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Analysis and Forecast of Tracking Performance of Hong Kong Exchange-Traded Funds: Evidence from Tracker Fund and X iShares A50

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This study examines the tracking performance of two Hong Kong exchange-traded funds (ETFs): Tracker Fund and X iShares A50. The turnover of these two ETFs was more than half the total turnover of the 141 ETFs in the Hong Kong market during 2005–2013. Tracking performance is assessed using pricing deviation, which is found to be nonzero and predictable. This indicates that the premium paid by investors is of considerable economic interest. The significant differences in the tracking performance of physical ETFs and synthetic ETFs highlight the relative inability of synthetic ETF to track the market. Additionally, we document the existence of co-integration between the ETF prices and stock market prices. An econometric model is estimated to forecast the pricing deviation, which shows different price dynamics between the two ETFs, but an absence of arbitrage opportunities. The time series regression model of pricing deviation is significantly influenced by market value, dividend yield, trading volume, bid-ask spread, and market risk. The size of the regression coefficients indicates that synthetic ETFs have relatively poor ability to track the market during market fluctuations.

Keywords: Exchange-traded funds; tracking ability; pricing deviation; co-integration; economic correction model.

JEL Classifications: G15, G23

1. Introduction

The first exchange-traded fund (ETF) in the United States was Standard & Poor's 500 Depository Receipts (SPDRs); this ETF was designed to passively mimic the S&P 500 index. Hong Kong's first ETF, the Hong Kong Tracker Fund, was launched on 12 November, 1999. ETFs are passively managed funds that are intended to closely track the performance of indices. ETFs combine the benefits of the diversification of investment through index investing and the flexibility of trading at any time during a market's trading hours. ETFs have become increasingly popular because they represent portfolios of securities designed to track the performance of indices, thereby offering an efficient way for investors to obtain cost-effective exposure. Moreover, ETFs have significantly lower transaction costs compared to actively managed mutual funds since there is no subscription fee for ETFs. Additionally, in Hong Kong, ETFs that track indices that do not include any Hong Kong stocks are exempt from stamp duties. Other features that make ETFs attractive are their high degree of transparency in identifying the underlying constituents of funds, their intraday valuation, their ability to be traded by brokers like stocks, and their liquidity, which is enhanced by market makers. Moreover, ETFs are eligible for short selling in some markets, which provides investment opportunities when investors foresee a bear market in the near future. Portfolio managers can use ETFs as investment tools to help execute dynamic trading strategies, and individual investors can use them to participate in foreign stock markets and as tools to diversify their investments. Miffre (2006) empirically demonstrates that country-specific ETFs can enhance global asset allocation strategies at a low cost, with a low level of tracking error, and in a tax-efficient manner. The ETF industry in the U.S. has grown rapidly over the last decade, with a 5-year average annual growth rate of 33% (Schuster, 2008).

Exchange-traded funds currently play an increasingly important role in Hong Kong. The number of ETFs has increased from 18 in 2008 to 141 as of May 2014. However, compared to other developed financial markets, the Hong Kong ETF segment is still in a nascent stage. Of these 141 ETFs, 86 are physical ETFs, which directly buy all of the assets needed to replicate the composition and weighting of their benchmarks or buy a portion of the assets needed to replicate the composition along with other assets that have a high degree of correlation with the underlying benchmark. The remaining 55 are synthetic ETFs, which typically invest in financial derivative instruments to replicate their benchmarks' performance. The synthetic ETFs listed on the Hong Kong Stock Exchange (HKEx) can be identified by the letter X at the beginning of their stock names.

This study uses price deviation to analyze the tracking performance of two ETFs, namely, Tracker Fund (HKEX stock code: 2800) and X iShares

A50 (HKEX stock code: 2823). The overall monthly turnover of these two ETFs is always more than half the total monthly turnover of all 141 ETFs. The results show that their price deviation is stationary and predictable. The listing date of these two ETFs is 12 November 1999 and 8 November 2004, respectively. Because of the difference in the listing date of the two ETFs, we have to unify the study period from 1 January 2005 to 31 December 2013.

Although the stated purpose of ETFs is to track underlying indices, not all ETFs track these benchmarks with the same level of accuracy. An index fund that is not able to replicate the return on a benchmark index perfectly is regarded as being unable to meet its investment objectives. Persistent inability to track the market could trigger redemption or the creation of ETF units. ETFs are traded easily in the stock market such that their prices are subject to the forces of market demand and supply. Roll (1992) suggests that the level of tracking error may be an important criterion for assessing an index fund's tracking performance because the differential returns of funds could indicate whether their managers' investment processes have been implemented successfully, even in the case of non-indexed equity funds. Pope and Yadav (1994) agree that tracking errors are crucial for structuring and managing index funds. The performance of an ETF is not guaranteed to be identical to that of its underlying tracking index because an index represents only a calculation derived from a portfolio of stocks, and it is not subject to the same market frictions as those to which an ETF is subject. Additionally, DeFusco *et al.* (2011) state that the price deviation that could measure the tracking performance is specific to ETFs, and it may be considered as an extra cost of trading and handling ETFs.

Traditionally, the specifics of dividend distribution, the costs of purchasing all the stocks in the index to replicate the chosen underlying market index, the forces of supply and demand, and the costs to track the chosen index are the significant reasons for the persistent inability to track the market index that is associated with the price forming process of ETFs.

This study could provide some insights into Hong Kong ETFs for both fund managers and ETF investors. Fund managers who include some ETFs listed on the HKEx in their portfolios should be aware of the price deviations of the ETFs. Moreover, they should determine whether the price deviation could be predicted. This study highlights the challenges facing fund managers who seek to track markets at a relatively lower cost by investing in ETFs instead of physically holding stocks. Given the lack of comprehensive and general research on the pricing deviation of ETFs, this study intends to address the need for such a study in the Hong Kong stock market.

The rest of this paper is organized as follows. Section 2 presents a brief review of the prior studies on the performance of ETFs and the determinants of their ability to track the market index. Section 3 describes the data used in this study, and Sec. 4 explains the research methodology employed. Section 5 discusses the study's findings, and Sec. 6 concludes the paper.

