Is the Tracking Error Time-Varying? Evidence from Agricultural ETCs

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Abstract

This study extensively analyses a recently popularised asset class, 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 the leverage of the ETCs. Our findings are important for academics and market regulators as they indicate the structure of an ETC and the time-varying volatility of agricultural prices matters for its tracking performance.

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

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1. Introduction

Before the 2000s, commodity markets were broadly segmented, and commercial traders mainly used commodity investments 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 recognised the potential diversification benefits of investing in commodities. After that, commodities (including agricultural commodities) gained rising popularity as an asset class in portfolios along with other traditional assets, such as stocks and bonds.[1] This popularity was fuelled by significant 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 products (ETPs) (Tang and Xiong, 2012).

Due to their characteristics, the ETPs have evolved to be highly attractive investment instruments during the last decade. First, ETPs are listed on an exchange and traded. Second, ETPs track the performance of an underlying index. Hence, ETPs provide an opportunity for an investor to invest in a basket of assets (i.e., an index) at a lower management fee compared with other actively managed funds. ETPs are three different types: namely exchange-traded funds (ETFs), exchange-traded commodities (ETCs), and exchange-traded notes (ETNs). An ETF in Europe cannot provide exposure to a single commodity only. It requires a certain degree of diversification to comply with the Undertakings for Collective Investments of Savings (UCITS)[3] framework. Therefore, London Stock Exchange (LSE) first introduced ETCs structured as secured debt instruments under the European Prospectus Directive (EUPD).

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[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. In addition, there is another strand of literature highlighting the importance of introducing futures contracts on new commodities such as tea (Perera, Bialkowski and Bohl, 2020), salmon (Berjford, 2007) and distiller's dried grains (Berkman and Tejeda, 2017) in order to popularise the commodities as an investment asset in the market.

[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 creating ETFs providing exposure for a single commodity only in Europe. As a solution to this problem, the first ETCs in Europe were launched in 2004 by two providers: ETF Securities and BNP Paribas. Please refer to Marszk (2017) for further details.

The Securities Exchange Commission (SEC) of the United States defines ETFs as "SEC-registered investment companies that offer investors a way to pool their money in a fund that invests in stocks, bonds, or other assets. ETFs are not mutual funds. But, they combine features of a mutual fund, which can only be purchased or redeemed at the end of each trading day at its NAV per share, with the ability to trade throughout the day on a national securities exchange at market prices". ETCs in Europe are collateralised debt instruments that do not pay interest. The London Stock Exchange describes ETCs as investment vehicles (asset-backed bonds) that track the performance of an underlying commodity index, including total return indices based on a single commodity or multi-commodities. Investors can invest in a single commodity index such as wheat, sugar, etc. or a multi-commodities index such as grains (including wheat, corn, and soybeans). The ETCs passively replicate the performance of an underlying commodity index and aims to provide a return similar to the underlying index. ETCs may use either physical replication or synthetic replication method to replicate the performance of the underlying commodity index. However, the synthetic replication method is the widely adopted method in Europe due to the issues of high storage costs, the perishability nature of the agricultural commodities, and high transportation costs. ETCs have become easily accessible, less costly, highly transparent, and liquid instruments. These characteristics of ETCs enhanced their popularity as an investment asset.

Due to the rising cash inflows to the index investment instruments in commodities such as ETFs, the correlation structure between commodities and other investment assets has changed gradually (Basak and Pavlova, 2016; Silvennoinen and Thorp, 2013; Tang and Xiong, 2012). Jensen and Mercer (2011) find that agricultural commodities negatively correlate with stocks, treasury bonds, and treasury bills from 1970 to 1989. However, these correlations with agricultural commodities become positive in the later period from 1990 to 2009. The financialisation of commodity markets has changed the structure of this market during the past decades.

Furthermore, agricultural commodity markets experienced significant price increases in 2007/2008, 2010/2011, and 2012/2013. These price increases coincided with the popularity of index investment in agricultural commodities (Cheng and Xiong, 2014). Following the "Masters' Hypothesis" that claims a large volume of index investments in commodities was the main driver of the speculative bubble in commodity futures prices (Masters, 2008), other researchers also provided evidence to confirm this argument (Basak and Pavlova, 2016; Liu, Filler and Odenning, 2013). However, studies are providing opposing evidence to the Masters' Hypothesis as well and claim that index investments did not affect the price discovery process in the commodity futures markets (Hamilton and Wu, 2015; Irwin and Sanders, 2012; Krugman, 2008; Pirrong, 2008; Sanders and Irwin, 2010; Smith, 2009).

This increasing popularity of ETCs in the European region and the changing structure of agricultural commodity markets enhanced the importance of conducting more research studies on agricultural ETCs. Therefore, this study aims to fulfil this need by extensively studying the tracking performance of European agricultural ETCs and contributes to the literature in three ways.

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 analysed how the return of an ETF differs from the return of its benchmark index and have concluded that ETFs tracking equity, debt, sector, domestic and international indices do not replicate the underlying index precisely (Blitz and Huij, 2012; Chu, 2011; Drenovak, Urosevic, and Jelic, 2014; Jares and Lavin, 2004; Johnson, 2009; Milonas and Rompotis, 2006; Rompotis, 2009; Shin and Soydemir, 2010). This study is unique because it includes a large sample of European agricultural ETCs and investigates the performance of these ETCs extensively.[4]

Second, this study adopts a different methodology compared with previous studies. Being motivated by the fact that agricultural commodity prices have been highly volatile during past decades, this study aims to identify whether the tracking performance of agricultural ETCs will be different between high- and low-volatility periods. This high volatility in agricultural commodity prices possibly challenges ETC managers' ability to track the underlying index's performance. As a result, agricultural ETCs may not entirely replicate the benchmark index's performance during these high-volatility periods. Furthermore, it investigates whether or not this tracking performance is persistent over time.

Third, this study assesses the difference in the tracking performance of agricultural ETCs based on their characteristics, such as replication strategy and level of leverage.[5] Agricultural ETCs mainly create exposure to commodity markets by using a synthetic replication strategy, i.e. using either futures contracts or swap contracts on commodities instead

[4] To the best of my knowledge, only Dorfleitner, Gerl and Gerer (2018) investigate the tracking performance of ETCs, but they focus only on the German ETC market. 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. In addition, Bai and Xue (2021) find that price dynamics of agricultural commodity futures markets in China are influenced by the state policies.

