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Is the tracking error time varying? Evidence from agricultural ETCs

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This study conducts an extensive analysis of a recently popularized asset class, namely, exchange-traded commodities (ETCs). We demonstrate that the tracking error of ETCs is dependent on the volatility of the underlying commodity prices but not persistent. Furthermore, we find the tracking ability of agricultural ETCs is affected by the replication method and also by the leverage of the ETCs. Our findings are important for academics and market regulators, as they indicate the structure of an ETC matters for its tracking performance.

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1. Introduction

Before the 2000s, commodity markets were largely segmented, and commodity investments were mainly used by commercial traders to hedge their exposure to the price risk of commodities. With the empirical evidence on the negative or zero correlation structure of commodities with traditional investment assets (Erb and Harvey, 2006; Gorton and Rouwenhorst, 2006), investors recognized the potential diversification benefits of investing in commodities. Thereafter, commodities (including agricultural commodities) gained a rising popularity as an asset class in portfolios along with other traditional assets, such as stocks and bonds.[1] This popularity was fueled by the large investment flows made by institutional investors into the commodity markets[2] (Basak and Pavlova, 2016; Domanski and Heath, 2007) and with the emergence of index-based investment instruments, namely, exchange-traded funds (ETFs) (Tang and Xiong, 2012).

An exchange-traded commodity (ETC) is an exchange-traded investment product providing exposure to either a single-commodity index or to a multi-commodities index (Fassas, 2014). An ETF in Europe cannot provide the exposure to a single commodity only as it requires to ensure a certain degree of diversification to comply with the Undertakings for Collective Investments of Savings (UCITS)[3]. Therefore, ETCs are structured as debt instruments and secured by collateral, whereas ETFs are considered as equity instruments. The ETC fund manager passively replicates the performance of an underlying commodity index

[1] Jensen, Johnson and Mercer (2000) conclude that adding commodities allowed investors to achieve a higher efficient frontier. Conover et al. (2010) find that by adding at least 5% of commodity exposure to a portfolio reduces the risk of that portfolio but does not increase the portfolio's return.

[2] Institutional investors were searching for alternative assets to reduce the risk of investing only in traditional assets, such as equity and bonds. Investing in a basket of commodities through a commodity index fund became the most popular strategy of investment due to the potential diversification benefits of commodities and low cost of investment.

[3] UCITS is the regulatory framework for an investment vehicle that can be marketed across the European Union. This regulation allows only the development of products tracking diversified commodity indices and does not allow ETFs providing exposure for a single commodity only. As a solution to this problem, the issuers introduced ETCs as debt instruments under the European Prospectus Directive. Please refer to Marszk (2017) for further details.

and aims to provide a return similar to the underlying index. ETCs, being exchange traded, have become easily accessible, highly transparent and liquid instruments. They provide exposure to the commodity markets at a low cost, markets that are otherwise costly to invest in directly due to the high costs of storage. These characteristics of ETCs enhanced their popularity as an investment asset.

The world's first distinct ETC trading platform was established by the London Stock Exchange in 2004. As per the Bloomberg statistics (as at December 2018), there are 786 ETCs, 211 ETFs and 198 exchange-traded notes (ETNs) on commodities. These statistics suggest that ETC is the most popular fund type for commodities. There are 218 ETCs on agriculture and livestock, which is second only to the number of ETCs on energy (239). These agricultural and livestock ETCs have assets in total of approximately USD 1482 million and the average one-year flow into these products is approximately USD 50 million. Furthermore, out of these 786 commodity-based ETCs, 99% of the funds are primarily traded in European exchanges located in Germany, Luxembourg, Switzerland and the United Kingdom. Morningstar in 2017 predicted that the assets under management of the European exchange-traded products would reach 1 trillion euros by 2020.[4]

However, recent studies find a gradual change in the correlation structure between commodities and other investment assets because of this rise in index investment in commodities (Basak and Pavlova, 2016; Silvennoinen and Thorp, 2013; Tang and Xiong, 2012). Specifically, Jensen and Mercer (2011) find that agricultural commodities are negatively correlated with stocks, treasury bonds and treasury bills during the period from 1970 to 1989. However, these correlations with agricultural commodities become positive in the later period from 1990 to 2009. It is evident that the financialization of commodity markets has changed the structure of the market during the past decades.

[4] This information is extracted from a report issued by Morningstar titled 'A guided tour of the European ETF marketplace – 2017'.

Furthermore, agricultural commodity markets experienced significant price increases in the 2007/2008, 2010/2011 and 2012/2013 periods. These price increases coincided with the popularity of index investment in agricultural commodities (Cheng and Xiong, 2014). Therefore, researchers argue this speculative bubble in agricultural commodity prices was driven by the large volume of index investments in commodities (Basak and Pavlova, 2016; Liu, Filler and Odenning, 2013; Masters, 2008). This high volatility in agricultural commodity prices possibly challenges ETC fund managers in tracking the performance of the underlying index. As a result, agricultural ETCs may not be able to entirely replicate the performance of the benchmark index.

The agricultural commodity markets have undergone another structural change since the early 2000s. Adjemian, Saitone and Sexton (2016), MacDonald et al. (2004) and Peterson (2005) reveal that agricultural markets have now become highly concentrated due to the increased coordination between farmers and processors. This high concentration creates thinly traded agricultural commodity markets.[5] The concern related to a thinly traded market is that it creates excess volatility in prices (Peterson, 2005). Therefore, we expect agricultural ETCs to have a high level of tracking error (TE) due to this high volatility prices.

Due to this increasing popularity of ETCs in the European region and the changing structure of agricultural commodity markets in general, there is a growing need to conduct more research studies on agricultural ETCs. Our study aims to fulfil this need by conducting an extensive study on the tracking performance of European agricultural ETCs. Accordingly, we contribute to the literature in three respects.

First, the quality of a passively managed ETC will depend on its ability to replicate the underlying index as closely as possible. Previous studies have analyzed how the return of an

[5] 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.

ETF differs from the return of its benchmark index. These studies have concluded that ETFs tracking equity, debt, sector, domestic and international indices do not replicate the underlying index precisely.[6] Our study is unique because it includes a large sample of European agricultural ETCs and investigates the performance of these funds extensively.[7]

Second, we adopt a different methodology as well. First, we examine the performance of ETCs during the entire sample period. Then, we test whether there is a significant difference in the tracking performance of ETCs between high- and low-volatility periods of agricultural commodity prices. In addition, we test whether this tracking performance is persistent over time.

Third, we assess whether the tracking performance of agricultural ETCs will differ based on fund characteristics, such as replication strategy and level of leverage. Synthetical replication has affected negatively to the tracking ability of ETFs (Drenovak and Urosevic, 2010; Fassas, 2014; Guedj, Li and McCann, 2011; Naumenko and Chystiakova, 2015; Rompotis, 2016). Agricultural ETCs mainly create exposure to commodity markets by using synthetic replication strategy, i.e. using either futures contracts or swap contracts on commodities. Hence, it is reasonable to expect this synthetic replication in agricultural ETCs will generate a high level of TE.

The leveraged exchange-traded commodity (LETC) is another innovation of ETCs. LETCs are similar to ETCs, but their goal is to replicate the return of an underlying commodity index in either a positive (leveraged) or negative (inverse) multiple. LETCs use positive multiples such 2X, 3X and negative multiples such as -1X, -2X and -3X. These funds attempt

[6] 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 over perform the underlying index.

[7] To the best of our knowledge, only Dorfleitner, Gerl and Gerer (2018) investigate the tracking performance of ETCs, but they focus only on the German ETC market. In addition, Aroskar and Ogden (2012) examine the performance of commodity ETNs, whereas Guo and Leung (2015) and Rompotis (2016) investigate the tracking performance of commodity ETFs.

to maintain the desired level of leverage within a one day holding period by daily rebalancing the fund. Due to the difficulty of this dynamic rebalancing, these funds are likely to underperform or overperform the return target of the fund. In our sample of ETCs, we have both leveraged and non-leveraged ETCs. We expect these agricultural LETCs also to generate a higher TE compared with non-leveraged agricultural ETCs. Therefore, we finally examine whether there is a tracking performance difference between the leveraged and non-leveraged ETCs in our sample.

According to our results, European agricultural ETCs generate a high level of TE during high-volatility periods of commodity prices. However, we do not find this TE to be persistent. Furthermore, synthetic replication and leverage both lead to high tracking deviations in agricultural ETCs.

