the same state today. P12 and P21 represent the probabilities of being on either State 1 or 2 on the previous day and shifting into either State 2 or 1, respectively, today.

Commodity & Index	State 1			State 2			Transition Probabilities			
	μ	Standard Deviation	Duration (Days)	μ	Standard Deviation	Duration (Days)	P11	P12	P22	P21
Cocoa (BCOMCCTR)	-0.14%	2.58%	19	0.07%	1.28%	50	0.9460	0.0540	0.9800	0.0200
Coffee (BCOMKCTR)	-0.04%	24.92%	2	-0.02%	1.13%	2	0.5537	0.4463	0.5405	0.4595
Corn (BCOMCNTR)	-0.06%	2.64%	18	0.02%	1.32%	31	0.9458	0.0542	0.9680	0.0320
Cotton (BCOMCTTR)	-0.04%	2.48%	88	0.01%	1.25%	239	0.9889	0.0111	0.9958	0.0042
Lean Hogs (BCOMLHTR)	-0.19%	2.06%	42	-0.02%	1.22%	129	0.9762	0.0238	0.9922	0.0078
Live Cattle (BCOMLCTR)	-0.33%	3.40%	37	0.03%	1.51%	88	0.9731	0.0269	0.9887	0.0113
Orange Juice (BCOMOJT)	-0.13%	3.09%	3	0.07%	1.28%	7	0.7100	0.2900	0.8596	0.1404
Rough Rice (CTRRTR)	-0.05%	1.65%	49	0.01%	0.84%	31	0.9795	0.0205	0.9679	0.0321
Soybean Meal (BCOMSMT)	0.08%	2.44%	28	0.04%	1.31%	59	0.9637	0.0363	0.9829	0.0171
Soybean Oil (BCOMBOTR)	-0.12%	2.41%	106	0.01%	1.24%	596	0.9905	0.0095	0.9983	0.0017
Soybeans (BCOMSYTR)	-0.03%	2.30%	26	0.05%	1.11%	65	0.9620	0.0380	0.9847	0.0153
Sugar (BCOMSBTR)	0.10%	2.60%	87	-0.13%	1.39%	83	0.9886	0.0114	0.9879	0.0121
Wheat (BCOMWHTR)	0.09%	2.71%	40	-0.13%	1.50%	54	0.9751	0.0249	0.9814	0.0186

Table 4
Event Study Method Results

This table summarizes the results of the event study method. Abnormal return is the difference between the return of each commodity index and the Bloomberg Agriculture Total Return (AgriTR) Index return. This table presents the number of days each commodity has reported either a significant positive or negative abnormal return or no significant abnormal return. Positive (negative) percentage is the positive (negative) abnormal returns days as a percentage of the total number of days in the sample period.

Commodity & Index	Significant Abnormal Return Days				No Abnormal Returns Days
	Positive (Days)	Positive (Percentage)	Negative (Days)	Negative (Percentage)	
Cocoa (BCOMCCTR)	64	2.38%	78	2.90%	2546
Coffee (BCOMKCTR)	76	2.83%	75	2.79%	2537
Corn (BCOMCNTR)	67	2.49%	71	2.64%	2550
Cotton (BCOMCTTR)	70	2.60%	76	2.83%	2542
Lean Hogs (BCOMLHTR)	81	3.01%	85	3.16%	2525
Live Cattle (BCOMLCTR)	78	2.90%	76	2.82%	2537
Orange Juice (BCOMOJT)	80	2.97%	85	3.16%	2528
Rough Rice (CTRRTR)	52	1.96%	64	2.41%	2542
Soybean Meal (BCOMSMT)	90	3.35%	70	2.60%	2528
Soybean Oil (BCOMBOTR)	88	3.27%	58	2.16%	2542
Soybeans (BCOMSYTR)	78	2.90%	60	2.23%	2550
Sugar (BCOMSBTR)	66	2.46%	76	2.83%	2546
Wheat (BCOMWHTR)	71	2.64%	80	2.98%	2537

Table 5
Over/Underinvestment of Fund Managers

This table summarizes the TE1, difference between the TE1 and the distribution of TE1 with states and with abnormal and non-abnormal return days. TE1 is the difference between the ETC return and the underlying index return. Panel A presents the findings for single-commodity ETCs and Panel B presents the findings for multi-commodity ETCs. The significance of the TE1 is determined at the 5% significance level.