[5] Previous literature provide evidence that tracking error is affected by the fund size (Grinblatt and Titman, 1989; Frino et al., 2004), expense ratio (Charupat and Miu, 2013; Elton et al., 2002; Frino and Gallagher, 2001), liquidity of the underlying stock (Osterhoff and Kaserer, 2016), cost of rebalancing (Gastineau, 2002) and bid-ask spread (Delcoure and Zhong, 2007; Milonas and Rompotis, 2006).

of investing in the physical commodity itself. Studies confirm that synthetic replication negatively affects the tracking ability of ETFs (Drenovak and Urosevic, 2010; Fassas, 2014; Guedj, Li and McCann, 2011; Naumenko and Chystiakova, 2015; Rompotis, 2016). This study examines a unique research question: whether the tracking performance based on replication strategy will differ between high- and low-volatility periods of the underlying agricultural prices.

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 as 2X, 3X, and negative multiples such as -1X, -2X, and -3X. These ETCs attempt to maintain the desired leverage by daily rebalancing the ETC. Due to the difficulties of dynamic rebalancing, LETCs are likely to either underperform or overperform. The sample of this study includes both leveraged and non-leveraged agricultural ETCs. These agricultural LETCs are expected to generate a higher TE than non-leveraged agricultural ETCs. Based on this sample, we examine whether there is a tracking performance difference between leveraged and non-leveraged agricultural ETCs.

We find that European agricultural ETCs generate a higher TE level during high-volatility periods than low-volatility periods of commodity prices. However, there is no evidence of this TE being persistent. Furthermore, our findings suggest that both synthetic replication and leverage characteristics lead to high tracking errors in agricultural ETCs.

The remainder of this paper is organised as follows. Section 2 provides an overview of previous related literature. Section 3 describes the data and summarises the descriptive statistics of commodity returns and TEs. Section 4 discusses the methods adopted to identify the commodity price cycles and presents subsequent findings. Section 5 presents the empirical results on the tracking performance of agricultural ETCs. Section 6 discusses the findings on the persistence of TE. Section 7 provides evidence on the implications of a possible trading strategy based on the TE findings, and finally, Section 8 summarises and concludes the paper.

2. Literature Review

2.1. TE in exchange-traded products

Existing literature provides evidence for both the existence and non-existence of TE in ETFs. 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 ETFs on emerging market indices (Rompotis, 2015). In contrast, Gallagher and Segara (2006) conclude that Australian ETFs track their benchmark indices better than 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.

There is a limited number of empirical studies analysing tracking performance related to commodities. Guo and Leung (2015) examine the performance of 23 leveraged ETFs investing in gold, silver, oil, and building materials and find most of these ETCs 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 to analysing the performance of agricultural ETCs motivated us to conduct this study.

Furthermore, the existing literature on ETFs describes different factors that affect the magnitude of the TE. Since we do not have previous empirical evidence on ETCs in this regard, we develop our hypothesis based on the empirical evidence on ETFs. Theoretically, the higher the management fee or the expense ratio, the larger the TE (Elton et al., 2002; Rompotis, 2006; 2011). On a separate note, 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. In addition, Elton et al. (2002) and Frino et al. (2004) show that the accrual of dividends on the stocks included in the benchmark index explains the TEs of ETFs.

Another line of research examines the impact of ETF liquidity or the liquidity of the underlying asset on the TE of ETFs. The ETP trading occurs in two markets: primary markets and secondary markets. This trading mechanism is common for both ETFs, ETCs, and ETNs. ETC shares are created and redeemed by the authorised participants (APs) on-demand in the primary market. The issuer of an ETC is a special purpose vehicle (SPV) organisation that can be a limited liability company. APs include large financial institutions, brokers, and approved market participants allowed to engage in SPV transactions directly.[6] The price in the primary market is the net asset value calculated daily based on the underlying asset price. The liquidity

[6] Please refer to Dorfleitner et al. (2018) for more details on the structure of the ETC markets.

in the secondary market of ETCs is determined by the trading volume on the stock exchanges where ETC shares are bought and sold. The secondary market is where retail or institutional investors will trade ETC shares from the APs. The bid-ask spreads determine the market prices during trading hours of the secondary market. This study examines the daily prices of agricultural ETCs in the secondary market. However, we do not find sufficient and consistent data to analyse the impact of liquidity on the TE of ETCs.

Previous studies have acknowledged that liquidity is one of the critical determinants of TEs of ETFs (Bae and Kim, 2020; Buetow and Henderson, 2012; Bertone, Paeglis, and Ravi, 2015). Buetow and Henderson (2012) find a significant negative relationship between the liquidity of US ETFs measured by the daily dollar volume and the size of the tracking error. Bertnone et al. (2015) report a negative relationship between trading volume and the TEs using intraday data for an equity ETF listed in the US. By examining the tracking performance of 1307 US ETFs, Bae and Kim (2020) also find that illiquid ETFs report a higher level of TE. When the underlying asset has a low level of liquidity, that further increases the TE. Osterhoff and Kaserer (2016) examine the impact of the liquidity of the underlying stock on the daily tracking error of eight fully replicating German equity ETFs. They find that the liquidity of the underlying stock is a significant determinant of the daily TE of German equity ETFs. However, there is limited evidence in the existing literature examining the impact of liquidity on the TEs of agricultural ETCs.

Conversely, 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) found that ETFs had a low tracking ability compared with 2006 and 2007. Chen (2015) concludes that the TE of commodity ETFs also differs depending on the bullish and bearish conditions in the equity market. This study investigates whether the tracking ability of agricultural ETCs will be affected depending on the alternative market conditions of the underlying agricultural commodity. Accordingly, it examines the difference in the TE of agricultural ETCs between high- and low-volatility periods of the underlying agricultural commodity prices.

2.2. Physical versus synthetic replication

ETPs may 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 ETCs is synthetic replication. An ETC can synthetically replicate the benchmark index's performance using commodity futures contracts or swap contracts.