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 methods 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

2.1. TE in Exchange-Traded Products

There are a number of empirical studies providing evidence for both the existence and non-existence of TE in ETFs. Those studies provide inconclusive results regarding the tracking performance efficiency of these funds. Previous studies find TE in American, Asian and European ETFs (Shin and Soydemir, 2010), in Hong Kong ETFs (Chu, 2011; Johnson, 2009), in Malaysian and Taiwanese ETFs (Johnson, 2009), in German ETFs (Osterhoff and Kaserer, 2016), in Swiss ETFs (Milonas and Rompotis, 2006) and in 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. Buetow and Henderson (2012) find no significant TE on 845 ETFs on equity, fixed income, preferred stocks, real estate and diversified sectors.

With respect to commodities, there are a limited number of empirical studies analyzing their tracking performance. Guo and Leung (2015) analyze the performance of 23 leveraged ETFs investing in gold, silver, oil and building materials and find most of these funds underperform their benchmark index. However, Aroskar and Ogden (2012) conclude that commodity-based iPath ETNs perform well in tracking the benchmark index. Dorfleitner, Gerl and Gerer (2018) examine the pricing efficiency of ETCs traded on the German market. They conclude that German ETCs are more likely to trade at a premium on their theoretical price. This limited attention of researchers on the tracking performance of agricultural ETCs motivated us to conduct this study.

Furthermore, the literature describes factors that affect the magnitude of this TE. Theoretically, the higher the management fee or the expense ratio, the larger would be the TE. Elton et al. (2002) and Rompotis (2006; 2011) support this argument. Frino et al. (2004) find that TE is significantly affected by the changes in index composition arising due to share issuances, share repurchases and spin-offs. These factors will increase the TE of ETFs due to the high transaction cost involved in changing the index composition. Furthermore, Elton et al. (2002) and Frino et al. (2004) show that the TEs of ETFs can be explained by the accrual of dividends on the stocks included in the benchmark index.

The previous studies provide further evidence that the return volatility of the underlying index (Rompotis, 2006) and equity market conditions (Qadan and Yagil, 2012; Wong and

Shum, 2010) also affect the tracking performance of ETFs. During the financial crisis in 2008, Qadan and Yagil (2012) find that ETFs had a low level of tracking ability compared with 2006 and 2007. Furthermore, Chen (2015) concludes the TE of commodity ETFs differs depending on the bullish and bearish conditions in the equity market. In this study, we aim to investigate whether the tracking ability of agricultural ETCs will be affected depending on the alternative market conditions of the underlying agricultural commodity. Accordingly, we examine the difference of the TE of agricultural ETCs between high- and low-volatility periods of the underlying agricultural commodity prices.

2.2. Physical versus Synthetic Replication

Exchange-traded products can adopt two replication methods, either physical replication or synthetic replication. Due to the high cost of storage involved in obtaining commodities via physical replication, the most popular method in commodity investment is synthetic replication. An ETC can synthetically replicate the performance of the benchmark index either using futures contracts or swap contracts. Using futures contracts to replicate adds rolling costs; hence, there will be a high TE generated for such ETCs. In addition, ETCs using swap contracts may experience a high level of TE due to the added swap counterparty risk.

This argument related to the impact of replication strategy on the tracking ability of index funds has been studied earlier (Drenovak and Urosevic, 2010; Fassas, 2014; Guedj et al., 2011; Naumenko and Chystiakova, 2015; Rompotis, 2016). According to Guedj et al. (2011) and Rompotis (2016), the tracking deviation of futures-based commodity ETFs is larger compared with physically replicated commodity ETFs. Fassas (2014) and Naumenko and Chystiakova (2015) conclude that ETFs using swap-based replication generate a higher TE compared with physically replicated ETFs. However, the question of whether the replication method affects the tracking ability of agricultural ETCs remains unsolved. Hence, this study aims to add evidence for this research question.

2.3. Leveraged versus Non-leveraged Exchange-Traded Products

LETCs replicate an underlying index in either a positive or negative multiple and provide a leveraged return on daily basis. ETCs with a positive multiple are known as either bull or leveraged ETCs, whereas ETCs with a negative multiple are known as bear or inverse ETCs (IETCs). These LETCs require daily rebalancing, and this dynamic rebalancing process is likely to make the replication process difficult. Therefore, LETCs are likely to generate a high level of TE compared with traditional ETCs on the same benchmark index. Investors generally consider investing in these products only for short periods in order to avoid these high TEs.

There are a growing number of studies examining the tracking performance of LETFs but limited evidence on LETCs. These studies conclude that the tracking performance of LETFs deteriorates with the investment horizon (Charupat and Miu, 2011; Lu, Wang and Zhang, 2012). However, Lu et al. (2012) find that the US LETFs in their study do not deliver the benchmark return even during a one-week horizon, whereas Charupat and Miu (2011) conclude that Canadian LETFs delivered the promised leveraged benchmark return in a one-week horizon. In the long term, LETFs are reported to underperform the benchmark index (Carver, 2009; Guedj et al., 2011; MacKintosh, 2008; Sullivan, 2009).

3. Data

Our sample of data include the daily prices of 84 agricultural ETCs (with at least five years of price history) and the daily prices of their underlying agricultural commodity indices. We collect all these data from the Bloomberg database. The daily prices of ETCs are collected from the inception date of each fund until November 2016. The daily prices of commodity indices cover the period from January 2006 to November 2016.

Our sample consists of 50 ETCs issued by the Union Bank of Switzerland (UBS), Switzerland, and 34 ETCs issued by ETFS Commodity Securities Limited, UK. There are 60 funds invested in a single-commodity index and 24 funds invested in a multi-commodities index. Out of these ETCs, 52 funds are primarily traded in the London market and 32 funds are primarily traded in the Swiss market. There are 22 funds leveraged and 62 funds non-leveraged. Fifty funds use futures contracts to replicate the benchmark commodity index and 34 funds use collateralized swap contracts to replicate it. Furthermore, the ETCs in our sample invest in coffee, cotton, corn, cocoa, lean hogs, live cattle, orange juice, rough rice, soybeans, soybean meal, soybean oil, sugar and wheat.

In order to examine the difference in the tracking ability of ETCs during the high- and low-volatility periods of agricultural commodity prices, we are first required to identify the volatility periods of these commodities. Table 1 lists the single-commodity indices used to identify the volatilities of each agricultural commodity in which the ETCs in our study have invested.

[Insert Table 1 about here]

In addition, we use the Bloomberg Agriculture Total Return Index (AgriTR Index) as the benchmark 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, soybeans, soybean oil, soybean meal, sugar and wheat. Figure 1 displays the composition of the AgriTR Index as at 2 August 2017.

[Insert Figure 1 about here]

Thereafter, we present the descriptive statistics on ETC returns categorized by the agricultural commodity. Table 2 presents the annualized mean returns, volatilities of returns and their distribution by the commodity. ETC returns are calculated using daily ETC prices, and we present annualized returns in Table 2.

[Insert Table 2 about here]

During the period of our analysis, all single-commodity ETCs, except soybean meal, have generated negative annualized mean returns. The lowest mean return is -25.16% for wheat and the highest mean return is 13.91% for soybean meal. ETCs investing in multi-commodities indices also report a negative mean return of 6.09%. The annualized volatility of the daily commodity returns is at the highest (42.51%) for corn and at the lowest (20.12%) for rough rice. The distribution of ETC returns of cocoa, coffee, corn, rough rice, soybean oil and sugar are negatively skewed, whereas the distribution of ETC returns of cotton, soybeans, soybean meal and wheat are positively skewed.

4. Identifying Commodity Price Cycles

To examine the time-varying nature of the tracking performance of agricultural ETCs, we first need to identify the periods in which commodity prices have experienced significant fluctuations. We adopt two approaches to identify the volatilities in prices. The following sub-sections discuss each method and present the findings for these methods.

4.1. Identifying Commodity States Using the Markov Switching Regression Model

Theoretically, supply-and-demand forces determine commodity prices in the market. Schwartz and Smith (2000) decompose commodity spot prices into short-term deviations and long-term dynamics.[8] We model the short-term random shocks of commodity returns using the Markov switching (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 between these states is assumed to follow a Markov process. Finally, we assume the previous day's return of the benchmark agricultural commodity index (i.e., AgriTR Index) explains today's return of a

[8] 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.

single-commodity index. In this MS regression model, we calculate state-dependent intercept terms, slope coefficients and standard deviations using the following model.