2. Literature Review

While prior research on the prices and performances of active mutual funds and open-end index mutual funds is quite extensive, studies on the performance of ETFs are limited in number because of the limited data available, given their short period of existence. Some prior studies focus on SPDR, the first ETF in the U.S. Elton *et al.* (2002) find that the net asset value of SPDR could be kept close to the market price. However, they find that SPDR underperforms the S&P index, primarily because of the loss of income caused by holding the dividends received on underlying shares in cash. Ivanov (2011) finds that the volatility of SPDR around the NYSE close is quite similar to the volatility of the S&P 500 index's future contract — which is documented by Chang *et al.* (1995) as well — and reports that SPDR exhibits a U-shaped pattern. However, this volatility was found to consistently drop in the 15 min after the NYSE close. One possible reason for this is that SPDR's net asset value (NAV) should not change when the component stocks of the underlying indexes stop trading, as the trading price is determined only by supply and demand. Thus, it should remain close to NAV because the participants' arbitrage activities in the 16:00–16:15 period are virtually non-existent. Following the increasing popularity of the iShares ETF family in the global financial markets, some studies evaluate the various abilities of the iShares ETFs. Pennathur *et al.* (2002) evaluate the diversification ability of iShares and closed-end country funds using a single-index model and a two-factor model. The single-index model indicates that iShares replicate the home index, demonstrating their diversification ability. However, the two-factor model demonstrates that both iShares and closed-end country funds maintain considerable exposure to the U.S. stock market, and that there is apparently no diversification substitute for direct foreign investment. Cheng *et al.* (2008) find that Hong Kong's home market may drive the iShares FTSE/Xinhua China 25 Index ETF returns and S&P500 Index Fund returns in the U.S. Aroskar and Ogden (2012) study the tracking ability of a new exchange-traded product, exchange-traded notes (ETN), which provide investors with opportunities to invest in a specific commodity,

commodity sector, or broad-based commodities index. They find that ETNs track their respective indexes very well, except for currency ETNs and emerging market ETNs. Blitz and Huij (2012) report that the tracking errors of ETFs in emerging markets are substantially higher than the previously reported levels for developed markets ETFs.

Additionally, some prior studies investigated what factors explain the tracking ability of ETFs, measured by either tracking errors or premiums/discounts. Delcoure and Zhong (2007) find that the premiums of iShares are significantly associated with exchange rate volatility, political and financial crises, institutional ownership, bid-ask spread, trading volume, and conditional correlations between the U.S. market and the home market. Tse and Martinez (2007) find that the prices of international iShares are driven mainly by the information released during each local market's trading session. Madura and Ngo (2008) find that size, trading volume, and momentum are effective indicators of an ETF pricing performance; however, these indicators become ineffective when each type of ETF is isolated. Aber *et al.* (2009) find that iShares ETFs are unable to track their underlying benchmarks to a certain extent. Rompotis (2009) finds a positive association between tracking ability and expense ratios, which contradicts the commonly held belief that expenses usually erode ability. Johnson (2009) finds that variables such as the positive returns of foreign indices relative to U.S. indices and whether foreign exchanges trade simultaneously with U.S. markets are significant explanatory variables of the existence of tracking errors between foreign ETFs and underlying home indices, on daily and monthly return bases. Shin and Soydemir (2010) report that change in exchange rate is a significant source of tracking ability. According to DeFusco *et al.* (2011), the accumulation of dividends by ETFs and the number of stocks comprising the underlying index are determinants of price deviation. Blitz *et al.* (2012) find that fund expenses and dividend withholding taxes may explain the performance differences between funds that track different benchmarks and the time variations in fund performance. Qadan and Yagil (2012) find that the tracking ability of ETFs is lower in highly volatile periods, which could provide an indication of the factors underlying the tracking error; additionally, the liquidity of the underlying asset is found to contribute to the imperfect tracking ability. Kadapakkam *et al.* (2015) find that ETFs could serve as a proxy of the market index and are better suited for market efficiency tests since they avoid potential asynchronous trading problems, and their negligible bid-ask spreads greatly diminish noise because of the bid-ask bounce.

Some prior studies attempted to investigate the return predictability of ETFs. Yang *et al.* (2010) find that most of the evidence about the predictability of 18 global ETF indices comes from a conventional linear model and the nonlinear-in-variance generalized autoregressive conditional heteroscedasticity (GARCH) model, while the popular nonlinear-in-mean models such as neural network, semi-parametric functional coefficient model, and nonparametric kernel regression do not help much. Bollapragada *et al.* (2013) demonstrate that the frequently used forecasting techniques — including single exponential smoothing, Holt's exponential smoothing, simple linear regression, multiple linear regression, and Box–Jenkins model — may provide a good forecast of any given ETF in the trading market. Among the various techniques evaluated, the multiple regression techniques were found to produce promising results.

3. Data

Our sample contains Tracker Fund and X iShares A50, the two major ETFs listed on the HKEx for which daily prices are available for any complete year during the period 2005–2013. The daily prices of the ETFs were obtained from Datastream (Thomson Financial Limited) and were checked against the prices supplied directly by investment managers. The daily closing quotes of their underlying indices were also acquired from Datastream.

Tracker Fund and X iShares A50 were issued on 12 November, 1999 and 15 November, 2004, respectively. Therefore, our sample period starts on 1 January, 2005. Another reason for this choice of sample period is the dramatic increase in the volatility of stock markets during 2007–2008. We could evaluate the tracking ability of the two ETFs when the market is highly volatile. Because of the synchronization, the analyzed periods are shorter than the actual periods since the introduction of the ETFs. Since Tracker Fund is a physical ETF, and X iShares A50 is a synthetic ETF, we could compare the tracking performance of physical ETFs and synthetic ETFs.

4. Research Methodology

4.1. *Pricing deviations*

The major objective of an ETF is to attempt to track the price and yield of the underlying benchmark index. The ETFs included in this study are Tracker Fund and X iShares A50, which try to replicate the performances of the Hang Seng Index and FTSE China A50 Index, respectively. Some measures are developed to evaluate how well the ETF tracks the underlying market index. The inability of an ETF to track the market index is usually measured by the deviation in the price or the NAV of the ETF from the price of the index, instead of being evaluated by the premium or discount, which is the difference between the ETF's price and its NAV. Pope and Yadav (1994) suggest using the tracking error as a measure, which is the absolute difference between the performance of an ETF and that of its target index. DeFusco *et al.* (2011) propose the pricing deviation as a measure, which is the difference between the price of the underlying index and the price of the ETF. Pricing deviation is defined as:

$$PD_t = M_t - X_t, \tag{1}$$

where M_t is the price of the market index, X_t is the price of the ETF, and PD_t is the pricing deviation. In this study, X_t is the price of an ETF multiplied by 1,000 since one unit price of an ETF is equivalent to 1000 index points of the respective underlying index. The magnitude of pricing deviations may indicate (i) how closely the ETF is tracking its target index, and (ii) the size of the cost that routinely erodes the ETF returns.

DeFusco *et al.* (2011) suggest that there is a linear relationship between the ETF price and market price, and that the pricing deviation could be considered as an additional cost to the ETF investors. The linear form is defined as:

$$X_t = \beta_0 + \beta_1 M_t + PD_t \tag{2}$$

where M_t is the price of the market index, X_t is the price of the ETF, and PD_t is the pricing deviation. The pricing deviation PD_t in Model (2) resembles the regression's error term, and it should have some specific properties like the usual white noise regression error terms. These properties can be examined with the following hypothesis:

Hypothesis 1: The expected value of pricing deviation is zero

This hypothesis will be tested with the conventional *t*-test on the null hypothesis that the expected value of PD equals zero. The rejection of the null hypothesis ($H_0 : PD = 0$) would imply the inability of the ETF to track the market, and this would be the cost of investing in the ETF.