However, using futures contracts to replicate the return of an underlying index adds rolling costs to the investor. Hence, one could expect synthetically replicated ETCs to have a high level of TE compared with physically replicated ETCs. In addition, ETCs using swap contracts may also 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 ETCs 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), futures-based commodity ETFs' tracking deviation is more prominent than physically replicated commodity ETFs. Fassas (2014) and Naumenko and Chystiakova (2015) conclude that ETFs using swap-based replication generate a higher TE than physically replicated ETFs. However, whether the replication method affects the tracking ability of agricultural ETCs remains unsolved. Hence, this study aims to add evidence to 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 daily leveraged returns. ETCs with a positive multiple are either bullish or leveraged ETCs, whereas ETCs with a negative multiple are known as bearish or inverse ETCs (IETCs). These LETCs require daily rebalancing, and this dynamic rebalancing process will likely make replication difficult. Therefore, LETCs are likely to generate a high level of TE compared with traditional ETCs on the same benchmark index. Due to this fact, investors generally consider investing in LETCs for only short periods to avoid these high TEs.

A growing number of studies examine 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). Lu et al. (2012) find that the US LETFs in their study do not deliver the benchmark return even during a one-week horizon. In contrast, Charupat and Miu (2011) conclude that Canadian LETFs earned the promised leveraged benchmark return in a one-week horizon. LETFs are also reported to underperform the benchmark index in the long run (Carver, 2009; Guedj et al., 2011; MacKintosh, 2008; Sullivan, 2009). Following this previous evidence, we aim to examine whether the leverage affects the tracking ability of agricultural ETCs.

3. Data

The data sample includes 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 have collected data from the Bloomberg database. The daily prices of ETCs are collected from the inception date of each ETC until November 2016. The daily prices of commodity indices cover the period from January 2006 to November 2016.

This sample consists of 50 ETCs issued by the Union Bank of Switzerland (UBS), Switzerland, and 34 ETCs issued by ETFS Commodity Securities Limited, UK. 60 ETCs invested in a single-commodity index and 24 ETCs invested in a multi-commodities index. Of these ETCs, 52 ETCs traded in the London market, and 32 ETCs traded in the Swiss market. There are 22 ETCs leveraged and 62 ETCs non-leveraged. Fifty ETCs use futures contracts to replicate the benchmark commodity index, and 34 ETCs use collateralised swap contracts to replicate. Furthermore, 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. Multi-commodities ETCs invest in Bloomberg indices that invest in more than one underlying commodity. For example, the sample includes WisdomTree Grains ETC (Bloomberg ticker for the ETC is AIGG LN Equity). AIGG LN is a multi-commodities ETC designed to track the Bloomberg Grains Subindex Total Return Index. This Grains index comprises futures contracts on corn, soybeans, and wheat. Similarly, each multi-commodities ETC invests in a respective multi-commodities index designed by Bloomberg to reflect the return of more than one underlying commodity.

First, it is required to identify the volatility periods of these commodities to examine the difference in the tracking ability of ETCs during the high- and low-volatility periods of agricultural commodity prices. Table 1 lists the single-commodity indices used to identify the volatilities of each agricultural commodity in which the ETCs in this study have invested. Each commodity index invests in a single commodity and reflects the return of the underlying commodity futures price movements. For example, Bloomberg Cocoa Sub Index Total Return (BCOMCCTR) reflects the return on the price movements of cocoa futures contracts.

[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 total return investment in a comprehensive basket of agricultural commodity futures contracts on coffee, corn, cotton, soybean, soybean oil, soybean meal, sugar, and wheat. Figure 1 displays the composition of the AgriTR Index as of August 2 2017.

[Insert Figure 1 about here]

This study presents the descriptive statistics on ETC returns categorised by the agricultural commodity. Table 2 shows the mean returns, volatilities of returns, and their distribution by the commodity. ETC returns are calculated using daily prices, and Table 2 presents annualised returns and volatilities.

[Insert Table 2 about here]

All single-commodity ETCs, except soybean meal, have generated negative annualised mean returns during this analysis. The lowest mean return is -25.16 per cent for wheat, and the highest mean return is 13.91 per cent for soybean meal. ETCs investing in multi-commodities indices also report a negative mean return of 6.09 per cent. The annualised volatility of the daily commodity returns is at the highest (42.51 per cent) for corn and the lowest (20.12 per cent) for rough rice. The distribution of ETC returns of cocoa, coffee, corn, rough rice, soybean oil, and sugar is negatively skewed. In contrast, ETC returns of cotton, soybeans, soybean meal, and wheat distribution are positively skewed.[7]

4. Identifying Commodity Price Cycles

To examine the time-varying nature of the tracking performance of agricultural ETCs, first, it is required 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 in detail and present the findings of 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] This study investigates the short-term random shocks of commodity returns using the Markov switching (MS) regression model. First, we assume that commodity prices would only shift between high- or low-volatility states. Second, the transition between these states follows 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 single-

[7] In addition, we have regressed ETC return on Index Returns to diagnose the existence of serial correlation and heteroscedasticity in the data. We applied the Breusch-Pagan test for heteroscedasticity and the Durbin Watson statistic for testing the serial correlation. The detailed results are available from the authors upon request. The results suggested the presence of heteroscedasticity and serial correlation in some ETCs. In order to cater for these issues, all regressions included robust standard errors.

[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 continue to persist.

commodity index. This study calculates state-dependent intercept terms, slope coefficients, and standard deviations using the following MS regression 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 the AgriTR Index on day *t-1*, ε_{St} is the state-dependent error term on day t and s_t indicates 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 P11 or P22 is greater than or equals 0.85, then the commodity continues to be 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 has changed from state 1 to 2 or state 2 to 1, respectively.

For each single-commodity ETC and multi-commodities ETC, this study calculates the daily TE from the inception of the ETC until November 2016. This study estimates the TE using four alternative definitions discussed later. The objective of using different definitions of TE is to ensure the consistency of the findings.

For single-commodity ETCs, we test the significance of the difference in the mean TE of an ETC between state 1 and state 2 of the underlying commodity prices. For multi-commodities ETCs, we test the significance of the difference in mean TE between the states of each commodity included in the ETC. For example, consider a multi-commodities ETC investing in the Bloomberg Grains Total Return Index, including corn, soybeans, and wheat. This study examines whether multi-commodities ETCs show a difference in their tracking ability between the states of each commodity in which the ETC 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 equals zero. The alternative hypothesis is that this difference is not equal to zero. If the results reject the null hypothesis, we conclude that TE is different between high- and low-volatility periods. If the results fail to reject the null hypothesis, we conclude that TE is the same under both high- and low-volatility periods.