Panel A

Commodity	TE1 with States		TE1 (1-2)	Distribution of TE +/0/-	TE1 With Abnormal Return Days		TE1 (1-2)	Distribution of TE +/0/-
	1	2			1	2		
Cocoa	-0.09%	-0.01%	-0.07%	0/9/0	0.00%	-0.15%	0.14%	1/8/0
Coffee	-	-	-	-	0.00%	-0.27%	0.27%	0/6/0
Corn	0.00%	-0.02%	0.02%	0/8/0	-0.03%	0.20%	-0.23%	0/8/0
Cotton	-0.03%	-0.06%	0.03%	0/6/0	-0.01%	-0.59%	0.58%	1/5/0
Rough Rice	-0.01%	-0.02%	0.01%	0/3/0	0.00%	-0.26%	0.26%	0/3/0
Soybeans	-0.14%	-0.01%	-0.12%	0/5/0	-0.03%	-0.26%	0.23%	0/5/0
Soybean Meal	-0.05%	-0.01%	-0.03%	0/1/0	0.02%	-0.47%	0.49%	0/1/0
Soybean Oil	-0.03%	-0.01%	-0.02%	0/4/0	0.01%	-0.32%	0.33%	1/3/0
Sugar	-0.01%	-0.02%	0.01%	0/9/0	-0.03%	0.41%	-0.44%	0/8/1
Wheat	0.00%	-0.02%	0.02%	0/9/0	-0.03%	0.45%	-0.48%	0/9/0

Panel B

Commodity	TE1 with States		TE1 (1-2)	Distribution of TE +/0/-	TE1 With Abnormal Return Days		TE1 (1-2)	Distribution of TE +/0/-
	1	2			1	2		
Cocoa	0.03%	-0.04%	0.07%	0/12/0	0.00%	-0.23%	0.24%	1/11/0
Coffee	-	-	-	-	-0.01%	-0.01%	0.00%	0/20/0
Corn	-0.07%	-0.02%	-0.05%	0/20/0	-0.01%	-0.14%	0.13%	0/20/0
Cotton	-0.02%	-0.01%	-0.01%	0/15/0	-0.01%	-0.06%	0.05%	0/15/0
Lean Hogs	-0.03%	-0.03%	0.01%	0/6/0	-0.02%	0.12%	-0.13%	0/6/0
Live Cattle	-0.07%	-0.01%	-0.06%	0/6/0	-0.01%	0.02%	-0.04%	0/6/0
Orange Juice	-	-	-	-	-0.01%	-0.04%	0.03%	0/3/0
Soybeans	-0.07%	-0.01%	-0.06%	0/20/0	-0.01%	0.02%	-0.04%	0/20/0
Soybean Meal	-0.06%	-0.02%	-0.05%	0/16/0	-0.01%	-0.05%	0.04%	0/16/0
Soybean Oil	-0.07%	-0.02%	-0.05%	0/16/0	0.00%	-0.13%	0.12%	3/13/0
Sugar	-0.01%	-0.03%	0.02%	1/17/2	-0.01%	0.07%	-0.08%	0/20/0
Wheat	-0.01%	-0.02%	0.01%	0/20/0	-0.02%	0.17%	-0.20%	0/20/0

Table 6
Performance of the Single-Commodity ETCs

This table summarizes the TE, difference between the TE and the distribution of TE of single-commodity funds. TE2 defines TE as the absolute value of the difference between the ETC return and the underlying index return. TE3 defines TE as the standard error of a regression of ETC return on the underlying index return. TE4 defines TE as the standard deviation of the difference between the ETC return and the underlying index return. Panel A summarizes the results between State 1 and State 2. Panel B summarizes the results between abnormal returns and non-abnormal return days. The significance of the TE is determined at the 5% significance level.

Panel A

Commodity	TE2		TE2 (1-2)	Distribution of TE +/0/-	TE3		TE3 = 1/2	Distribution of TE +/0/-	TE4		TE4 = 1/2	Distribution of TE +/0/-
	1	2			1	2			1	2		
Cocoa	1.39%	0.79%	0.61%	9/0/0	1.33%	0.73%	1.8221	9/0/0	1.83%	1.12%	1.6444	9/0/0
Corn	2.86%	1.09%	1.77%	8/0/0	3.88%	1.16%	3.3455	8/0/0	4.37%	1.73%	2.5061	8/0/0
Cotton	2.38%	1.17%	1.22%	6/0/0	2.91%	1.22%	2.3865	6/0/0	3.38%	2.25%	1.8675	6/0/0
Rough Rice	1.25%	0.63%	0.62%	3/0/0	1.48%	0.56%	2.6407	3/0/0	1.69%	0.91%	1.8663	3/0/0
Soybeans	2.36%	0.96%	1.40%	5/0/0	2.65%	0.92%	2.8853	5/0/0	3.27%	1.30%	2.5546	5/0/0
Soybean Meal	1.83%	0.75%	1.08%	1/0/0	2.21%	0.77%	2.8835	1/0/0	2.37%	1.02%	2.3243	1/0/0
Soybean Oil	2.34%	1.16%	1.18%	4/0/0	2.45%	1.05%	2.3289	4/0/0	3.32%	1.49%	2.3479	4/0/0
Sugar	1.88%	0.84%	1.04%	9/0/0	2.24%	0.88%	2.5373	9/0/0	2.66%	1.16%	2.5361	9/0/0
Wheat	2.41%	1.15%	1.26%	9/0/0	3.09%	1.22%	2.5339	9/0/0	3.60%	1.61%	2.2165	9/0/0