Hypothesis 2: The time series of pricing deviation is stationary

A time series is said to be stationary if its mean and variance are constant over time, and the value of the covariance between two time periods depends only on the distance (gap or lag) between the two time periods and not the actual time at which the covariance is computed. If the time series is non-stationary, the deflection from the mean will be permanent. A time series is said to be $I(0)$ if it is stationary at the level form. A time series is said be integrated at order d if it has to be differenced d times to make it stationary. For example, if the time series is $I(2)$, $\Delta\Delta y_t = y_t - 2y_{t-1} + y_{t-2}$ will be stationary.

We conduct the unit root test based on the Augmented Dickey–Fuller (ADF) test, which is a widely used methodology to examine whether a time series is stationary. The ADF test may be used regardless of whether the error term u_t is correlated. The test is conducted by adding the lagged values of the dependent variable ΔPD_t. According to Dickey and Fuller (1979, 1981), the ADF test involves the following ordinary least squares (OLS) estimation:

$$\Delta PD_t = \beta_0 + \delta PD_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta PD_{t-i} + \varepsilon_t, \tag{3}$$

where ε_t is the pure white noise error term, and $\Delta PD_{t-1} = (PD_{t-1} - PD_{t-2})$, $\Delta PD_{t-2} = (PD_{t-2} - PD_{t-3})$, etc. The optimal number of lagged difference terms to be included (m) is determined using Akaike's Information Criteria (AIC), which determines the optimal choice of lag length such that the autocorrelations in the error term may be removed (Akaike, 1970). Thus, the unbiased estimate of the coefficient of lagged (PD_{t-1}) can be obtained (δ). The null hypothesis in ADF $(H_0 : \delta = 1)$, which indicates that the time series is non-stationary, will be tested against the alternative hypothesis $(H_a : \delta < 1)$. The rejection of the null hypothesis implies that the time series of pricing deviation is stationary, not a random walk series; thus, it is predictable. The ADF test follows the same asymptotic distribution as that of the DF statistic.

Hypothesis 3: The distribution of pricing deviation is normal

The hypothesis that the pricing deviation is normally distributed may be tested by a nonparametric test, namely, the Kolmogorov–Smirnov (K–S) test. The K–S statistic quantifies a distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution, i.e., normal distribution. The K–S statistic is calculated based on the hypothesis that the samples are drawn from the normal distribution. The empirical distribution function F_n for n observations Y_i is defined as:

$$F_n(X) = \frac{1}{n} \sum_{i=1}^{n} I_{x_i \le x}, \tag{4}$$

where $I_{x_i \leq x}$ is the indicator function that equals 1 if $x_i \leq x$, and 0 otherwise. The K–,,S statistic for a given cumulative normal distribution function $F(X)$ is:

$$KS = \sup_x |F_n(X) - F(X)|, \tag{5}$$

where $\sup_x$ is the supreme of the set of distances. If the sample is drawn from the normally distributed population, the K–S statistic will converge to zero. The rejection of the hypothesis that the pricing deviation is normally distributed would imply that the pricing deviation is a mixture of different distributions.

4.2. *Time series analysis*

We may assume the price discovery process of ETFs is similar to that of the stocks traded in the markets. The price discovery process of the ETF (F_t) and that of the market could be described as:

$$\begin{matrix} M_t = M_{t-1} + \nu_t \\ X_t = M_{t-1} + u_t \end{matrix}, \tag{6}$$

where M_t is the price of the market index, X_t is the price of the ETF, and ν_t and u_t are white-noise disturbances. Co-integration between the ETF price and the stock market price would suggest that the two series share a common trend; thus, the regression of one on the other would not necessarily be spurious, and the ETF price would be subject to deviation from the long-run movement dictated by the market. A certain level of co-integration and predictability based on the Engle–Granger representation theorem is expected to exist. The pricing deviation defined in Eq. (1) would result in the following:

$$PD_t = M_t - X_t = (M_{t-1} + \nu_t) - (M_{t-1} + u_t) = \nu_t - u_t. \tag{7}$$

The procedure proposed by Johansen (1991) could be used to determine whether the series are co-integrated of the same order. If r co-integrated vectors exist, the linear combinations of these co-integrated vectors would be stationary. The trace statistics in Johansen's (1991) procedure takes the following form:

$$\lambda_{\text{trace},r} = -T \sum_{i=r+1}^{g} \ln(1 - \hat{\lambda}_i), \tag{8}$$

where $\hat{\lambda}_i$ is the ordered eigenvalue, and r is the number of non-zero characteristic roots. A trace statistics that is significantly different from zero indicates the existence of significant co-integration. Since there are two variables in the system, there is at most one linear independent co-integration vector.

If the two series are co-integrated with each other, Eq. (7) could be converted to an error correction model (ECM), which could be used to test the existence of causality if the two time series are expected or found to be co-integrated:

$$\Delta X_t = \alpha_0 + \gamma \cdot EC_{t-1} + \sum_{i=1}^{m} \beta_{1i} \Delta X_{t-1} + \sum_{j=1}^{m} \beta_{2i} \Delta M_{t-j} + \varepsilon_i \tag{9}$$

where M_t is the price of the market index, X_t is the price of the ETF, ε_t is the residual term from Eq. (9), EC_{t-1} is the equilibrium error correction term that describes how the short-run variance between the ETF price and the index price is consistent with a long-run co-integrating relationship, and γ is the coefficient of the error correction term. Granger (1988) indicates that within the ECM, causality could arise from the lagged differences and from the error correction term. The statistical significance of γ would indicate that the ETF pricing error corrects back to the index price. The lagged differences of the variables may capture the short-term dynamics, and the tests of causality could be carried out based on the significance of these terms. The hypothesis involves two joint-hypothesis tests: the coefficients of lagged variables and the error correction term are jointly zero. Note that the changes in the ETF price would depend on not only the changes in the market price but also the long-run relationship between them, which allows for any previous disequilibrium measured by the error correction term (EC_{t-1}) to exert potential influence on the movement of the ETF price. The significance of the error correction term in each equation indicates the tendency of each variable to restore equilibrium in the fund NAV. According to Toda and Phillips (1994), the ECM could combine the short-run dynamics and long-run adjustment of the series, thereby introducing two channels of causality from the market price to the ETF price. The present study investigates only the unidirectional causality of the market price to ETF price; the reverse causation from the ETF price to market price by reversing the roles of the dependent variable and independent variables will not be tested. Since the results of the test are sensitive to the selection of lag length, AIC are used to determine the appropriate lag length.

4.3. *Determinants of pricing deviation*

Chu (2011) finds that two operating characteristics of ETFs — size of ETFs (measured by total assets of ETFs) and the expense ratios — are the determinants of tracking error, which is another measure of the inability of ETFs to track the markets. The data related to these two operating characteristics are available on an annual basis. This study attempts to use some variables that are available on a daily basis. To determine whether pricing deviations are associated with these selected operating characteristics, the pricing deviations of ETFs were regressed on these selected ETF operating characteristics. Each of the factors that are expected to affect tracking errors will be discussed in this section.