4.2. Results of the MS regression model

This section presents the results of the MS regression model (given in equation 1 above). Table 3 depicts the values of the state-dependent intercept (i.e., μ) and the standard deviation of each commodity. Further, it summarises each state's average duration (in days) and the average transition probabilities between states for each commodity. P11 and P22 represent the probabilities of being on state 1 or 2 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 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, 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 than in state 2. Except for coffee, all other commodities reported a standard deviation between 26.19 per cent and 49.05 per cent during state 1 and a standard deviation between 13.33 per cent and 23.81 per cent during state 2. 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 that in state 1. The average duration 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. Figures 2 and 3 illustrate daily transitional probabilities (P11 and P22) for cocoa under states 1 and 2, respectively. It shows that cocoa has primarily 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 coffee and orange juice, for which the daily transitional probabilities did not meet the cut-off criteria.

[Insert Figure 2 and 3 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. 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 each commodity listed in Table 1 significantly outperforms the return on a benchmark agricultural commodity index (i.e., AgriTR Index). This analysis aims to examine whether the tracking performance of agricultural

ETCs differs between abnormal return days and normal return days of the underlying commodity. This study uses 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*. This study tests the null hypothesis that an abnormal return on a single-commodity index *i* on day *t* equals zero. The alternative hypothesis is that an abnormal return on a single-commodity index *i* on day *t* does not equal zero. The test aims to identify 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. This analysis's null hypothesis is that the mean TE of an ETC between abnormal return days and normal return days equals zero. If the results reject the null hypothesis, it implies that the TE of ETCs is not the same under the commodity's abnormal and normal return days. ETCs will likely report a higher level of TE on abnormal return days compared with normal return days.

For multi-commodities ETCs, the objective is to test whether these ETCs 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 ETC investing in the Bloomberg Grains Total Return Index, which includes corn, soybeans, and wheat. We analyse whether the difference in the mean TE of an ETC is significant between the abnormal and normal return days of each commodity, which is, for corn, soybeans, and wheat separately. Rejecting the null hypothesis implies that multi-commodities ETCs generate a higher TE on the abnormal return days of each underlying commodity compared with the normal return days of these commodities.

4.4. Results of the abnormal return days of commodities

Table 4 summarises the abnormal return days and normal return days, calculated using equation (2) above, for each single-commodity index listed in Table 1. The 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 per cent positive abnormal return days and

2.73 per cent 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 return days (i.e., 52 days). Lean hogs and orange juice have the largest negative abnormal return days (i.e., 85 days), and soybean oil has the lowest negative abnormal return days (i.e., 58 days).

[Insert Table 4 about here]

5. Tracking Performance of Agricultural ETCs

5.1. Definitions of TE

Following previous research, this study also calculates daily TEs of ETCs using alternative definitions[9] to measure the tracking performance of ETCs. First, TE1 is the average of the difference between the ETC return on day *t* (r_t^{ETC}) and the underlying index return on day *t* (r_t^I) as shown in equation (3) (Drenovak et al., 2014; Rompotis, 2016). T is the total number of days. TE1 is generally expressed in basis points (or 0.01 per cent). A positive (negative) TE1 indicates the ETC is overperforming (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 ETC return on day *t* and the underlying index return on day *t* or the absolute value of TE1, as shown in equation (4) (Charupat and Miu, 2013; Rompotis, 2016). The positive and negative values of TE1 might offset 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.

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

We regress ETC returns on the underlying index returns using the model depicted in equation (5) for the third definition. According to the previous studies (Charupat and Miu, 2013; Drenovak et al., 2014; Pope and Yadav, 1994; Rompotis, 2008; 2016), TE3 is the standard error of this regression, or it is the standard deviation of the residuals (ε_t) of this regression.

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

[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.

Finally, TE4 is the standard deviation of the difference between the ETC 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 in equation (6). TE3 and TE4 measure the co-movement between the ETC return and the underlying index return. Further, TE3 and TE4 are standard deviations and are always expressed as positive numbers. Therefore, these standard deviations represent the total tracking error (i.e. an aggregate of 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 equal zero. This study argues that the TE will be different between states and abnormal and normal return days and tests the significance of the difference in the mean TE. The hypothesis test between MS regression states will be as follows.[10]

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

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

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, this section presents 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

[10] We used two sample t test on the equality of means in Stata to test this hypothesis. We use this t test on means for testing the difference of the mean TE between states and abnormal and normal return days using the definitions: TE1 and TE2. We use the sd test for testing the equality of standard deviations of two samples in Stata for testing the above hypothesis using the definitions TE3 and TE4.

are not statistically significant. The lowest negative TE is reported for soybeans (-0.042 per cent), whereas the highest negative TE is reported for wheat (-0.007 per cent).

[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 ETC 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 have conducted a sign test[11] to analyse the equality of the signs between ETC returns and underlying index returns. The findings of the sign test proved 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 ETC returns.

Furthermore, as mentioned previously, TE3 and TE4 are standard deviations and will be expressed as a positive value. They consider both the negative deviations of the TE (underperformance) and the positive deviations of the TE (overperformance). Hence, TE3 and TE4 demonstrate the aggregate level of TE of a commodity. Theoretically, both underperformance and overperformance of an ETC are deviations from the expected return and, therefore, a tracking error. We could also observe the same pattern in the results of the TE1 and other definitions in the later results. Since the same explanation will be applicable in the later discussions, we avoid repeating this explanation.

Finally, we conclude that agricultural ETCs do not effectively replicate the benchmark index's performance during the overall sample period. The TE of single-commodity ETCs ranges from 1 per cent to 2.8 per cent. In contrast, the TE of multi-commodities ETCs is less than 1.5 per cent, suggesting that multi-commodities ETCs perform better than single-commodity ETCs. This could be due to the diversification benefits of investing in a basket of agricultural commodities rather than a single commodity.

[11] 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 analyse 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 thesis, but the results are available upon request.

5.3. Time-varying tracking performance results

This section investigates the time-varying nature of the tracking performance of agricultural ETCs based on the volatility of agricultural commodity prices. Section 4 identified states 1 and 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 each commodity's abnormal and normal return days in section 4. This study tests 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, soybean, soybean meal, and soybean oil, the TE1 are higher in state 2 (low volatility) than in state 1 (high volatility). In contrast, for all the other commodities, TE1 increases more in state 1 than in state 2. However, these differences based on TE1 are not statistically significant. According to the results for TE1, there is no significant difference in tracking performance between these alternative volatility periods.