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

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 either state 1 or 2 when *t=1* or *t=2,* respectively. This model estimates the state of each commodity 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 continued in the same state as on the previous date. If the probabilities of P12 or P21 are greater than or equal to 0.85, then the commodity is considered to have changed the state from 1 to 2 or 2 to 1 compared with the previous date.

For each single-commodity fund and multi-commodities fund, we calculate the daily TE from the inception of the fund until November 2016. We initially calculate the TE using four alternative definitions that will be discussed in a subsequent section. The objective of using different definitions of TE is to ensure the consistency of our findings.

For single-commodity ETCs, we test the significance of the difference of the mean TE of an ETC between state 1 and state 2 of the underlying commodity prices. For multi-commodities funds, we test the significance of the difference of the mean TE of an ETC between the states of each commodity that is included in the fund. For example, consider a multi-commodities fund investing in the Bloomberg Grains Total Return Index, which includes corn, soybeans and wheat. We examine whether these multi-commodities ETCs show a difference in their tracking ability between the states of each commodity in which the fund invests. We test the significance of the TE difference between the states 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 reject the null hypothesis, we conclude that TE is different between high- and low-volatility periods. If we fail to reject the null hypothesis, we conclude that TE is same under both high- and low-volatility periods.

4.2. Results of the MS Regression Model

In this section, we present the results of the MS regression model (given in equation (1) above). Table 3 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 today, respectively. The higher the probabilities of P11 and P22, the more likely the commodity prices would remain in the same state that they were on the previous day. We also estimate daily transition probabilities (in addition to average probabilities) for each commodity and based on those daily values we 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 26.19% and 49.05% during state 1 and a standard deviation between 13.33% and 23.81% 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 average duration in state 2 is higher than the average duration in state 1. This reveals that all commodities (except coffee, rough rice and sugar), on average, spend most of the time in state 2, that is, in low-volatility periods.

Finally, we identify the daily state of each commodity based on the daily transitional probabilities of P11 and P22 and consider equal to or above 0.85 as the cut-off level. Figure 2A and 2B illustrate the daily transitional probabilities (P11 and P22) for cocoa under state 1 and state 2, respectively. It shows that cocoa has mostly been in state 2 during this period of concern as we found for many days P22 of cocoa being greater than 0.85. Accordingly, we could identify the daily states of all commodities except for coffee and orange juice, for which the daily transitional probabilities did not meet the cut-off criteria.

[Insert Figure 2A and 2B about here]

4.3. Identifying Abnormal Return Days of Commodities

We use this approach to test the consistency and robustness of the findings with the MS regression model. In their studies, 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 abnormal returns on the equity market.

Following their approach, 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). The objective of this analysis is to examine whether the tracking performance of agricultural ETCs differs between abnormal return days and normal return days of the underlying commodity. 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 single-commodity index *i* on day *t*, $r_{i,t}$ is the return on single-commodity index *i* on day *t* and $r_{ag,t}$ is the return on the AgriTR Index (multi-commodities index representing the return on total agricultural commodity market) on day *t*. We test the null hypothesis that an abnormal return on a single-commodity index *i* on day *t* equals to zero and the alternative hypothesis that an abnormal return on a single-commodity index *i* on day *t* does not equal to zero. The objective of the test is to identify the days on which each commodity has reported significant positive or negative abnormal returns.

After identifying significant abnormal return days (both positive and negative), we examine the significance of the tracking difference of each ETC between abnormal return days and normal return days. We test the null hypothesis that the difference of the mean TE of an ETC between abnormal return days and normal return days is equal to zero. Failure to reject the null hypothesis implies that the TE of ETCs is not same on both abnormal and normal return days. If we reject the null hypothesis, it implies that the TE of ETCs are same under both abnormal and normal return days of the commodity.

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

4.4. Results of the Abnormal Return Days of Commodities

Table 4 summarizes the abnormal return days and normal return days identified for each single-commodity index listed in Table 1 calculated using equation (2) above. Our results reveal that, on average, for all the agricultural commodities, there are only 74 and 73 days of significant positive and negative abnormal return days, 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]

5. Tracking Performance of Agricultural ETCs

5.1. Definitions of TE

We calculate daily TEs of ETCs to measure their tracking performance. Previous studies used different alternative definitions of TE.[9] Following these studies, we also measure the tracking performance of agricultural ETCs using four widely adopted definitions.

First, TE1 is defined as the average of the difference between the fund return on day *t* (r_t^{ETC}) and the underlying index return on day *t* (r_t^I) as shown in Eq. (3) (Drenovak et al., 2014; Rompotis, 2016). The T is the total number of days. TE1 is generally expressed in basis points or (0.01 percent). A positive (negative) TE1 indicates the ETC is over performing (underperforming) compared with the benchmark index.

$$TE_1 = \sum_t^T \frac{r_t^{ETC} - r_t^I}{T} \tag{3}$$

Second, TE2 is the average of the absolute value of the difference between the fund return on day *t* and the underlying index return on day *t* or the absolute value of TE1 as shown in Eq. (4) (Charupat and Miu, 2013; Rompotis, 2016). The positive and negative values of TE1

[9] See Charupat and Miu (2013), Drenovak et al. (2014), Frino et al., (2004), Gallagher and Segara (2006), Milonas and Rompotis (2006), Rompotis (2016) and Shin and Soydemir (2010) for different definitions of TE.

might off-set each other and will not indicate the true magnitude of the TE in that case. Either positive or negative, TE represents a deviation from the promised return. Therefore, TE2 indicates the total of the positive and negative TEs or the absolute value of the TE.

$$TE_2 = \sum_t^T \frac{|r_t^{ETC} - r_t^I|}{T} \tag{4}$$

For the third definition, we regress fund returns on the underlying index returns using the model depicted in Eq. (5). TE3 is the standard error of this regression or it is the standard deviation of the residuals (ε_t) of this regression (Charupat and Miu, 2013; Drenovak et al., 2014; Pope and Yadav, 1994; Rompotis, 2008; 2016).

$$r_t^{ETC} = \alpha + \beta r_t^I + \varepsilon_t \tag{5}$$

Finally, TE4 is defined as the standard deviation of the difference between the fund return and the underlying index return (Charupat and Miu, 2013; Drenovak et al., 2014; Frino and Gallagher, 2001; Roll, 1992; Rompotis, 2016). The formula for calculating the TE4 is given in Eq. (6). TE3 and TE4 measure the co-movement between the fund return and the underlying index return. Further, TE3 and TE4 are both standard deviations and hence, will be expressed as a positive number always. These standard deviations therefore represent the total tracking error (i.e. an aggregate of both negative and positive tracking errors).

$$TE_4 = \sqrt{\frac{1}{T-1} \sum_{t-1}^T (r_t^{ETC} - r_t^I)^2} \tag{6}$$

Accordingly, we calculate the daily TEs using these four definitions. In all four definitions of TE, if the ETC is precisely replicating the return of the underlying commodity index, the TE should be equals to zero. As we argue that the TE will be different between states and between abnormal and normal return days, we test the significance of the difference of the mean TE. The hypothesis test between MS regression states will be as follows.

$$H0: TE_{S1,J} - TE_{S2,J} = 0 \tag{7}$$

$$H1: TE_{S1,J} - TE_{S2,J} \neq 0, \tag{8}$$

where $TE_{S1,J}$ is the TE of commodity *J* in state 1 and $TE_{S2,J}$ is the TE of commodity *J* in state 2. The hypothesis test between abnormal and normal return days of the underlying commodity will be as follows.

$$H0: TE_{Ab,J} - TE_{N,J} = 0 \tag{9}$$

$$H1: TE_{Ab,J} - TE_{N,J} \neq 0, \tag{10}$$

where $TE_{Ab,J}$ is the TE of commodity *J* on abnormal return days and $TE_{N,J}$ is the TE of commodity *J* on normal return days.

5.2. Tracking Performance Results – Overall Sample Period

First, we present the tracking performance of agricultural ETCs calculated for the entire sample period using the daily price data from the inception of each ETC until November 2016. In this section, we test the null hypothesis that the mean TE of an ETC is equal to zero. Table 5 presents the mean TEs calculated under the above four definitions and the respective distribution of each TE. As per TE1, the mean TE is negative for all the commodities. This indicates that agricultural ETCs, on average, underperform the benchmark index, but the results are not statistically significant. The lowest negative TE is reported for soybeans (-0.042%), whereas the highest negative TE is reported for wheat (-0.007%).