(1) The size of ETFs (measured by an ETF's market capitalization) is hypothesized to be one of the factors that determine the pricing deviations. Since larger ETFs may have economies of scale and, therefore, lower transaction costs, market capitalization is expected to be negatively related to pricing deviation.
(2) Dividend yield could also change the size of pricing deviation. When the index constituent stocks pay dividends, the index computation firm immediately assumes that the dividends are re-invested in the stocks on the ex-dividend day. However, in reality, physical ETF managers face delays in receiving dividends in cash; additionally, their reinvestment activities incur transaction costs. Synthetic ETFs may not even receive any dividends in cash because they use derivatives to replicate the index returns. These two situations could erode the ETFs' ability to replicate index performance. There is a possible positive relationship between the level of dividends paid by the constituent stocks in an index and an ETF's pricing deviation.
(3) The trading volume of ETFs is hypothesized to be related to pricing deviation. Higher trading volume leads to greater cash inflows to ETFs. Blume *et al.* (1994) argue that trading in the market is induced by different investor beliefs about an asset's fundamental value. A larger difference in investor beliefs may lead to a greater difference between the stock price and its fundamental value. Trading volume may be used as a proxy of the difference in investor beliefs. A positive relationship between trading volume and pricing deviation is hypothesized.
(4) The bid-ask price spread could also be one of the factors leading to pricing deviation. The bid-ask price spread may be considered as a

measure of the time-varying transaction costs of the ETF investors. The bid-ask spread is expected to have a positive effect on pricing deviation.

(5) The risk level in the financial markets that an ETF is tracing could be another factor. Higher risk in the market could make it more difficult for an ETF to replicate performance, thereby leading to a higher level of pricing deviation. Thus, market risk is expected to have a positive relationship with pricing deviation.

To test the significance of these five variables in explaining pricing deviation, the following model is estimated, with t-statistics adjusted for heteroscedasticity and autocorrelation using the procedures developed by White (1980):

$$|PD_{i,t}| = \beta_0 + \beta_1 \cdot MV_{i,t} + \beta_2 \cdot DIV_{i,t} + \beta_3 \cdot VOL_{i,t} + \beta_4 \cdot SPRD_{i,t} + \beta_5 \cdot RISK_{i,t} + \varepsilon_{i,t}, \tag{10}$$

where $|PD_{i,t}|$ is the absolute value of ETF i's pricing deviation on day t. $MV_{i,t}$ is the ETF's market value measured by the natural logarithm of market capitalization, which is originally in thousand HKD. $DIV_{i,t}$ is the dividend yield measured by the ratio of average dividends and the average trading prices of the ETF. $VOL_{i,t}$ is the natural logarithm of the average daily trading volume of the ETF. $SPRD_{i,t}$ is the bid-ask spread between the highest bid and the lowest ask prices of each ETF traded at the end of each trading day. $RISK_{i,t}$ is the market risk measured by the 5-year historical volatility. The R-square value and F-test statistics from the time series regression model could be used to judge the explanatory power of the regressors simultaneously. The t-statistic associated with each regression coefficient could be used to determine the existence of significant effect of each regressor on the dependent variable. If the pricing deviation is affected purely by the selected determinants, the t-statistic should indicate that each regressor is individually significant, while the intercept is insignificant.

5. Empirical Results

5.1. *Analysis of pricing deviations*

The pricing deviations of Tracker Fund and X iShares A50 are reported in Table 1. Tracker Fund is \$0.277 or 27 cents higher on average than the price of Hang Seng Index. X iShares A50 is \$2.35 higher on average than the price of FTSE China A50 Index. The pricing deviation of Tracker Fund is reasonable compared to the results reported in similar studies in the

Table 1. Summary statistics of price deviations.

	Tracker Fund		X iShares A50	
	Prices	Log. Prices	Prices	Log. Prices
Mean	−277.8994	−0.0138	−2350.4939	−0.2254
Median	−230.8400	−0.0122	−2548.8400	−0.2465
Standard deviation	163.2440	0.0078	1204.2722	0.0933
Skewness	−0.8370	−0.7370	0.4500	0.8220
Kurtosis	−0.0230	−0.1200	−0.7540	−0.0160

Note: Summary statistics of the price deviations in the study period 3 Jan 2005–31 December 2013 are reported. Price deviation is defined as the difference between the underlying index or the log index and the ETF's price or logprice. The ETF's price is adjusted by multiplying 1000 times because $1 of ETF price is equivalent to 1000 points of the underlying index.

U.S. context (DeFusco *et al.*, 2011). However, X iShares A50 has quite a large premium, especially in recent years. Currently, investing in China is hot, and ETF investors are not reluctant to pay high premiums. Since X iShares A50 is a synthetic ETF, there are not many derivatives in the markets for the ETF manager to replicate the performance of FTSE China A50 Index.

The time series plot of the pricing deviation of ETF prices and logarithmic prices are presented in Fig. 1. The pricing deviation of Tracker Fund has a seasonal pattern: the deviation was low in the first two quarters, and it increased gradually in the last two quarters every year during the studied period. The price of Tracker Fund even had a discount rather than a premium in the first quarter of 2005, 2007, and 2008. The pricing deviation of X iShares A50 shows a cyclical pattern instead: the deviation was low around the time of the ETF's introduction and increased in the subsequent years, especially in 2007, when the Binhai District of Tianjin was planned for developing an experimental special economic zone where the direct trading of Hong Kong stocks would be allowed. Investors find that X iShares A50 ETF is the only investment vehicle for investing in Greater China stock markets. After the plan was dropped, and following the financial crisis in the third quarter of 2007, the pricing deviation gradually decreased.

According to Hypothesis 1, the expected value of pricing deviation is zero. The t-test results are presented in Table 2. All the pricing deviations of price and logarithmic price of Tracker Fund and X iShares A50 are statistically different from zero. Thus, Hypothesis 1 is rejected. The empirical results indicate that investors have to pay a significant premium when buying these two ETFs, especially X iShares A50. Since an individual investor would find it very difficult to replicate the index by holding a stock portfolio that has the same proportions as the stocks included in the index, he/she may use