[Insert Table 6 about here]

Based on TE2 (i.e., the absolute value of TE1), single-commodity ETCs generate, on average, 1.13 per cent higher TE in state 1 than in state 2 and 1.25 per cent higher TE during abnormal return days than in normal return days for all the commodities. The TE3 and TE4 also support 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 varies depending on the volatility of the underlying commodity prices.

Table 7 shows the time-varying tracking performance of multi-commodities ETCs. This study tests whether multi-commodities ETCs perform differently when at least one commodity they have invested in experiences periods of high volatility or abnormal returns. In this table, Panel A presents the TE difference under state 1 and state 2, and Panel B exhibits the TE difference under abnormal and normal return days.

[Insert Table 7 about here]

In the case of multi-commodities ETCs with TE1, only three and four ETCs (out of 24 multi-commodities ETCs) report both positive and negative significant tracking deviations between states and between abnormal and normal returns days, respectively. Under the other three definitions, most 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 ETCs is 0.46 per cent between state 1 and state 2 and 0.35 per cent between abnormal and normal return days. This indicates that multi-commodities ETCs cannot track the benchmark commodity index during high-volatility periods of agricultural commodity prices compared with low-volatility periods. The TE differences calculated based on TE3 and TE4 also confirm 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. By comparing the tracking error values in Table 6 and Table 7, we identified that the TE values of multi-commodities ETCs are lower than those of single-commodity ETCs. This indicates that multi-commodities ETCs better track the underlying index during high-volatility periods than single-commodity ETCs. The diversification effect could be a possible explanation for this improved tracking performance of multi-commodities ETCs.

5.4. Tracking performance differences based on replication strategy

The next aim is to investigate the tracking performance difference in ETCs depending on the replication method adopted. A priori, we expect synthetically replicated ETCs to produce a higher TE level than physically replicated ETCs.

In the selected sample of ETCs, there are only three matching pairs of ETCs tracking the same underlying index, trading on the same exchange and denominating in the same currency. Still, one ETC uses physical replication, whereas the other adopts synthetic replication. 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 physically or synthetically. He does not compare the tracking performance difference using exactly matching pairs of ETCs. In this approach, it is not possible to test the significance of the difference between TEs as there are no matching pairs of ETCs.

In this study, 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 categorise these ETCs by commodity and then by the replication strategy. Then, we calculate the difference in the mean TE of the categorised ETCs using the abovementioned four TE definitions.

Table 8 presents the mean TE values of ETCs based on the replication strategy. These TEs are calculated separately for the entire sample period, high- and low-volatility periods. 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 these 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. Furthermore, the TE is higher under the high-volatility period than in the low-volatility period of agricultural commodity prices under both replication strategies.

[Insert Table 8 about here]

Thereafter, Table 9 summarises the tracking performance of multi-commodities ETCs based on the replication strategy under states 1 and 2 of each underlying commodity in which they have invested. This study examines 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, the findings of this study conclude that synthetic replication is not a better method of tracking the benchmark index. In particular, agricultural ETCs replicated using swap contracts display inefficient tracking abilities than agricultural ETCs replicated using futures contracts. Furthermore, the results suggest that both synthetic replication strategies generate a higher TE during the high-volatility periods than during low-volatility periods of the underlying commodity.

5.5. Tracking performance differences based on leverage

This section examines the difference in tracking performance of ETCs based on the level of leverage of an ETC. There are 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. In line with the theory, we expect LETCs and IETCs to produce a higher TE due to the daily rebalancing required to maintain the leverage. Therefore, this study tests the alternative hypothesis that the TE of a LETC/IETC is higher than the TE of a traditional ETC. The null hypothesis is that the TE of a LETC/IETC is lower or greater than that of a traditional ETC.

Table 10 presents the results of this analysis. Under LETCs, the results consistently reject the null hypothesis with TE2, TE3, and TE4. Under IETCs, the results consistently reject the null hypothesis with TE2 and TE4 (whereas we found mixed evidence for the TE3). TE2 measures the absolute deviation of the TE, whereas TE3 and TE4 measure the variability of

TE. This evidence supports the alternative hypothesis that leverage increases the TE of an agricultural ETC compared with the TE of a traditional ETC. In conclusion, this study adds supportive evidence for the argument that leverage increases the level of TE.

[Insert Table 10 about here]

6. Persistence of TE

6.1. Measuring the persistence of TE

Section 5 presented evidence for the existence of significant TE for agricultural ETCs during the sample period. The results also suggest that TE is time-varying depending on the volatility periods of agricultural commodities. Next, we investigate the persistence of this TE in the short run. The persistence hypothesis assumes that the TE of the previous two days will also continue impacting today's TE.

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, for 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 behaviour.

This study follows Rompotis (2016) and adopts the following autoregressive model to test the persistence of TE in agricultural ETCs. However, we conducted this test considering one to four lags. Beyond two lags, the model did not concave. The model with two lags is the statistically best model; hence, we present the results of that model only in the paper. We test the persistence using the absolute value definition (i.e., TE2) to avoid underestimating the TE that would occur if we use the TE1 definition. The model for testing the persistence of TE 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, day *t-1*, and day *t-2*, respectively. This model assumes that today's TE depends on the previous two days' *t-1* and *t-2*. The error variance of this regression is modelled with a generalised 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. If an ETC has shown either under-or over-exposure to the benchmark index in the previous two days, it will continue today. Negative and significant β coefficients show a mean-reverting behaviour of TE. If β coefficients are insignificant, it suggests that TE is not persistent. If α_i terms are significant, and it reflects a proportion of TE that the lagged values of the TE cannot explain. Hence, this analysis tests 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 summarises 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 ETCs) in the sample reporting a positive and significant $\beta_{1,i}$ coefficient and only 9 ETCs reported a positive and significant $\beta_{2,i}$ coefficient. There is no sufficient evidence to conclude that today's TE is independent of the TE of the past two days. We find only one ETC reporting negative and significant $\beta_{1,i}$ and $\beta_{2,i}$ coefficients and this reflects a mean-reverting behaviour in TE. For all 84 ETCs, 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, a significant portion of TE is not explained by the past two days' TE of an agricultural ETC.