Panel B

Commodity	TE2		TE2 (1-2)	Distribution of TE +/0/-	TE3		TE3 = 1/2	Distribution of TE +/0/-	TE4		TE4 = 1/2	Distribution of TE +/0/-
	1	2			1	2			1	2		
Cocoa	1.96%	0.89%	1.07%	9/0/0	1.42%	0.89%	1.5963	9/0/0	2.38%	1.31%	1.8203	8/1/0
Coffee	3.41%	1.56%	1.86%	6/0/0	2.87%	1.70%	1.6949	6/0/0	4.32%	2.21%	1.9576	6/0/0
Corn	3.06%	1.45%	1.61%	8/0/0	3.11%	1.86%	1.6747	8/0/0	4.01%	2.43%	1.6492	8/0/0
Cotton	2.95%	1.43%	1.53%	5/1/0	2.86%	1.67%	1.7130	6/0/0	3.75%	2.71%	1.3823	5/0/1
Rough Rice	1.12%	0.93%	0.19%	0/3/0	0.90%	1.05%	0.8571	0/3/0	1.58%	1.32%	1.1961	0/3/0
Soybeans	2.25%	1.24%	1.01%	5/0/0	1.89%	1.42%	1.3361	4/1/0	2.87%	1.84%	1.5642	4/1/0
Soybean Meal	2.23%	1.04%	1.18%	1/0/0	1.94%	1.27%	1.5277	1/0/0	2.66%	1.45%	1.8389	1/0/0
Soybean Oil	2.25%	1.30%	0.94%	4/0/0	1.74%	1.36%	1.2815	3/1/0	2.81%	1.85%	1.4687	3/1/0
Sugar	2.57%	1.26%	1.32%	9/0/0	2.29%	1.55%	1.4740	8/1/0	3.27%	2.07%	1.5814	8/0/1
Wheat	3.25%	1.46%	1.79%	9/0/0	3.05%	1.80%	1.6966	9/0/0	4.13%	2.20%	1.8757	9/0/0

Table 7
Performance of the Multi-Commodity ETCs

This table summarizes the TE, difference between the TE and the distribution of TE of multi-commodity funds. TE2 defines TE as the absolute value of the difference between the ETC return and the underlying index return. TE3 defines TE as the standard error of a regression of ETC return on the underlying index return. TE4 defines TE as the standard deviation of the difference between the ETC return and the underlying index return. Panel A summarizes the results between State 1 and State 2. Panel B summarizes the results between abnormal returns and non-abnormal return days. The significance of the TE is determined at the 5% significance level.

Panel A

Commodity	TE2		TE2	Distribution	TE3		TE3 =	Distribution	TE4		TE4 =	Distribution of
	1	2	(1-2)	of TE +/0/-	1	2	½	of TE +/0/-	1	2	1/2	TE +/0/-
Cocoa	0.82%	0.65%	0.17%	5/6/0	1.05%	0.78%	1.3451	5/5/1	1.09%	1.05%	0.9823	11/0/0
Corn	1.59%	0.71%	0.88%	20/0/0	2.08%	0.73%	2.8556	20/0/0	2.25%	1.01%	2.1900	20/0/0
Cotton	1.40%	0.84%	0.56%	14/0/0	1.54%	0.87%	1.7709	14/0/0	1.97%	1.18%	1.6804	14/0/0
Lean Hogs	0.60%	0.56%	0.04%	0/6/0	0.84%	0.70%	1.2119	3/3/0	0.97%	0.83%	1.1801	5/1/0
Live Cattle	0.60%	0.51%	0.09%	2/4/0	0.81%	0.62%	1.3019	6/0/0	0.93%	0.72%	1.2917	6/0/0
Soybeans	1.51%	0.77%	0.74%	20/0/0	1.77%	0.85%	2.0879	20/0/0	2.07%	1.09%	1.8672	20/0/0
Soybean Meal	1.25%	0.68%	0.57%	16/0/0	1.47%	0.72%	2.0500	16/0/0	1.69%	0.98%	1.7346	16/0/0
Soybean Oil	1.31%	0.74%	0.57%	11/5/0	1.56%	0.87%	1.8008	16/0/0	1.77%	1.10%	1.5891	16/0/0
Sugar	1.13%	0.73%	0.41%	20/0/0	1.29%	0.79%	1.6357	20/0/0	1.57%	1.11%	1.4214	16/4/0
Wheat	1.35%	0.73%	0.62%	20/0/0	1.57%	0.80%	1.9536	20/0/0	1.95%	1.07%	1.7896	20/0/0