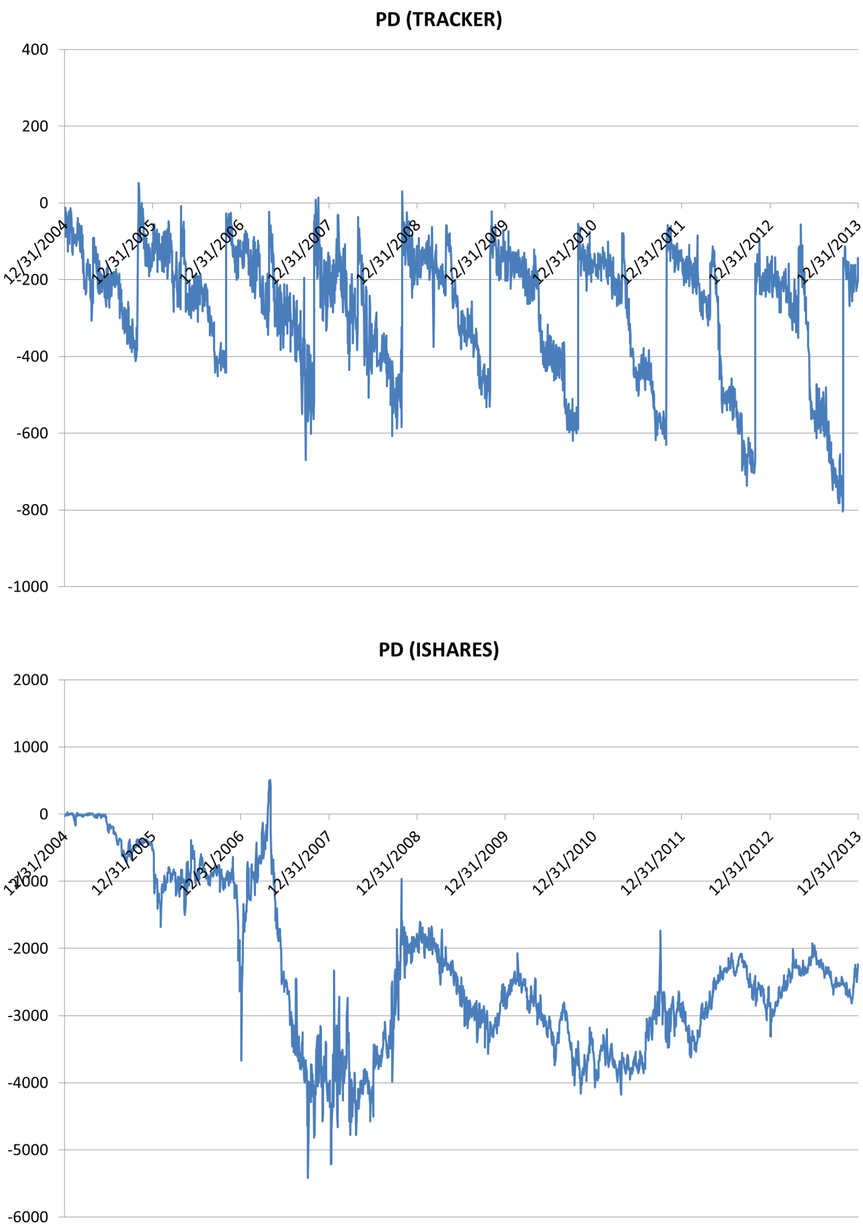

Fig. 1. Time series plot of pricing deviation.

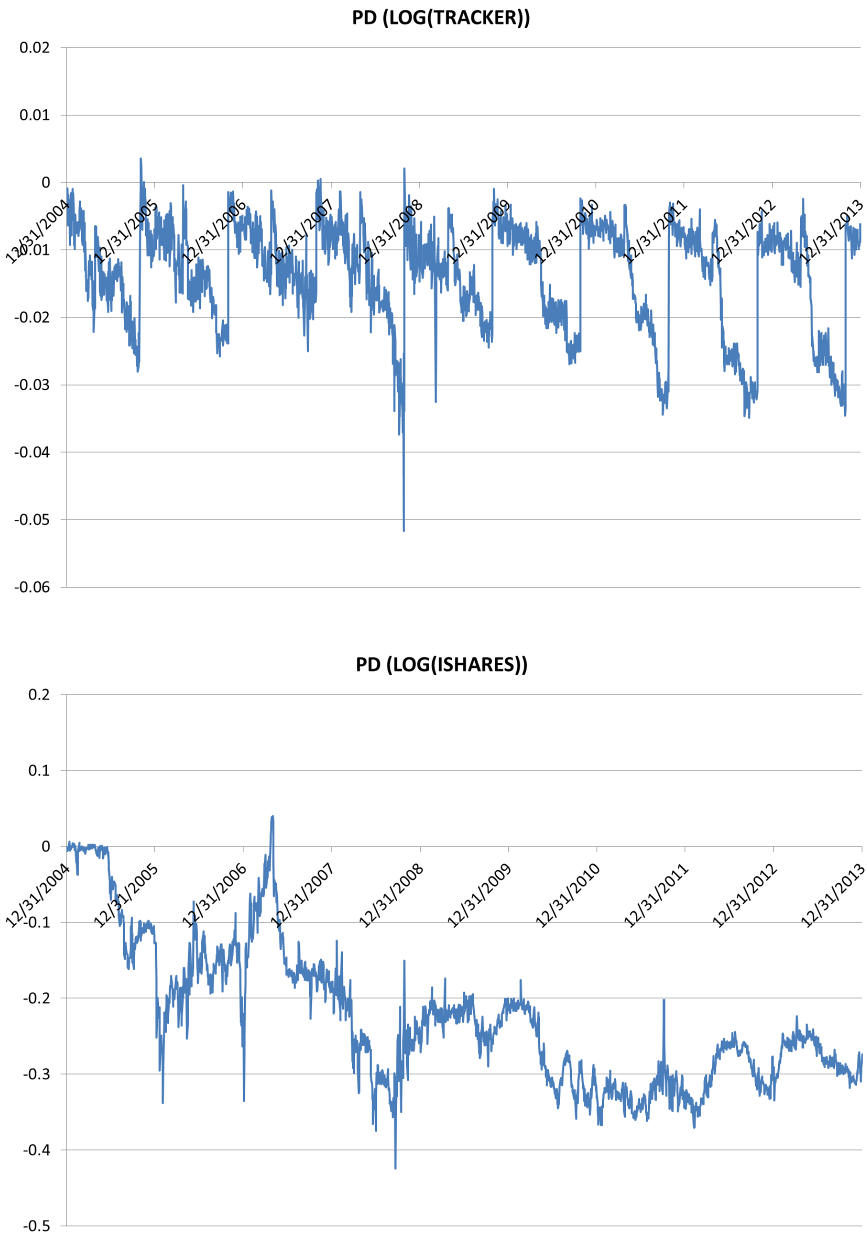

Fig. 1. (*Continued*)

ETFs to invest in the "whole" market. Thus, the premium paid by the ETF investors could have economic significance.

Synthetic ETFs are considered to have higher tracking errors compared to physical ETFs. The differences in the ETF pricing deviations are tested

Table 2. *T*-test results of the hypothesis that the expected price deviation is zero.