[Insert Table 11 about here]

7. Implications for a Possible Trading Strategy

7.1. Methodology

Next, we investigate if an investor can exploit TE knowledge to generate economic benefits by using a simple trading strategy. In Section 6, we found some evidence for the existence of TE. We extend our analysis here by applying the filter trading rule to identify the profitability of a possible trading strategy based on the TE. Filter trading is a technical analysis trading rule that generates buy and sell signals when the prices violate a certain lower and upper boundary. The theoretical framework of filter trading has been applied to test the market efficiency of stock markets (Fama and Blume, 1966; Kozyra and Lento, 2011; Xin, Lam, and Yu, 2021) and stock index futures markets (Bialkowski and Jakubowski, 2008; Chung, 1991).

Out of all 84 ETCs, there were only six ETCs that reported persistent TEs in Table 11 (i.e. both statistically significant $\beta_{1,i}$ and $\beta_{2,i}$). For each of these six ETCs, we identified days on which TE violates an upper and lower boundary of Mean TE +/- 2*Standard deviations of

TE.[12] When the daily TE violates the lower boundary, we consider that a buy signal. An investor can buy the ETC on that day, hold it, and close out the position on the first day when this negative trend in the TE reverses. When the daily TE violates the upper boundary, we consider that a sell signal. Accordingly, we assumed investors could short sell the ETC and buy it later on the first day when this positive trend in the TE reverses. The main objective of this trading strategy is to identify if investors can generate a profit by exploiting the mispricing of ETCs.

First, we used the filter trading rule to analyse the profitability of the entire sample of daily TEs of the selected ETCs. Following that, we classified such trading days into high- and low-volatility periods (states 1 and 2) as described in section 4 above. We intended to identify whether the profitability of the filter trading method differed across these states. The following sub-section presents the findings of this analysis.

7.2. Results of the trading strategy

Table 12 summarises the findings of this filter trading strategy based on the entire sample period of daily TEs of the selected ETCs. The first observation is that less than 6% violations of the lower and upper boundaries. Hence, an investor will not be able to trade frequently applying the filter rule based on these boundary violations of TE. The table shows the average return per trade for each ETC. Except for two ETCs (LCOC LN and TKCCI SW), short sell arbitrage has been more profitable than long arbitrage, considering the entire sample of daily TEs. The COFF LN reports the highest average short-selling strategy return per trade (2.004%). The TKCCI SW reports the long arbitrage's highest average return per trade (2.7045%). Table 12 also presents the minimum and maximum returns for each ETC under both arbitrage strategies. The SSUG LN (trading sugar) has the highest maximum return (44.43%), and SCOC LN (trading cocoa) has the lowest minimum return (-18.48%). Overall, we find mixed evidence on the profitability of the trading strategy based on the TE.

[Insert Table 12 about here]

Thereafter, we analysed the profitability of applying the filter trading rule under high- and low-volatility periods of the underlying commodity. State 1 is the high-volatility period, and state 2 is the low-volatility period. As mentioned in section 4.2, we could not identify different states for coffee and orange juice for which the daily transitional probabilities did not meet the cut-off criteria. Therefore, we eliminate two funds (TKCCI SW and COFF LN) from

[12] The lower and upper boundaries for each ETC are given in the parenthesis, respectively: COCG LN (-2.17%, 2.15%), LCOC LN (-4.25%, 4.15%), SCOC LN (-6.82%, 6.79%), COFF LN (-2.86%, 2.85%), TKCCI SW (-3.59%, 3.58%) and SSUG LN (-8.31%, 8.26%).

our analysis. Table 13 summarises the number of lower and upper boundary violations and the average return per trade under each state. We find that trading during state 1 has always been more profitable for long arbitrage than during state 2. For short-sell arbitrage, we do not find strong evidence to conclude that trading during state 1 is more beneficial than trading during state 2. Based on our findings, we cast doubt if investors would generate a considerable profit by trading based on TEs of ETCs.

[Insert Table 13 about here]

8. Conclusion

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

The results show that agricultural ETCs do not accurately replicate the benchmark index during the period. In particular, we find 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. We do not find strong evidence for the persistence of this significant TE. Finally, the results confirm that ETC characteristics, such as replication strategy and the level of leverage, affect the tracking ability of ETCs significantly.

The implications of this study are essential for both issuers and investors. Since this study provides evidence that the structure of an ETC matter for its tracking ability, issuers must consider this fact when designing new ETCs on agricultural commodities. In addition, issuers need to pay attention to the finding that single-commodity ETCs have a poor tracking ability compared with multi-commodities ETCs during high-volatility periods compared with low-volatility periods. The quality of an ETC depends on providing the promised benchmark return for investors. Therefore, issuers of these ETCs are responsible for designing ETCs with the best possible structure to avoid this limitation.

Conversely, investors should pay attention to these findings, as these ETCs expose investors to a high level of time-varying TE. The lack of persistence in TE shows no systematic problem in how ETCs operate. This study also provides evidence that ETC characteristics, such as replication strategy and leverage, affect tracking performance. However, we do not find strong evidence of generating consistent economic benefits by utilising the knowledge on these TEs of ETCs.

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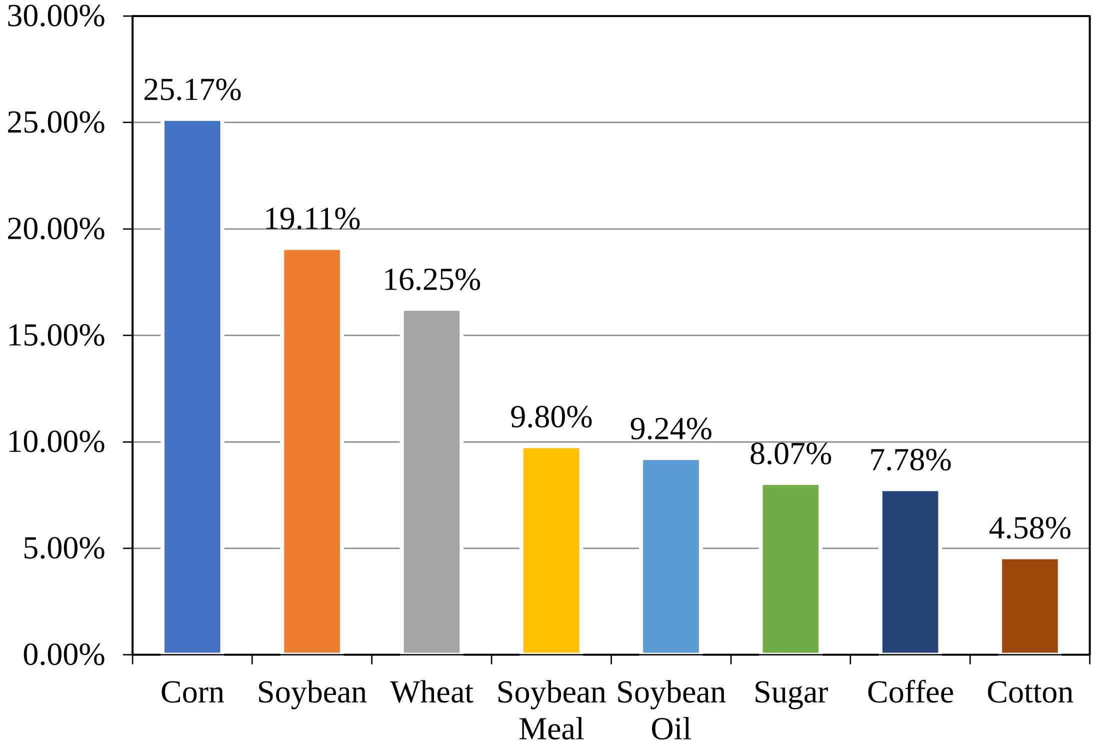