[Insert Table 5 about here]

The TEs calculated for the entire sample period using TE2, TE3 and TE4 in Table 5 indicate a significant tracking deviation in agricultural ETCs. We find all ETCs to generate significant TEs under all these three definitions. This difference in the results between TE1 and other definitions is possible. Shin and Soydemir (2010) and Rompotis (2016) argue that tracking performance measured as the difference between the fund return and the underlying index return (i.e., TE1) underestimates the error because positive and negative differences in daily returns may cancel out each other. Therefore, we conducted a sign test[10] to analyze the equality of the signs between fund returns and underlying index returns. The findings of our sign test suggested that ETC returns are equally distributed between positive and negative signs. Therefore, we attribute the lack of significant evidence under TE1 to this characteristic of the distribution of returns.

Furthermore, as mentioned previously, TE3 and TE4 are standard deviations and consequently will be expressed as a positive value. When we calculate TE3 and TE4, they take both the deviations of the negative TE (underperformance) and the deviations of the positive TE (overperformance) into consideration. Hence, TE3 and TE4 also demonstrate the aggregate level of TE of a commodity. Theoretically, both underperformance and overperformance of an ETC is considered as a deviation from the expected return. We could observe the same pattern in the results (depending on the definition of the TE) in the rest of the analysis as well. Since this same explanation will be applicable in those analysis as well and we avoid repeating this explanation in later discussion.

Therefore, we conclude that agricultural ETCs do not effectively replicate the performance of the benchmark index during the overall sample period. On average, the TE of single-commodity ETCs ranges from 1% to 2.5%, whereas the TE of multi-commodities is less than 1.5%, suggesting that multi-commodities ETCs perform better than single-commodity ETCs. This could be due to the diversification benefits arising from investing in a basket of agricultural commodities rather than investing in a single commodity.

[10] A sign test is a non-parametric test used to investigate whether 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 2 and during abnormal and normal 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.

5.3. *Time-Varying Tracking Performance Results*

This section aims at investigating the time-varying nature of the tracking performance of agricultural ETCs based on the volatility of agricultural commodity prices. In Section 4, we identified state 1 and state 2 of the commodity prices using the MS regression model. State 1 is the high-volatility period and state 2 is the low-volatility period of agricultural commodity prices. Furthermore, we have identified the abnormal and normal return days of each commodity as well. We test whether ETCs show a difference in tracking ability depending on the state of agricultural commodity prices or when the underlying commodity outperforms the overall agricultural commodity market return.

Table 6 demonstrates TE and its distribution for single-commodity ETCs. Panel A presents the TE difference between state 1 and state 2, and Panel B presents the TE difference between abnormal and normal return days. For cocoa, soybeans, soybean meal and soybean oil, the TE1 is higher in state 2 (low volatility) than state 1 (high volatility), whereas for all the other commodities TE1 is higher in state 1 than state 2. However, these differences based on TE1 are not statistically significant. According to our results for TE1, there is no significant difference in tracking performance between these alternative volatility periods.

[Insert Table 6 about here]

When we consider TE2 (i.e., the absolute value of TE1), single-commodity ETCs generate, on average, 1.13% higher TE in state 1 than in state 2 and 1.25% higher TE during abnormal return days than in normal return days for all the commodities. The TE3 and TE4 results also support the fact that the TE of single-commodity ETCs is significantly higher in high-volatility periods and on abnormal return days. In summary, based on TE2, TE3 and TE4, we conclude that tracking performance of single-commodity ETCs vary depending on the volatility of the underlying commodity prices.

Table 7 displays the tracking performance of multi-commodities ETCs and their distributions. We test whether multi-commodities ETCs perform differently when at least one commodity in which they have invested experiences periods of high volatility or abnormal returns. In this table as well, Panel A presents the TE difference under state 1 and state 2, and Panel B presents the TE difference under abnormal and normal return days.

[Insert Table 7 about here]

In the case of multi-commodities ETCs with TE1, there are only three and four funds (out of 24 multi-commodities ETCs) reporting significant tracking deviations between states and between abnormal and normal returns days, respectively. Under the other three definitions, a majority of multi-commodities ETCs report positive and significant TE differences during the price cycle of each commodity. According to TE2, on average, the difference in daily TE of multi-commodities funds is 0.46% between state 1 and state 2 and 0.35% between abnormal and normal return days. This indicates that multi-commodities ETCs also are unable to better track the benchmark commodity index precisely during high-volatility periods of agricultural commodity prices compared with low-volatility periods. The TE differences calculated based on TE3 and TE4 also confirm the fact that the volatility of TEs is higher in state 1 than in state 2 and higher in abnormal return days than normal return days.

There is another noteworthy fact revealed in the reported results. The comparison of tracking difference values in Table 6 and Table 7 shows that the TE values of multi-commodities ETCs are lower than those of single-commodity ETCs. This indicates that multi-commodities ETCs show a better ability in tracking the underlying index during high-volatility periods than single-commodity ETCs. A possible explanation for this improved tracking performance of multi-commodities ETCs could be the diversification effect.

5.4. Tracking Performance Difference Based on Replication Strategy

Our next aim is to investigate whether there is any tracking performance difference in ETCs depending on the replication method adopted. A priori, we expect synthetically replicated ETCs to produce a higher level of TE compared with physically replicated ETCs.

In our sample of ETCs, we have only three exactly matching pairs of ETCs tracking the same underlying index, trading on the same exchange and denominated in the same currency, but one ETC is replicated physically, whereas the other is replicated synthetically. Given this limitation in the matching pairs, we follow the methodology of Rompotis (2016), who examines this tracking performance difference by calculating the mean TE values of all the ETCs replicated either physically or synthetically. He does not compare the tracking performance difference using exactly matching pairs of ETCs.

Accordingly, we have single-commodity ETCs and multi-commodities ETCs replicated using futures contracts or swaps. These ETCs invest in the same underlying commodity but are not traded in the same exchange. We categorize these ETCs by commodity and by replication strategy. Then, we calculate the difference of the mean TE of the categorized ETCs using the four TE definitions mentioned above.

Table 8 presents the mean TE values of ETCs based on the replication strategy. These TEs are calculated for the entire sample period, high-volatility period and low-volatility period separately. As we could not identify the states for coffee in Section 4, we could not calculate the TE for coffee under alternative market states. According to our results, single-commodity ETCs replicated using swap contracts produce a higher level of TE than single-commodity ETCs replicated using futures contracts (except in the case of TE1) during the examined period. Our findings confirmed that the same TE pattern between replication strategies holds during high-volatility and low-volatility periods as well. Furthermore, the TE is higher under the high-volatility period than the low-volatility period of agricultural commodity prices, approving the findings in the previous subsections.

[Insert Table 8 about here]

Furthermore, Table 9 summarizes the tracking performance of multi-commodities ETCs based on the replication strategy under state 1 and state 2 of each underlying commodity in which they have invested. We examine whether multi-commodities ETCs also display a tracking performance difference based on the replication strategy under each state. The results presented in Table 9 support the above two findings. First, multi-commodities ETCs replicated using swap contracts report higher TEs than multi-commodities ETCs replicated using futures contracts. Second, both replication strategies generate a higher level of TE in state 1 than in state 2.

[Insert Table 9 about here]

Accordingly, our findings conclude that synthetic replication is not a better method of tracking the benchmark index. In particular, agricultural ETCs replicated using swap contracts do not show better tracking abilities than agricultural ETCs replicated using futures contracts. Furthermore, the results suggest synthetic replication using swaps generate high TEs during the high-volatility periods of agricultural commodity prices.

5.5. Tracking Performance Difference Based on Leverage

Next, we study whether there is a difference in the tracking performance of ETCs based on the level of leverage. We have nine trios of ETCs investing in the same agricultural commodity index. The trio includes a traditional ETC, a leveraged ETC and an inverse ETC investing in the same agricultural commodity index. Theoretically, we expect LETCs and IETCs to produce a higher TE due to the daily rebalancing required to maintain the leverage. Therefore, we test the alternative hypothesis that the TE of a LETC/IETC is higher than the TE of a traditional

ETC during the period of concern in this study. The null hypothesis is that the TE of an LETC/IETC is lower or greater than that of a traditional ETC.