	Tracker Fund		X iShares A50	
	Prices	Log. Prices	Prices	Log. Prices
T-Test Statistics	−82.490*	−86.673*	−94.577*	−117.010*

Note: This table presents the results of the *t*-test of the null hypothesis that the expected value of price deviation equals zero.
*denotes significant at 1%.

using the conventional *t*-test. The *t*-test results for the differences between the means of the two ETFs are reported in Table 3. The results support the hypothesis that the mean pricing deviation of X iShares A50 (which is a synthetic ETF) is different from that of Tracker Fund. Similarly, the directional one-tailed result supports the hypothesis that the mean pricing deviation of X iShares A50 is significantly higher than that of Tracker Fund. It is easy to understand why synthetic ETFs have higher tracking errors. The managers of synthetic ETFs may not find derivatives that exactly match the stocks that are included in their benchmark indices; thus, they may not track the performance of their benchmark indices perfectly.

According to Hypothesis 2, the time series of pricing deviation is stationary. The results of the ADF test for unit roots are summarized in Table 4. The results show that the pricing deviations of price and logarithmic price of both Tracker Fund and X iShares A50 are stationary at the 1% level. Thus, the results support the hypothesis of stationarity; i.e., Hypothesis 2 is supported. This implies that the time series of pricing deviation does not stem from a random walk process; thus, it could be predictable.

Table 3. Results of *t*-test for difference between the means of ETFs pricing deviations.

	Prices	Log. Prices
	Tracker Fund	
X iShares A50	82.50*	109.18*

Note: This table presents the results of the *t*-test of equal means of price deviations measured by using prices and logarithmic prices between the two sampled ETFs.
*denotes significant at 1%.

Table 4. Results of augmented Dickey Fuller test on stationarity of price deviations.

	Tracker Fund		X iShares A50	
	Prices	Log. Prices	Prices	Log. Prices
ADF Test Statistics	−48.423*	−13.167*	−11.249*	−21.526*

Note: This table presents the results of the ADF (Augmented Dickey-Fuller) test on the hypothesis that the price deviation is stationary. The ADF test tests the null hypothesis that α coefficient in the regression $\Delta PD_t = \beta_0 + \delta PD_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta PD_{t-i} + \varepsilon_t$ equals 1, which indicates the time series is not stationary.
*denotes significant at 1%.

Table 5 summarizes the results of the Kolmogorov-Smirnov normality test. The test results indicate that the hypothesis that pricing deviation is normally distributed (Hypothesis 3) should be rejected. The summary statistics summarized in Table 1 indicate that the pricing deviations of price and logarithmic price of Tracker Fund are negatively skewed and platy kurtosis (negative kurtosis), while those of X iShares A50 are positively skewed and platy kurtosis. The rejection of Hypothesis 3 suggests that the distributions of the pricing deviations involve a mixture of different distributions. We attempt to test whether the series have autoregressive conditional heteroscedasticity (ARCH) behavior, which is autoregressive behavior conditional on earlier information. The results of the ARCH Lagrange multiplier (LM) test for the ARCH effect in these series are presented in Table 6; the results reject the null hypothesis that there is no ARCH effect.

The ARCH LM test indicates there is ARCH effect in the series of pricing deviations. We attempt to determine which ARCH model is appropriate for describing the series. We consider nine different ARCH models: GARCH

Table 5. Results of Kolmogorov–Smirnov test on normality of price deviations.

	Tracker Fund		X iShares A50	
	Prices	Log. Prices	Prices	Log. Prices
KS Test Statistics	0.120*	0.095*	0.107*	0.091*

Note: This table presents the results of the KS (Kolmogorov-Smirnov) test on the null hypothesis that the price deviation is normal.
*denotes significant at 1%.

Table 6. Results of ARCH LM test on price deviations.

	Tracker Fund		X iShares A50	
	Prices	Log. Prices	Prices	Log. Prices
LM Statistics	1931.89*	1502.61*	2173.93*	2271.53*

Note: This table presents the results of the ARCH LM test on the null hypothesis that there is no first-order ARCH effects in the price deviations. The LM statistics is $LM = n \cdot R^2$ where $R^2$is from the auxiliary regression $\hat{e}_t^2 = \gamma_0 + \gamma_1 \hat{e}_{t-1}^2 + \nu_t$.
*denotes significant at 1%.

(1,1), EGARCH(1,1) (exponential GARCH), and PARCH(1,1) (power ARCH) models, each with normally distributed residuals, t-distributed residuals, and generalized error distributed (GED) residuals. The AIC of the different ARCH models developed are summarized in Table 7 (the model specifications are not reported in this paper; they are available on request). Based on the AIC, the best selected model is EGARCH(1,1) with GED residuals, since it exhibits the lowest AIC value. The existence of ARCH effect in the series of pricing deviation suggests that volatility is clustered before and after the financial crisis.

One objective of this study was to test whether the ETF price and the stock market price (i.e., price of the underlying index) are co-integrated. Two prices are considered to be co-integrated if they share a stochastic trend; the relationship between arbitrage pricing and co-integration should follow a stationary linear combination. Linear arbitrage pricing gives the exact combination of the other assets needed to duplicate one asset. Thus, such linear pricing not only leads to co-integrated systems of assets but also provides the exact combinations of the assets needed to establish co-integration. The presence of common stochastic trends further restricts the set of statistical models that could be used to test and implement financial theories (Brenner and Kroner, 1995).

Table 8 presents the results of the bivariate co-integration test. The trace statistics for the price and log-price of the two ETFs are mostly significant at either 5% or 10%. The results provide support for the existence of co-integration and the absence of arbitrage opportunities.

5.2. *Time series analysis*

The ETF price and the index price are found to be co-integrated. Therefore, the error correction model (ECM) described in Model (9), which includes an

Table 7. Akaike Info Criteria (AIC) of different ARCH models on price deviations.

	Tracker Fund		X iShares A50	
	Prices	Log. Prices	Prices	Log. Prices
GARCH(1,1)				
Normal	11.978	−7.629	15.897	−3.000
Student's t	12.752	−7.628	16.676	−2.997
GED	11.978	−7.754	15.759	−3.225
EGARCH(1,1)				
Normal	12.106	−7.645	15.912	−2.993
Student's t	12.419	−7.643	16.441	−2.990
GED	11.963#	−7.789#	15.691#	−3.218#
PARCH(1,1)				
Normal	12.103	−7.643	15.894	−3.000
Student's t	12.123	−7.641	16.075	−2.990
GED	11.967	−7.776	15.695	−3.213

Note: This table reports the Akaike Info Criteria (AIC) of different ARCH models. GARCH(1,1), EGARCH (1,1) and PARCH(1,1) with Gaussian normally distributed errors, Student's t distributed errors, and generalized errors (GED) are generated respectively on the price deviations.
#denotes the best ARCH model based on AIC.

Table 8. Bivariate cointegration test by Johansen procedure.