Figure 1: Composition of AgriTR Index
Source: Bloomberg (As of August 2 2017)

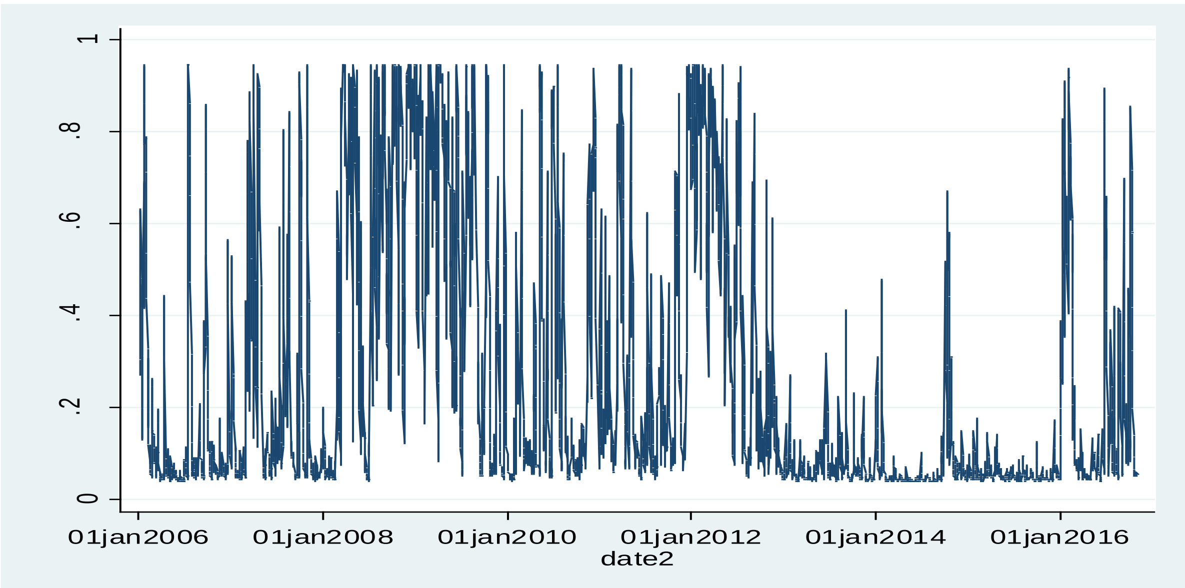

Figure 2: Daily Transitional Probabilities of Cocoa for State 1

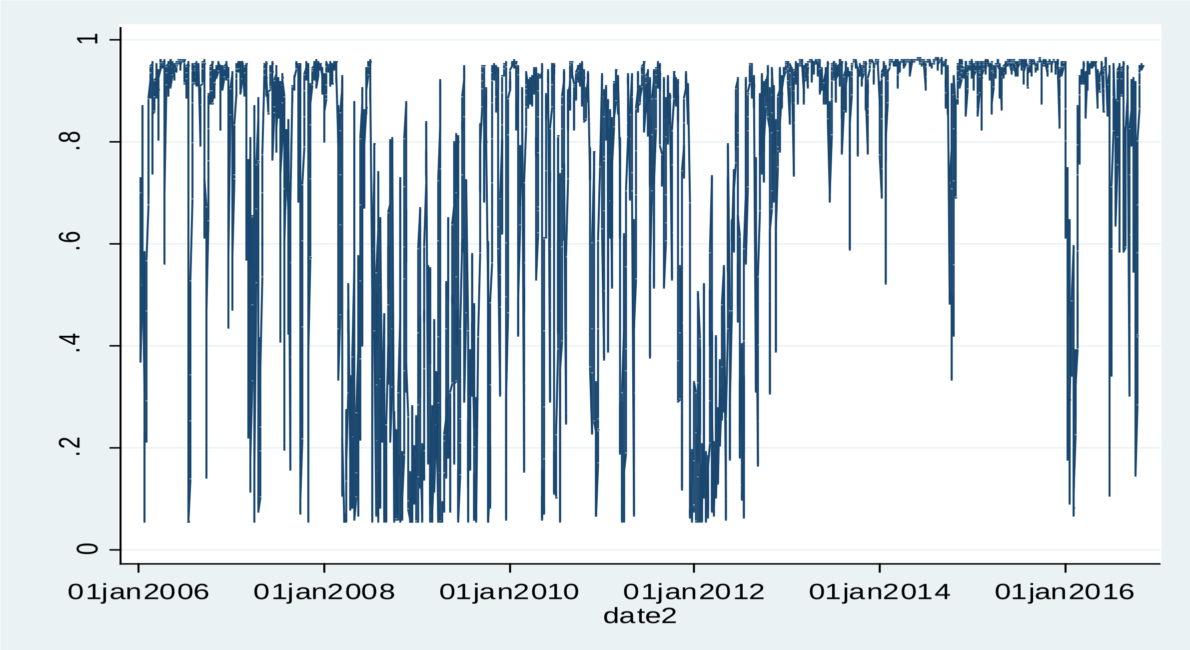

Figure 3: Daily Transitional Probabilities of Cocoa for State 2

Table 1: List of commodities and their respective indices

This table lists the agricultural commodities and their separate 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 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 ETCs in the sample. The single-commodity ETCs are categorised based on their underlying commodity, and multi-commodities ETCs are reported separately. The data covers the period from the inception of an ETC until November 2016. The table summarises the number of ETCs under each commodity category and the number of observations (No of Obs). All mean returns and standard deviations (SD) of ETC returns are annualised. The last column reports the skewness of the return distribution.