Table 10 presents the results of this analysis. Under LETCs, our results consistently reject the null hypothesis with TE2, TE3 and TE4. Under IETCs, our results consistently reject the null hypothesis with TE2 and TE4 (whereas the findings with TE3 are mixed). TE2 measures the absolute deviation of the TE whereas TE3 and TE4 measures the variability of TE. With this evidence, we support the alternative hypothesis that leverage increases the TE of an agricultural ETC compared with the TE of a traditional ETC. In conclusion, our study adds supportive evidence for the argument that LETCs/IETCs tend to show poor tracking performance.

[Insert Table 10 about here]

6. Persistence of TE

6.1. Measuring the Persistence of TE

In Section 5, we confirmed the existence of significant TE for agricultural ETCs during the sample period. We also found that TE is time varying depending on the volatility periods of agricultural commodities. Finally, we investigate the persistence of this TE in the short run. The hypothesis of persistence assumes that the TE of the previous two days will continue and will have an impact on the TE of today as well.

Previous studies have adopted different methods to test the persistence of TE. Shin and Soydemir (2010) employ a serial correlation test 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, and finds negative coefficients which conclude that the TE of commodity ETFs has a mean-reverting behavior.

Our 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) to avoid underestimating the TE if we use the TE1 definition. Our model is as follows.

$$TE2_{i,t} = \alpha_i + \beta_{1,i} TE2_{i,t-1} + \beta_{2,i} TE2_{i,t-2} + \varepsilon_{i,t}, \tag{11}$$

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 days *t-1* and *t-2*. We model the error variance of this regression with a generalized autoregressive conditional heteroscedasticity model, that is, GARCH (1,1) process.

The persistence of the TE is determined based on the significance of the β coefficients. TE is persistent if at least one β coefficient is positive and significant. This implies that if an ETC has shown either under- or over-exposure to the benchmark index in the previous two days, it will continue to 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 terms 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 TE

Table 11 presents the results of the persistence test of TEs. 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. For all 84 funds, we find positive and significant α_i coefficients. In conclusion, though agricultural ETCs report a significant level of TE, there is no strong evidence for its persistence. Furthermore, there is a significant portion of TE that is not explained by the past two days' TE of an agricultural ETC.

[Insert Table 11 about here]

7. Summary and Conclusion

This study aims to add evidence on the tracking performance of European agricultural ETCs. We investigate whether the tracking error (TE) is time varying depending on the high- and low-volatility periods in agricultural commodity prices. Then, we examine whether the tracking performance varies depending on the characteristics of the structure of ETC. Finally, we test whether the TE is persistent in the short term.

Our results show that agricultural ETCs do not replicate the benchmark index exactly during the period of concern. Specifically, we find that these ETCs produce a high level of TE when agricultural commodity prices are highly volatile. Furthermore, the results reveal that single-commodity ETCs, on average, generate more TE than multi-commodities ETCs. At the same time, we do not find strong evidence for the persistence of this significant TE. Finally, our results also confirm the fact that fund characteristics, such as replication strategy and the level of leverage, affect the tracking ability of ETCs significantly.

The implications of this study are important for both issuers and investors. Since we provide evidence that the structure of an ETC matters for its tracking ability, issuers must consider this fact when designing new ETCs on agricultural commodities. Further, issuers need to pay attention to our finding that single-commodity ETCs have a lower tracking ability compared with multi-commodities ETCs. The quality of an ETC depends on the ability to provide the promised benchmark return for investors. Therefore, issuers have an accountability to design ETCs with the best possible structure.

Conversely, investors should pay attention to our findings, 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. Second, this study supports the argument that fund characteristics, such as replication strategy and leverage, affect the level of tracking performance. Hence, investors should pay attention to such fund characteristics as well when they select ETCs to invest in.

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Appendix A

Figure 1
Composition of AgriTR Index as at 2 August 2017

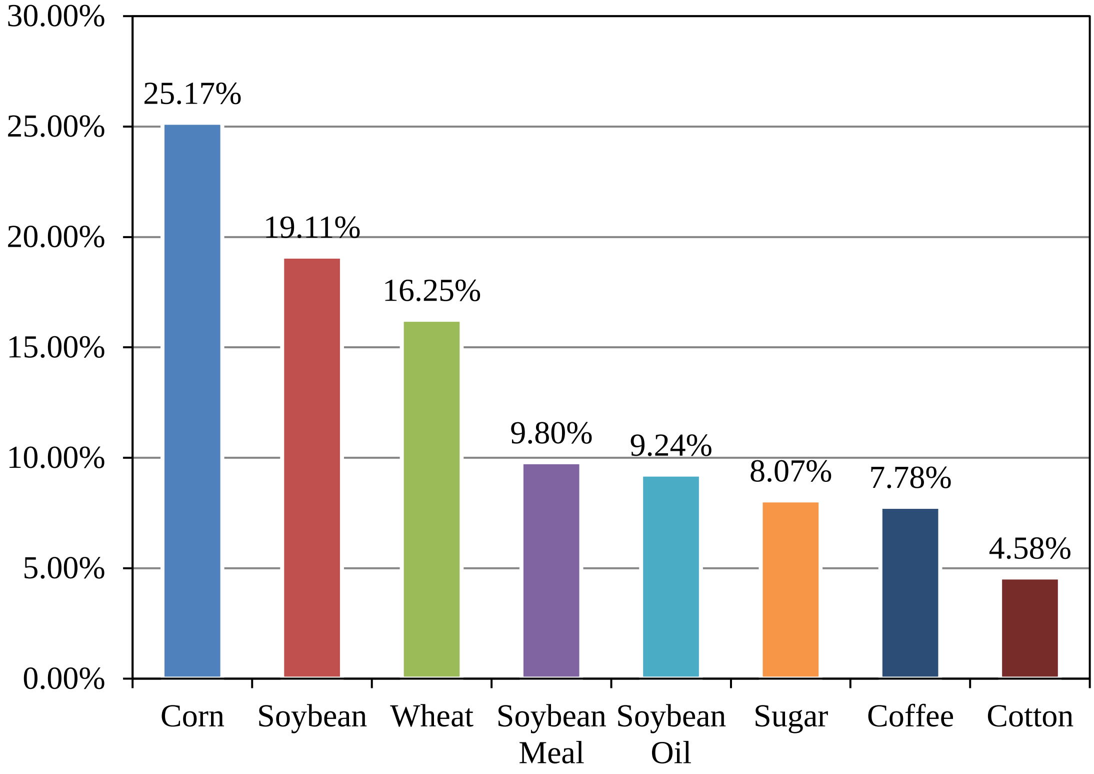
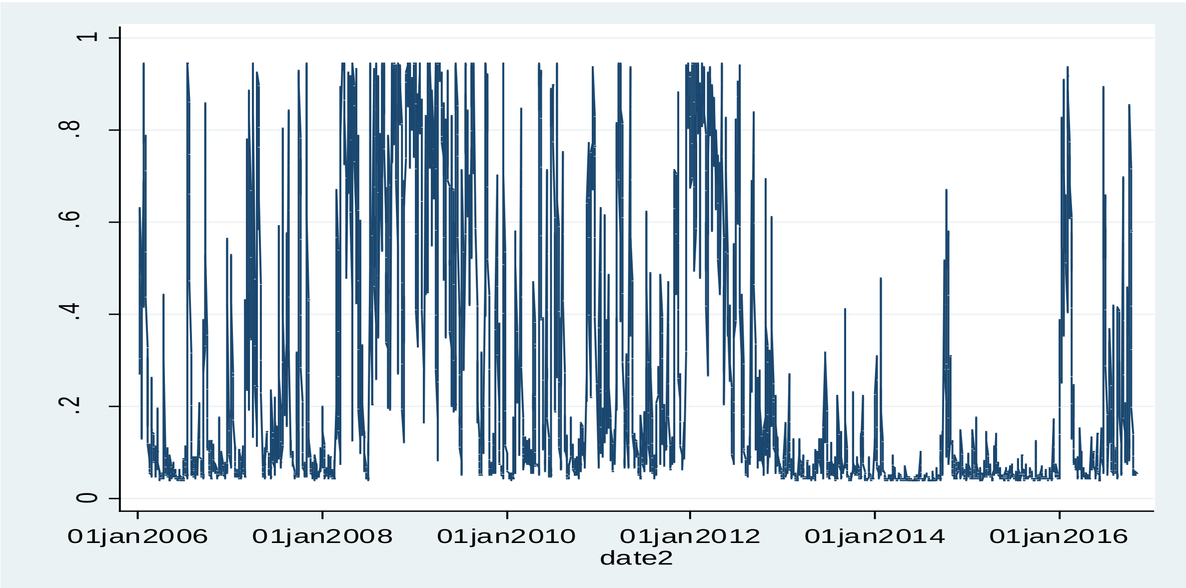
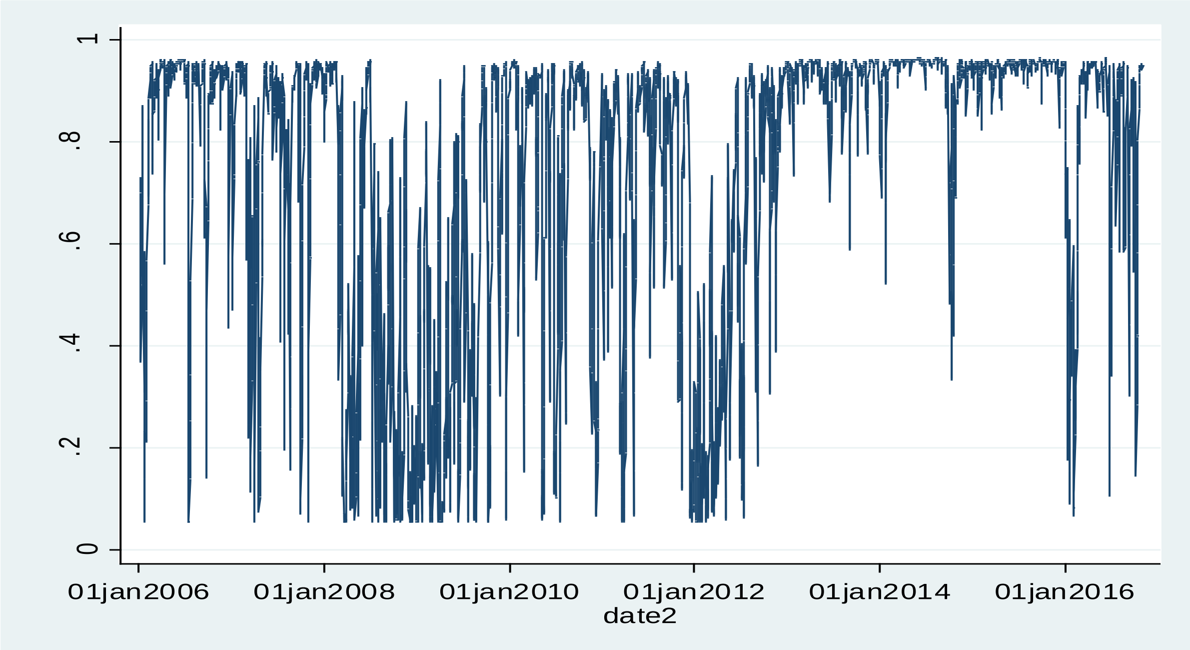