ETF	Number of Co-Integrations	Eigenvalue	Trace Statistic	Critical Value at 5%	Critical Value at 1%
Tracker fund (Prices)	$r = 0$	0.0126	35.1249*	15.41	20.04
	$r \leq 1$	0.0022	5.3180**	3.76	6.65
Tracker fund (Log. prices)	$r = 0$	0.0133	36.4927*	15.41	20.04
	$r \leq 1$	0.0021	5.0193**	3.76	6.65
X iShares A50 (Prices)	$r = 0$	0.0064	18.3617**	15.41	20.04
	$r \leq 1$	0.0013	3.2776***	3.76	6.65
X iShares A50 (Log. prices)	$r = 0$	0.0052	14.8673***	15.41	20.04
	$r \leq 1$	0.0010	2.4183	3.76	6.65

* Indicates significant at 1%; ** indicates significant at 5%; ***indicates significant at 10%
The critical values of the ADF tests are developed by MacKinnon *et al.* (1999).

error correction term when modeling the co-integrated variables, may be estimated. According to Granger (1986), including an error correction term as a regressor could provide a better forecasting ability compared to traditional time-series models. The specification of the ECM constructed is shown in Table 9. Most of the model estimates do not have any significant regression coefficient, and all the coefficients are jointly not significant, except the price of X iShares A50. All the β_2 coefficients — which represent the impact of the underlying index on the ETF price — are positive, although they are not significant. This finding indicates that the ETF price is positively affected by the price of the underlying index. The sign of the error correction coefficient (γ) is different for Tracker Fund and X iShares A50. This indicates a difference in the responses of the two sampled ETFs with regard to adjusting to the previous day's deviation in the ETF price relative to the underlying index price. The adjustment represented by the error correction term indicates the arbitrage forces that constantly act to reduce the continuous mispricing of the ETFs.

5.3. *Determinants of pricing deviations*

Table 10 presents the results of the time series regression model of the pricing deviations of Tracker Fund and iShares A50 ETF based on the selected determinants over the period 2005–2013. The selected determinants include the ETFs' logarithmic market value, dividend yields, logarithmic trading volumes, bid-ask spread, and market volatility. All the individual time series of the selected determinants are proved to be stationary according to the ADF test. The results indicate that the pricing deviations are significantly influenced by the selected determinants at either 0.05 or 0.01 significance level, and they exhibit the expected signs. Thus, larger funds produce less deviation in pricing, which confirms our expectation that larger funds should have lower transaction costs for trading stocks because of the economies of scale involved. Dividend yield is found to have a positive impact on pricing deviation, which supports the theory that the delays in receiving dividends and the costs associated with re-investment could erode the ETFs' ability to replicate index performance. Larger trading volume reflects a larger difference in investor opinions about the market, which drives the ETFs' price away from the market index. The positive relation between bid-ask spread and pricing deviation indicates the premiums of the ETFs, which are associated with the investors' transaction costs. Higher risk in the market could make it more difficult for ETFs to replicate performance, leading to higher pricing deviation.

Overall, the time series regression results show that pricing deviation increases with lower market value, higher dividend yield, larger trading volume, larger bid-ask spread, and higher market volatility. The F-statistics

Table 9. Error correction models (ECM) for ETF's prices and underlying index.

	Tracker Fund		X iShares A50	
	Prices D(PRICES)	Log. Prices D(LOG_PRICES)	Prices D(PRICES)	Log. Prices D(LOG_PRICES)
EC(-1)	0.04856 [1.15167]	0.02852 [0.65773]	−0.02570 [−3.99624]*	−0.01660 [−3.41305]*
D(PRICES(-1))	−0.19869 [−1.63810]	−0.19715 [−1.63508]	−0.07160 [−2.02533]**	−0.05505 [−1.67101]
D(PRICES(-2))	−0.06655 [−0.55792]	−0.25280 [−2.13027]**	−0.17209 [−4.85861]*	−0.10050 [−3.04596]*
D(INDEX(-1))	0.00015 [1.24464]	0.15273 [1.28735]	0.00008 [1.59182]	0.03470 [0.87490]
D(INDES(-2))	0.00004 [0.39718]	0.25243 [2.17108]**	0.00013 [2.55810]**	0.07641 [1.93746]
Alpha	0.00426 [0.65250]	0.00023 [0.69600]	0.00251 [0.42900]	0.00038 [0.85559]
F-Statistics	1.6975	1.9241	10.0101#	5.0328

Note: Error correction models for ETF prices are estimated. The table reports the results of two lag lengths of ETF prices and index prices. D denotes the difference operator, EC denotes the equilibrium errors, and Alpha denotes the intercept of the ECM. The *t*-statistics of the test of significance of the coefficients in ECM are shown in parentheses. The F-statistics of the test of joint significance of all coefficients in ECM are presented in the last row.
*denotes significant at 1%, ** denotes significant at 5%
#deontes significant at 1% to reject the null hypothesis of no causality.

Table 10. Determinants of pricing deviations.

	Tracker Fund		X iShares A50	
	Prices	Log. Prices	Prices	Log. Prices
MV	−217.9869 [−7.9195]**	−0.0039 [−3.1327]**	−856.5437 [−28.9915]**	−0.0575 [−33.6684]**
DIV	25.9529 [3.9346]**	0.0004 [1.3080]	599.3022 [19.6478]**	0.0123 [5.5399]**
VOL	18.3105 [4.1666]**	0.0006 [2.6357]**	104.1349 [3.3701]**	0.0109 [6.7058]**
SPRD	460.6588 [2.5197]*	0.0238 [2.3596]*	189.8200 [6.3388]**	0.0783 [0.9880]
RISK	618.5570 [4.9762]**	0.0011 [0.2011]	659.1076 [2.4771]*	0.1538 [9.1935]**
Constant	193.0230 [1.4970]	0.0335 [1.8440]	505.5420 [1.4815]	0.3972 [1.7297]
R-Square	0.5457	0.5250	0.7031	0.7010
F-Statistics	79.9366**	25.9555**	110.0270**	109.8900**

Note: The table presents the results of time series regression model of pricing deviations on the natural logarithm of market value (MV), dividend yield (DIV), natural logarithm of trading volume (VOL), bid-ask spread ($SPRD$), and the market risk ($RISK$), as well as the values of R^2 to and F-statistics for testing the overall significance of the model, over the period 2005–2013. The t-statistics of the regression coefficients are in the parentheses.
Model number (10): $|PD_{i,t}| = \beta_0 + \beta_1 \cdot MV_{i,t} + \beta_2 \cdot DIV_{i,t} + \beta_3 \cdot VOL_{i,t} + \beta_4 \cdot SPRD_{i,t} + \beta_5 \cdot RISK_{i,t} + \varepsilon_{i,t}$
*denotes significant at 5%; **denotes significant at 1%.

for the overall significance of the selected determinants are highly significant. However, the R-square values are 52–70%, which indicates that a significant portion of pricing deviation remains unexplained.

The magnitude of the regression coefficients of the determinants (except bid-ask spread) are relatively higher for X iShares A50. This implies that the inability to track market performance is more sensitive to market factors in the case of synthetic ETFs, which use financial derivatives to replicate the market performance. This result could provide insights to investors as to why synthetic ETFs are unable to track the market during market fluctuations.