Commodity	No of ETCs	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 summarises the results of the Markov switching regression model for state 1 and state 2. It reports the state-dependent mean return and the standard deviation. These mean returns and standard deviation values are calculated using daily data and then annualised. 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 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 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 days each commodity has reported either a significant positive or negative abnormal return or no significant abnormal return. The 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				Normal 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 TE distribution. The single-commodity ETCs are categorised based on their underlying commodity, and the 24 multi-commodities ETCs are reported separately. The data covers the period from the inception of an ETC until November 2016. The second column reports the number of ETCs 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 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 distribution column reports the distribution of each TE as follows: the number of positive and significant ETCs (+)/ the number of insignificant ETCs (0)/ and the number of negative and significant ETCs (-). The significance of the TE is determined at the 5% significance level.

Commodity	No of ETCs	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 summarises the difference between the TE and TE distribution of single-commodity ETCs. The data covers the period from the inception of an ETC 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 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 distribution column reports the distribution of each TE as follows: the number of positive and significant ETCs (+)/ the number of insignificant ETCs (0)/ and the number of negative and significant ETCs (-). Panel A summarises the results between state 1 and state 2. Panel B summarises 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 summarises the difference between the TE and TE distribution of single-commodity ETCs. The data covers the period from the inception of an ETC 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 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 distribution column reports the distribution of each TE as follows: the number of positive and significant ETCs (+)/ the number of insignificant ETCs (0)/ and the number of negative and significant ETCs (-). Panel A summarises the results between states 1 and 2. Panel B summarises 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%	0/12/0	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 – 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	0.24%	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 of single-commodity ETCs

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 using futures contracts or fully funded collateralised 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 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 covers the period from the inception of an ETC until November 2016.

Commodity	Replication Strategy	No of ETCs	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 of multi-commodities ETCs

This table presents the mean TE values of multi-commodities ETCs categorised based on both the underlying commodity and the replication strategy of the ETC under the high- and low-volatility periods. The ETCs selected in this study are either replicated using futures contracts or fully funded collateralised 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 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 covers the period from the inception of an ETC until November 2016.

Commodity	Replication Strategy	Number of ETCs	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 differences based on leverage

This table shows the results of the null hypothesis test that the TE of a LETC/IETC is lower than that of a traditional ETC tracking the same underlying commodity index. The alternative hypothesis is that the TE of a LETC/IETC is higher than that of a traditional ETC. There are 9 trios of ETCs replicating the same index: 6 single commodity ETCs and 3 multi-commodities ETCs. The data covers the period from the inception of each ETC 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 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 the p values of the test and * 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 summarises 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). This study models the error variance using a GARCH (1,1) process. The table summarises 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 ETCs	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)

Table 122: Results of the filter trading strategy – Entire sample period

This table summarises the number of upper and lower boundaries violations, violations as a percentage of the total number of days in the sample of data, and the average return per trade for the selected ETCs. The data covers the period from the inception of an ETC until November 2016. The upper and lower boundaries of TE are calculated as Mean TE +/- 2*Standard deviations of TE. The lower and upper boundaries for each ETC are given in the parenthesis, respectively: COCG LN (-2.17%, 2.15%), LCOC LN (-4.25%, 4.15%), SCOC LN (-6.82%, 6.79%), COFF LN (-2.86%, 2.85%), TKCCI SW (-3.59%, 3.58%) and SSUG LN (-8.31%, 8.26%).

ETC	Commodity	Total Violations as a percentage	No of Upper Bound Violations	Average Return of Short Sell Arbitrage (Per Trade)	Minimum Return of Short Sell Arbitrage	Maximum Return of Short Sell Arbitrage	No of Lower Bound Violations	Average Return of Long Arbitrage (Per Trade)	Minimum Return of Long Arbitrage	Maximum Return of Long Arbitrage
COCG LN	Cocoa	1.3%	12	1.68%	-7.30%	6.82%	10	0.64%	-1.65%	4.05%
LCOC LN	Cocoa	4.3%	42	-0.51%	-10.76%	13.33%	55	2.17%	-7.90%	20.54%
SCOC LN	Cocoa	5.1%	62	0.05%	-8.03%	5.84%	53	-0.42%	-18.48%	6.76%
COFFLN	Coffee	4.9%	66	2.00%	-5.89%	8.28%	62	1.38%	-5.19%	9.47%
TKCCISW	Coffee	3.2%	37	1.62%	-15.67%	10.80%	36	2.70%	-4.63%	19.37%
SSUGLN	Sugar	4.7%	55	0.53%	-13.80%	44.43%	52	-0.02%	-16.15%	7.84%

Table 133: Results of the time-varying filter trading strategy

This table summarises the number of upper and lower boundaries violations and the average return per trade under different volatility periods. State 1 is the high-volatility period, and state 2 is the low-volatility period. The data covers the period from the inception of an ETC until November 2016. The upper and lower boundaries of TE are calculated as Mean TE +/- 2*Standard deviations of TE. The lower and upper boundaries for each ETC are given in the parenthesis, respectively: COCG LN (-2.17%, 2.15%), LCOC LN (-4.25%, 4.15%), SCOC LN (-6.82%, 6.79%), COFF LN (-2.86%, 2.85%), TKCCI SW (-3.59%, 3.58%) and SSUG LN (-8.31%, 8.26%).

		State 1				State 2			
ETC	Commodity	No of Upper Bound Violations	Average Return of Short Sell Arbitrage (Per Trade)	No of Lower Bound Violations	Average Return of Long Arbitrage (Per Trade)	No of Upper Bound Violations	Average Return of Short Sell Arbitrage (Per Trade)	No of Lower Bound Violations	Average Return of Long Arbitrage (Per Trade)
COCG LN	Cocoa	5	0.9961%	4	1.0651%	1	0.5678%	2	-1.5904%
LCOC LN	Cocoa	10	-0.2200%	9	3.7807%	9	0.0202%	12	-0.9326%
SCOC LN	Cocoa	7	0.5193%	8	0.4565%	17	0.1151%	11	-0.4619%
SSUGLN	Sugar	39	0.4712%	28	0.5203%	2	1.7552%	6	-2.8837%