Figure 2
Daily Transitional Probabilities of Cocoa for State 1 and State 2



2A: State 1


1
.8
.6
.4
.2
0
01jan2006
01jan2008
01jan2010
01jan2012
01jan2014
01jan2016
date2

2B: State 2

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 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 multi-commodities ETCs are reported separately. The data cover the period from the inception of a fund until November 2016. The table summarizes the number of funds under each commodity category and the number of observations (No of Obs). All mean returns and standard deviations (SD) of fund returns are annualized. The last column reports the skewness of the return distribution.

Commodity	No of Funds	No of Obs	Mean Return	SD of Return	Skewness
Cocoa	9	14532	-6.89%	30.30%	-43.16%
Coffee	6	10499	-19.49%	40.91%	-58.57%
Corn	8	13306	-12.59%	42.51%	-88.24%
Cotton	6	10431	-8.61%	39.26%	17.24%
Rough Rice	3	2882	-24.25%	18.55%	-12.03%
Soybeans	5	7980	-11.09%	37.73%	46.48%
Soybean Meal	1	1085	13.91%	26.16%	1.22%
Soybean Oil	4	7906	-13.12%	32.59%	-26.78%
Sugar	9	15411	-7.95%	38.53%	-16.19%
Wheat	9	15820	-25.16%	42.25%	15.89%
Multi- Commodities	24	45967	-6.09%	28.88%	-81.14%

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 mean return and the standard deviation. These mean returns and standard deviation values are calculated using daily data and then annualized. 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			
	Mean Return	Standard Deviation	Duration (Days)	Mean Return	Standard Deviation	Duration (Days)	P11	P12	P22	P21
Cocoa (BCOMCCTR)	-39.61%	40.96%	19	28.65%	20.32%	50	0.946	0.054	0.98	0.02
Coffee (BCOMKCTR)	-13.41%	395.59%	2	-6.95%	17.94%	2	0.5537	0.4463	0.5405	0.4595
Corn (BCOMCNTR)	-19.43%	41.91%	18	7.46%	20.95%	31	0.9458	0.0542	0.968	0.032
Cotton (BCOMCTTR)	-13.41%	39.37%	88	3.67%	19.84%	239	0.9889	0.0111	0.9958	0.0042
Lean Hogs (BCOMLHTR)	-49.57%	32.70%	42	-6.95%	19.37%	129	0.9762	0.0238	0.9922	0.0078
Live Cattle (BCOMLCTR)	-69.58%	53.97%	37	11.40%	23.97%	88	0.9731	0.0269	0.9887	0.0113
Orange Juice (BCOMOJT)	-37.39%	49.05%	3	28.65%	20.32%	7	0.71	0.29	0.8596	0.1404
Rough Rice (CTRRTR)	-16.48%	26.19%	49	3.67%	13.33%	31	0.9795	0.0205	0.9679	0.0321
Soybean Meal (BCOMSMT)	33.36%	38.73%	28	15.49%	20.80%	59	0.9637	0.0363	0.9829	0.0171
Soybean Oil (BCOMBOTR)	-35.10%	38.26%	106	3.67%	19.68%	596	0.9905	0.0095	0.9983	0.0017
Soybeans (BCOMSYTR)	-10.24%	36.51%	26	19.72%	17.62%	65	0.962	0.038	0.9847	0.0153
Sugar (BCOMSBTR)	43.31%	41.27%	87	-37.39%	22.07%	83	0.9886	0.0114	0.9879	0.0121
Wheat (BCOMWHTR)	38.24%	43.02%	40	-37.39%	23.81%	54	0.9751	0.0249	0.9814	0.0186

Table 4
Abnormal and normal return days of commodities

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 return 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
Tracking performance of ETCs – Entire sample period

This table reports average daily TEs measured using the four definitions and the distribution of TE. The single-commodity funds are categorized based on their underlying commodity and the 24 multi-commodities ETCs are reported separately. The data cover the period from the inception of a fund until November 2016. The second column reports the number of funds in each commodity. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: 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. Distribution column reports the distribution of each TE as follows: the number of positive and significant funds (+)/ the number of insignificant funds (0)/ and the number of negative and significant funds (-). The significance of the TE is determined at the 5% significance level.

Commodity	No of Funds	TE1	Distribution of TE1 +/0/-	TE2	Distribution of TE2 +/0/-	TE3	Distribution of TE3 +/0/-	TE4	Distribution of TE4 +/0/-
Cocoa	9	-0.010%	0/9/0	0.941%	9/0/0	0.922%	9/0/0	1.393%	9/0/0
Coffee	6	-0.020%	0/6/0	1.670%	6/0/0	0.844%	6/0/0	2.396%	6/0/0
Corn	8	-0.017%	0/8/0	1.513%	8/0/0	1.922%	8/0/0	2.519%	8/0/0
Cotton	6	-0.036%	0/6/0	1.509%	6/0/0	1.755%	6/0/0	2.818%	6/0/0
Rough Rice	3	-0.009%	0/3/0	0.934%	3/0/0	1.050%	3/0/0	1.326%	3/0/0
Soybeans	5	-0.042%	0/5/0	1.298%	5/0/0	1.450%	5/0/0	1.921%	5/0/0
Soybean Meal	1	-0.013%	0/1/0	1.124%	1/0/0	1.323%	1/0/0	1.560%	1/0/0
Soybean Oil	4	-0.012%	0/4/0	1.358%	4/0/0	1.388%	4/0/0	1.923%	4/0/0
Sugar	9	-0.010%	0/9/0	1.319%	9/0/0	1.591%	9/0/0	2.158%	9/0/0
Wheat	9	-0.007%	0/9/0	1.552%	9/0/0	1.885%	9/0/0	2.343%	9/0/0
Multi- Commodities	24	-0.013%	0/24/0	0.998%	24/0/0	1.125%	24/0/0	1.479%	24/0/0

Table 6

Time-varying tracking performance of single-commodity ETCs

This table summarizes the difference between the TE and the distribution of TE of single-commodity funds. The data cover the period from the inception of a fund until November 2016. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: 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. Distribution column reports the distribution of each TE as follows: the number of positive and significant funds (+)/ the number of insignificant funds (0)/ and the number of negative and significant funds (-). Panel A summarizes the results between state 1 and state 2. Panel B summarizes the results between abnormal return days and normal return days. The significance of the TE is determined at the 5% significance level.