6. Conclusion

Exchange-traded funds (ETFs) have become increasingly popular since their introduction in Hong Kong in 1999. From the investors' perspective, this study provides better understanding of and information about the two most popular ETFs in Hong Kong, Tracker Fund and X iShares A50. The turnover of these two ETFs is more than half the total turnover of all the ETFs in the Hong Kong market. We showed that the pricing deviation is non-zero. Additionally, we found that the deviation increases in the years following the ETF's introduction. The pricing deviation could be considered to be the premium paid by individual investors to invest in the "whole" market, since there is a high cost associated with replicating the whole market by investing in individual stocks separately. The pricing deviation of the two ETFs are found to be predictable since their corresponding time series are found to stem from stationarity (i.e., they do not follow a random walk process).

The time series analysis showed that both series of pricing deviations are not normally distributed; they exhibit the ARCH effect. This indicates that the volatility was clustered around the financial crisis. The co-integration analysis provided evidence for the co-integration between the price of each ETF and the price of its tracing index. The existence of co-integration implies the absence of arbitrage opportunities for the individual investors. An error correction model (ECM) that can suit both ETF price dynamics and the investors' behavior was constructed. The ECM indicated that the ETF price is positively affected by the index price, and the arbitrage forces constantly reduce the continuous mispricing of ETFs. Finally, a time series regression model of pricing deviation based on the five selected time series variables was constructed. The regression model indicated that the pricing deviation increases with lower market value, higher dividend yield, larger trading volume, larger bid-ask spread, and higher market volatility. The size of the regression coefficients of the selected determinants (except the bit-ask spread) are relatively higher for the synthetic ETF, X iShares A50 ETF. This explains why synthetic ETFs have relatively poor ability to track the market during financial market fluctuations. The results reported in this study may lead to arguments about whether ETFs are good alternatives to actively managed funds and retail passively managed funds. The results seem to suggest that it is not sensible for investors to rush into investing in ETFs, despite the increasing popularity of these investment vehicles over the last years.

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References

Aber, JW, D Li and L Can (2009). Price volatility and tracking ability of ETFs. *Journal of Asset Management*, 10, 210–221.

Akaike, H (1970). Autoregressive model fitting for control. *Annals of the Institute of Statistical Mathematics*, 22, 163–180.

Blitz, D, J Huij and L Swinkels (2012). The performance of European index funds and exchange-traded funds. *European Financial Management*, 18, 649–662.

Blume, L, D Easley and M O'Hara (1994). Market statistics and technical analysis: The role of volume. *Journal of Finance*, 49, 153–181.

Bollapragada, R, I Savin and L Kerbache (2013). Price forecasting and analysis of exchange traded fund. *Journal of Mathematical Finance*, 3, 181–191.

Brenner, RJ and FK Kroner (1995). Arbitrage, cointegration, and testing the unbiasedness hypothesis in financial crisis. *Journal of Financial and Quantitative Analysis*, 30, 23–42.

Chang, EC, PC Jain and PR Locke (1995). Standard & poor's 500 index futures volatility and price changes around the New York stock exchange close. *Journal of Business*, 68, 61–84.

Cheng, LTW, HG Fung and Y Tse (2008). China's exchange traded fund: Is there a trading place bias?*Review of Pacific Basin Financial Markets and Policies*, 11, 61–74.

Chu, PKK (2011). Study on the tracking errors and their determinants: Evidence from Hong Kong exchange traded funds. *Applied Financial Economics*, 21, 309–315.

DeFusco, RA, SI Ivanov and GV Karels (2011). The exchange traded funds' pricing deviation: Analysis and forecasts. *Journal of Economics and Finance*, 35, 181–197.

Delcoure, N and M Zhong (2007). On the premiums of iShares. *Journal of Empirical Finance*, 14, 168–195.

Dickey, F and WA Fuller (1979). Distribution of the estimates for autoregressive time series with a unit root. *Journal of American Statistical Association*, 74, 427–431.

Dickey, F and WA Fuller (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49, 1057–1072.

Elton, EJ, MJ Gruber, G Comer and K Li (2002). Spiders: Where are the bugs? *Journal of Business*, 75, 453–472.

Granger, CWJ (1986). Developments in the study of cointegrated economic variables. *Oxford Bulletin of Economics and Statistics*, 48, 213–228.

Granger, CWJ (1988). Some recent developments in the concept of causality. *Journal of Econometrics*, 39, 199–211.

Ivanov, S (2011). ETF volatility around the New York stock exchange close. *Journal of Accounting and Finance*, 11, 37–46.

Johansen, S (1991). Estimation and hypothesis testing of cointegration vectors. *Econometrica*, 59, 1551–1580.

Johnson, W (2009). Tracking errors of exchange traded funds. *Journal of Asset Management*, 10, 253–262.

Kadapakkam, P, T Krause and Y Tse (2015). Exchange traded funds, size-based portfolios, and market efficiency. *Review of Quantitative Finance and Accounting*, 45, 89–110.

Madura, J and T Ngo (2008). Clustered synergies in the takeover market. *Journal of Financial Research*, 31, 333–356.

MacKinnon, JG, A Haug and L Michelis (1999). Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of Applied Econometrics*, 14, 563–577.

Miffre, J (2006). Country-specific ETFs: An Efficient approach to global asset allocation. EDHEC Business School Working Paper.

Pennathur, AK, N Delcoure, and D Anderson (2002). Diversification benefits of iShares and closed-end country funds. *Journal of Financial Research*, 25, 541–557.

Pope, P and P Yadav (1994). Discovering errors in tracking error. *Journal of Portfolio Management*, 20, 27–32.

Qadan, M and J Yagil (2012). On the dynamics of tracking indices by exchange traded funds in the presence of high volatility, *Managerial Finance*, 38, 804–832.

Roll, R (1992) A mean/variance analysis of tracking error. *Journal of Portfolio Management*, 18, 13–22.

Rompotis, G (2009). Interfamily competition on index tracking: The case of the vanguard ETFs and index funds. *Journal of Asset Management*, 10, 263–278.

Schuster, AJ (2008). ETFs: The next 10 years. *Global Exchanges and ETFs Report*, pp. 34–35.

Shin, S and G Soydemir (2010). Exchange-traded funds, persistence in tracking errors and information dissemination. *Journal of Multinational Financial Management*, 20, 214–234.

Toda, HY and PCB Phillips (1994). Vector autoregression and causality: A theoretical overview and simulation study. *Econometrics Review*, 13, 259–285.

Tse, Y and V Martinez (2007). Price discovery and informational efficiency of international iShares funds. *Global Finance Journal*, 18, 1–15.

White, H (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48, 817–838.

Yang, J, J Cabrera and T Wang (2010). Nonlinearity, data-snooping, and stock index ETF return predictability. *European Journal of Operational Research*, 200, 498–507.