Panel B

Commodity	TE2		TE2	Distribution	TE3		TE3 =	Distribution	TE4		TE4 =	Distribution of
	1	2	(1-2)	of TE +/0/-	1	2	½	of TE +/0/-	1	2	1/2	TE +/0/-
Cocoa	1.07%	0.70%	0.37%	6/6/0	1.25%	0.91%	1.3819	11/1/0	1.57%	1.11%	1.4146	11/1/0
Coffee	1.10%	0.90%	0.20%	3/17/0	1.07%	1.03%	1.0381	3/16/1	1.51%	1.33%	1.1306	15/4/1
Corn	1.50%	0.92%	0.58%	18/2/0	1.55%	1.08%	1.4290	19/1/0	2.00%	1.39%	1.4419	18/2/0
Cotton	1.32%	0.99%	0.33%	13/2/0	1.36%	1.09%	1.2447	13/1/1	1.81%	1.45%	1.2546	12/2/1
Lean Hogs	0.88%	0.59%	0.29%	4/2/0	1.08%	0.76%	1.4195	6/0/0	1.42%	0.96%	1.4796	6/0/0
Live Cattle	1.00%	0.58%	0.41%	6/0/0	1.25%	0.75%	1.6631	6/0/0	1.45%	0.96%	1.5094	6/0/0
Orange Juice	1.05%	0.78%	0.27%	2/1/0	1.14%	0.95%	1.1981	2/1/0	1.40%	1.26%	1.1065	1/2/0
Soybeans	1.30%	0.93%	0.38%	19/1/0	1.35%	1.09%	1.2385	18/2/0	1.70%	1.40%	1.2155	14/6/0
Soybean Meal	1.17%	0.81%	0.36%	16/0/0	1.29%	0.96%	1.3357	15/1/0	1.57%	1.23%	1.2775	13/4/0
Soybean Oil	0.99%	0.82%	0.18%	3/13/0	1.11%	0.97%	1.1442	7/9/0	1.43%	1.24%	1.1570	8/8/0
Sugar	1.22%	0.89%	0.32%	10/10/0	1.22%	1.02%	1.2000	13/6/1	1.63%	1.34%	1.2197	11/8/1
Wheat	1.47%	0.92%	0.55%	20/0/0	1.52%	1.08%	1.4125	19/1/0	1.96%	1.38%	1.4206	18/2/0

Table 8
Results of the Persistence of Tracking Error

This table summarizes the results of the persistence of tracking error of agricultural ETCs. We examine the persistence through an autoregressive model where the TE(t) is assumed to be dependent on TE(t-1) and TE(t-2). We model the error variance using a GARCH (1,1) process. The table summarizes the values of α, β1 and β2 coefficients, respectively. Distributions of α, β1 and β2 indicate the number of positive and significant p values (+), number of p values not significant (0) and the number of negative and significant p values (-). The significance is determined at the 5% significance level.

Commodity	No of Funds	Constant (α)	Distribution of α +/0/-	β1	Distribution of β1 +/0/-	β2	Distribution of β2 +/0/-
Cocoa	8	0.0089	(8,0,0)	-0.0205	(2,5,1)	-0.0094	(2,5,1)
Coffee	5	0.0119	(5,0,0)	0.1859	(4,1,0)	0.0863	(3,2,0)
Corn	5	0.0141	(5,0,0)	0.0153	(2,3,0)	0.0192	(0,5,0)
Cotton	6	0.0129	(6,0,0)	0.0651	(2,4,0)	0.0359	(1,4,0)
Rough rice	3	0.0089	(3,0,0)	-0.0321	(0,3,0)	0.0498	(0,3,0)
Soybean	4	0.0126	(4,0,0)	0.0461	(1,3,0)	0.0266	(0,4,0)
Soybean Oil	1	0.0189	(1,0,0)	0.0640	(1,0,0)	0.0155	(0,1,0)
Sugar	5	0.0142	(5,0,0)	0.0124	(1,4,0)	0.0349	(1,4,0)
Wheat	6	0.0130	(6,0,0)	0.0283	(1,5,0)	0.0243	(0,6,0)
Multi-Commodities	19	0. 0104	(19,0,0)	0.0098	(1,18,0)	0.0113	(2,17,0)