Panel A – State 1 (High volatility) versus State 2 (Low volatility)

Commodity	TE1	Distribution of TE +/0/-	TE2	Distribution of TE +/0/-	TE3	Distribution of TE +/0/-	TE4	Distribution of TE +/0/-
Cocoa	-0.07%	0/9/0	0.61%	9/0/0	1.8221	9/0/0	1.6444	9/0/0
Corn	0.02%	0/8/0	1.77%	8/0/0	3.3455	8/0/0	2.5061	8/0/0
Cotton	0.03%	0/6/0	1.22%	6/0/0	2.3865	6/0/0	1.8675	6/0/0
Rough Rice	0.01%	0/3/0	0.62%	3/0/0	2.6407	3/0/0	1.8663	3/0/0
Soybeans	-0.12%	0/5/0	1.40%	5/0/0	2.8853	5/0/0	2.5546	5/0/0
Soybean Meal	-0.03%	0/1/0	1.08%	1/0/0	2.8835	1/0/0	2.3243	1/0/0
Soybean Oil	-0.02%	0/4/0	1.18%	4/0/0	2.3289	4/0/0	2.3479	4/0/0
Sugar	0.01%	0/9/0	1.04%	9/0/0	2.5373	9/0/0	2.5361	9/0/0
Wheat	0.02%	0/9/0	1.26%	9/0/0	2.5339	9/0/0	2.2165	9/0/0

Panel B – Abnormal Return Days versus Normal Return Days

Commodity	TE1	Distribution of TE +/0/-	TE2	Distribution of TE +/0/-	TE3	Distribution of TE +/0/-	TE4	Distribution of TE +/0/-
Cocoa	0.14%	1/8/0	1.07%	9/0/0	1.5963	9/0/0	1.8203	8/1/0
Coffee	0.27%	0/6/0	1.86%	6/0/0	1.6949	6/0/0	1.9576	6/0/0
Corn	-0.23%	0/8/0	1.61%	8/0/0	1.6747	8/0/0	1.6492	8/0/0
Cotton	0.58%	1/5/0	1.53%	5/1/0	1.7130	6/0/0	1.3823	5/0/1
Rough Rice	0.26%	0/3/0	0.19%	0/3/0	0.8571	0/3/0	1.1961	0/3/0
Soybeans	0.23%	0/5/0	1.01%	5/0/0	1.3361	4/1/0	1.5642	4/1/0
Soybean Meal	0.49%	0/1/0	1.18%	1/0/0	1.5277	1/0/0	1.8389	1/0/0
Soybean Oil	0.33%	1/3/0	0.94%	4/0/0	1.2815	3/1/0	1.4687	3/1/0
Sugar	-0.44%	0/8/1	1.32%	9/0/0	1.4740	8/1/0	1.5814	8/0/1
Wheat	-0.48%	0/9/0	1.79%	9/0/0	1.6966	9/0/0	1.8757	9/0/0

Table 7
Time-varying tracking performance of the multi-commodities ETCs

This table summarizes the difference between the TE and the distribution of TE of single-commodity funds. The data cover the period from the inception of a fund until November 2016. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: 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. Distribution column reports the distribution of each TE as follows: the number of positive and significant funds (+)/ the number of insignificant funds (0)/ and the number of negative and significant funds (-). Panel A summarizes the results between state 1 and 2. Panel B summarizes the results between abnormal return days and normal return days. The significance of the TE is determined at the 5% significance level.

Panel A

Commodity	TE1	Distribution of TE +/0/-	TE2	Distribution of TE +/0/-	TE3	Distribution of TE +/0/-	TE4	Distribution of TE +/0/-
Cocoa	0.07%	0/12/0	0.17%	5/6/0	1.3451	5/5/1	0.9823	11/0/0
Corn	-0.05%	0/20/0	0.88%	20/0/0	2.8556	20/0/0	2.1900	20/0/0
Cotton	-0.01%	0/15/0	0.56%	14/0/0	1.7709	14/0/0	1.6804	14/0/0
Lean Hogs	0.01%	0/6/0	0.04%	0/6/0	1.2119	3/3/0	1.1801	5/1/0
Live Cattle	-0.06%	0/6/0	0.09%	2/4/0	1.3019	6/0/0	1.2917	6/0/0
Soybeans	-0.06%	0/20/0	0.74%	20/0/0	2.0879	20/0/0	1.8672	20/0/0
Soybean Meal	-0.05%	0/16/0	0.57%	16/0/0	2.0500	16/0/0	1.7346	16/0/0
Soybean Oil	-0.05%	0/16/0	0.57%	11/5/0	1.8008	16/0/0	1.5891	16/0/0
Sugar	0.02%	1/17/2	0.41%	20/0/0	1.6357	20/0/0	1.4214	16/4/0
Wheat	0.01%	0/20/0	0.62%	20/0/0	1.9536	20/0/0	1.7896	20/0/0

Panel B

Commodity	TE1	Distribution of TE +/0/-	TE2	Distribution of TE +/0/-	TE3	Distribution of TE +/0/-	TE4	Distribution of TE +/0/-
Cocoa	0.24%	1/11/0	0.37%	6/6/0	1.3819	11/1/0	1.4146	11/1/0
Coffee	0.00%	0/20/0	0.20%	3/17/0	1.0381	3/16/1	1.1306	15/4/1
Corn	0.13%	0/20/0	0.58%	18/2/0	1.4290	19/1/0	1.4419	18/2/0
Cotton	0.05%	0/15/0	0.33%	13/2/0	1.2447	13/1/1	1.2546	12/2/1
Lean Hogs	-0.13%	0/6/0	0.29%	4/2/0	1.4195	6/0/0	1.4796	6/0/0
Live Cattle	-0.04%	0/6/0	0.41%	6/0/0	1.6631	6/0/0	1.5094	6/0/0
Orange Juice	0.03%	0/3/0	0.27%	2/1/0	1.1981	2/1/0	1.1065	1/2/0
Soybeans	-0.04%	0/20/0	0.38%	19/1/0	1.2385	18/2/0	1.2155	14/6/0
Soybean Meal	0.04%	0/16/0	0.36%	16/0/0	1.3357	15/1/0	1.2775	13/4/0
Soybean Oil	0.12%	3/13/0	0.18%	3/13/0	1.1442	7/9/0	1.1570	8/8/0
Sugar	-0.08%	0/20/0	0.32%	10/10/0	1.2000	13/6/1	1.2197	11/8/1
Wheat	-0.20%	0/20/0	0.55%	20/0/0	1.4125	19/1/0	1.4206	18/2/0

Table 8
Tracking performance based on replication strategy

This table presents the mean TE values of each commodity based on the replication strategy of the ETC for the overall period, under the high-volatility period and low-volatility period. The ETCs selected in this study are either replicated based on futures contracts or fully funded collateralized swaps. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: 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. The data cover the period from the inception of a fund until November 2016.

Commodity	Replication Strategy	No of Funds	Overall Period				State 1 (High Volatility)				State 2 (Low Volatility)			
			TE1	TE2	TE3	TE4	TE1	TE2	TE3	TE4	TE1	TE2	TE3	TE4
Cocoa	Futures	6	-0.0020%	0.6776%	0.9115%	1.0699%	-0.0892%	1.0959%	1.3227%	1.3929%	-0.0158%	0.5595%	0.7111%	0.8592%
Cocoa	Swap	3	-0.0215%	1.4678%	0.9427%	2.0405%	-0.0787%	1.9823%	1.2734%	2.6086%	-0.0092%	1.2371%	0.7431%	1.6489%
Coffee	Futures	3	-0.0198%	1.3826%	1.2181%	2.0220%	-	-	-	-	-	-	-	-
Coffee	Swap	3	-0.0195%	1.9584%	0.4698%	2.7705%	-	-	-	-	-	-	-	-
Corn	Futures	6	-0.0075%	1.2106%	1.5171%	1.9771%	0.0553%	2.2084%	2.6943%	2.9118%	-0.0290%	0.8801%	1.0314%	1.5321%
Corn	Swap	2	-0.0471%	2.4217%	3.1369%	4.1456%	-0.1706%	4.8022%	7.3164%	8.7433%	-0.0068%	1.7226%	1.5078%	2.3112%
Cotton	Futures	3	-0.0289%	1.1631%	1.3404%	2.8036%	0.0131%	1.8012%	2.3481%	2.4998%	-0.0975%	0.9354%	0.8934%	2.4888%
Cotton	Swap	3	-0.0421%	1.8550%	2.1691%	2.8327%	-0.0720%	2.9648%	3.3086%	4.2628%	-0.0212%	1.3947%	1.5306%	2.0039%
Soybeans	Futures	3	-0.0341%	0.9020%	1.1080%	1.3163%	-0.1973%	1.8090%	2.1312%	2.3224%	-0.0047%	0.6383%	0.6889%	0.9017%
Soybean	Swap	2	-0.0547%	1.8930%	1.9633%	2.8285%	-0.0447%	3.1824%	3.4125%	4.6982%	-0.0298%	1.4451%	1.2505%	1.8978%
Soybean Oil	Futures	1	-0.0191%	0.9172%	1.0761%	1.2519%	-0.0415%	1.6051%	1.7981%	2.0324%	-0.0139%	0.7368%	0.7979%	0.9632%
Soybean Oil	Swap	3	-0.0093%	1.5043%	1.4924%	2.1466%	-0.0268%	2.5872%	2.6720%	3.7439%	-0.0043%	1.3020%	1.1360%	1.6670%
Sugar	Futures	6	0.0039%	0.9586%	1.4283%	1.8201%	0.0231%	1.4939%	2.0695%	2.2141%	-0.0282%	0.5871%	0.7418%	0.8472%
Sugar	Swap	3	-0.0391%	2.0389%	1.9165%	2.8339%	-0.0621%	2.6644%	2.4674%	3.5485%	0.0067%	1.3462%	0.9902%	1.7752%
Wheat	Futures	6	-0.0058%	1.2445%	1.6068%	1.8748%	-0.0143%	2.0021%	2.5480%	2.7912%	-0.0386%	0.9216%	1.1214%	1.3734%
Wheat	Swap	3	-0.0104%	2.1667%	2.4421%	3.2788%	0.0164%	3.2150%	4.1422%	5.2029%	0.0064%	1.5984%	1.4038%	2.0734%
Multi- Commodities	Futures	12	-0.0059%	0.7185%	0.9254%	1.1341%	-	-	-	-	-	-	-	-
Multi- Commodities	Swap	12	-0.0194%	1.2768%	1.3249%	1.8233%	-	-	-	-	-	-	-	-

Table 9
Tracking performance based on the replication strategy – Multi-commodities ETCs

This table presents the mean TE values of multi-commodities ETCs categorized based on the commodity and based on the replication strategy of the ETC under the high-volatility period and low-volatility period. The ETCs selected in this study are either replicated based on futures contracts or fully funded collateralized swaps. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: 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. The data cover the period from the inception of a fund until November 2016.

Commodity	Replication Strategy	Number of Funds	State 1 (High Volatility)				State 2 (Low Volatility)			
			TE1	TE2	TE3	TE4	TE1	TE2	TE3	TE4
Corn	Futures	12	-0.0380%	1.2518%	1.5746%	1.7167%	-0.0237%	0.5401%	0.6414%	0.8252%
Corn	Swap	8	-0.1192%	2.1071%	2.3767%	3.0435%	-0.0067%	0.9665%	0.9117%	1.2942%
Cotton	Futures	6	0.0023%	1.1050%	1.3789%	1.4880%	-0.0144%	0.6179%	0.7472%	0.9584%
Cotton	Swap	8	-0.0420%	1.6196%	1.6307%	2.3312%	-0.0038%	1.0031%	0.9539%	1.3424%
Soybeans	Futures	12	-0.0751%	1.1610%	1.4770%	1.5651%	-0.0135%	0.5809%	0.7200%	0.8778%
Soybeans	Swap	8	-0.0535%	2.0334%	2.1568%	2.8165%	-0.0082%	1.0451%	1.0229%	1.4113%
Soybean Meal	Futures	12	-0.0764%	1.0903%	1.3833%	1.4810%	-0.0190%	0.5876%	0.7336%	0.8790%
Soybean Meal	Swap	4	-0.0211%	1.7124%	1.6719%	2.3158%	-0.0031%	0.9477%	0.9228%	1.2832%
Soybean Oil	Futures	12	-0.0741%	1.1282%	1.4309%	1.5170%	-0.0238%	0.6462%	0.8112%	1.0049%
Soybean Oil	Swap	4	-0.0650%	1.8392%	1.7711%	2.5380%	-0.0088%	1.0206%	1.0183%	1.3866%
Sugar	Futures	12	0.0009%	0.9263%	1.1600%	1.2707%	-0.0612%	0.5893%	0.6953%	1.0123%
Sugar	Swap	8	-0.0250%	1.4468%	1.4412%	2.0261%	0.0062%	0.9301%	0.8909%	1.2525%
Wheat	Futures	12	-0.0247%	1.0484%	1.3526%	1.5644%	-0.0327%	0.5622%	0.6864%	0.8906%
Wheat	Swap	8	0.0084%	1.7944%	1.8786%	2.5166%	-0.0057%	0.9847%	0.9738%	1.3292%

Table 10
Tracking performance difference based on leverage

This table shows the results of the null hypothesis test that the TE of a LETC/IETC is lower than the TE of a traditional ETC tracking the same underlying commodity index. The alternative hypothesis is that the TE of a LETC/IETC is higher than the TE of a traditional ETC. There are 9 trios of ETCs replicating the same index. There are 6 single commodity indices and 3 multi-commodities indices. The data cover the period from the inception of each fund until November 2016. TE1 defines TE as the difference between the ETC return and the underlying index return: TE2 defines TE as the absolute value of TE1: 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. The table reports p values of the test and * reports the significance at the 5% level.

Commodity	Index	No of observations	Leverage versus Traditional				Inverse versus Traditional			
			TE1	TE2	TE3	TE4	TE1	TE2	TE3	TE4
Soybean Oil	BCOMBOTR	2056	0.9685	0.0000*	0.0000*	0.0000*	0.1937	0.0000*	0.0000*	0.0000*
Cocoa	BCOMCCTR	1629	0.8758	0.0000*	0.0000*	0.0000*	0.4510	0.0000*	0.6911	0.0000*
Cotton	BCOMCTTR	2067	0.8191	0.0000*	0.0000*	0.0000*	0.5898	0.0000*	0.0060*	0.0000*
Coffee	BCOMKCTR	2077	0.9311	0.0000*	0.0000*	0.0000*	0.3682	0.0000*	0.7159	0.0000*
Sugar	BCOMSBTR	2081	0.9538	0.0000*	0.0000*	0.0000*	0.5789	0.0000*	0.0000*	0.0000*
Wheat	BCOMWHTR	2071	0.9892	0.0000*	0.0000*	0.0000*	0.0679	0.0000*	0.3793	0.0000*
Multi-commodities (Agriculture)	BCOMAGTR	2065	0.9156	0.0000*	0.0000*	0.0000*	0.3683	0.0000*	0.6541	0.0000*
Multi-commodities (Grains)	BCOMGRTR	2070	0.9124	0.0000*	0.0000*	0.0000*	0.3733	0.0000*	0.3724	0.0000*
Multi-Commodities (Soft)	BCOMSOTR	2069	0.9153	0.0000*	0.0000*	0.0000*	0.4753	0.0000*	0.6679	0.0000*

Table 11
Results of the persistence of tracking error

This table summarizes the results of the persistence of TE 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)
Soybeans	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)