ACTIVE MANAGEMENT AND PRICE EFFICIENCY OF EXCHANGE-TRADED FUNDS

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Abstract

This paper extends the debate over the benefits of active management by investigating its impact on price efficiency using data from available ETFs traded on the US market. After accounting for various tests in terms of price efficiency, we find that active management matters to the efficiency improvement. One practical implication of this study is that more active management element might be considered by fund managers in designing and managing their ETFs so as to reflect all available information into fund prices.

Keywords: active management, price efficiency, exchange-traded funds
JEL Classification: G11, G14

1. Introduction

As indicated by Investment Company Institute Fact Book (2014)[1], the total number of Exchange-Traded Funds (ETFs) had grown to 1,332, and total net assets were 1.675 trillion USD by the end of 2013. This explosive growth of ETFs is attributable to a more convenient and easier way to buy a diversified portfolio by investors. Since the occurrence of ETFs, the debate over whether active management pays for the investors has continued for more than 40 years. Proponents argue that active management is beneficial in case of institutional constraint and limits to arbitrage (Dyck *et al*., 2013). Opponents advocate that active management fails to create value, net of fees and expenses (Busse *et al*., 2010). However, prior work seldom addresses the impact of active management on financial markets. Does active management lead to more or less price efficiency?

In contrast with previous literature focusing on returns, persistence, risk-taking, fees, fund flows and governance of mutual funds, we examine whether active management matters to price efficiency by picking a setting with higher *ex ante* possibilities for

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1 Refer to the Internet resource www.ici.org.

efficiency to active management. Active management is taken into account because it probably enables ETFs managers to reap profit by exploiting potential mispricing. As a result, traded prices of ETFs would be pushed towards the efficient ones. In this article, price efficiency is measured by the extent to which prices include all available information. Specifically, our paper adopts various proxies for price efficiency in terms of random walks, profits from trading strategies, and transaction costs. We use data from the Center for Research in Security Prices (CRSP) survivor-bias-free US mutual fund database over 1998–2011, which involves the identification flag to differentiate the active ETFs from the passive ones. To the best of our knowledge, this paper is the first one to study the impact of active management on pricing efficiency. Although Petajisto (2013) is closest in spirit to our work, he just focuses on pricing inefficiencies of ETFs itself rather than the effect of active management on price efficiency.

Overall, our main findings suggest that active management has a positive impact on price efficiency. Specifically, actively-managed ETFs are associated with higher price efficiency relative to passively managed ETFs. First, less deviation from a random walk is observed in actively managed ETFs for various tests and over different time horizons. Second, both contrarian and momentum strategies earn significant profits in passively managed ETFs, while this finding holds invalid for active management. Third, using two measures of trading costs (Bekaert *et al*., 2007; Lesmond *et al*., 1999), we find intuitive results: actively managed ETFs have lower trading costs in comparison with passively managed ETFs. The inference from empirical tests provide support for the view expressed by Grossman and Stiglitz (1980) that prices of active funds incorporate information in a quicker way than those of passive funds. However, they fail to substantiate Admati and Pfleiderer's (1988) claim that excessive trading triggered by active managers is likely to cause a market failure, resulting in an inefficient price discovery.

The remainder of the paper proceeds as follows. Section 2 provides a review of the literature. The construction of the measures of price efficiency is presented in Section 3. Section 4 describes the data and the distribution of samples over time. Section 5 examines the effect of active management on price efficiency. Finally, our conclusions are drawn in Section 6.

2. Literature Review

The academic literature about active management is extensive in terms of theory and empirical analysis. Jensen (1968) wrote the first article to look into whether active management improves fund performance. Similar to Jensen (1968), subsequent studies also find the underperformance of active management after netting fees and expenses (Wermers, 2000; Kosowski *et al.,* 2006; Barras *et al*., 2010; Fama and French, 2010). However, there are still more and more investors choosing active investment management.

The above apparent inconsistency motivates the researchers to explore the rationale behind the preference for active management. Various explanations are thus developed in the literature to justify this contradiction from the rational expectation perspective. Gruber (1996) attributes this phenomenon to the fact that funds are bought and sold at net asset value without pricing management ability. In this sense, performance and cash flows into and out of funds are predictable so that sophisticated investors can earn above-average returns in these funds. Savov (2009) builds a noisy rational expectations model with wealth shocks to show that active funds and index funds are equally attractive as long as time-varying exposure is considered. Another model proposed by Glode (2011) also documents the active funds' significant better realized performance in bad states of the economy than in good states. Pastor and Stambaugh (2012) rationalize this puzzle by the impact of slow Bayesian updating. Given decreasing returns to scale for active managers, investors would continue allocating capital to active funds until their desired expected return is achieved. More recently, Foster and Warren (2013) suggest that the preference over active management is due to investors' perception that they have some ability to identify good managers.

Another emerging line of studies tries to address this concern with the recent development of behavioural finance (Christoffersen and Musto, 2002; Gil-Bazo and Ruiz-Verdu, 2009; Choi *et al*., 2010; Boldin and Cici, 2011). Unsophisticated investors can be so easier affected by marketing material and consultant advices that they make their suboptimal investment decisions following such incomplete information. As a result, these investors tend to pay higher fees to the active management in spite of funds' poor performance. In terms of sophisticated investors, Agarwal *et al.,* (2010) documents that active management is always employed by institutional investors because they can take an advantage of their private information.

The above literature, both rational and behavioural, seems to suggest that information is a significant consideration for investors to select active management. Compare to active funds, passive funds might behave like noise traders. One common feature is that they cannot have access to any superior information about the asset value in their portfolios. The reflection of information into asset prices is realized by informed traders through active management (Grossman and Stiglitz, 1980). Therefore, mispricings generated by excessive transaction from passive traders could lead to the engagement of informed traders *via* active management, which helps to attain price efficiency. Following the prediction of Grossman and Stiglitz (1980) model, active management can accelerate the inclusion of private information into prices and thus enhancing price efficiency of ETFs. Therefore, we propose price efficiency to justify why investors attach importance to active management. In our view, prices of ETFs would be more efficient when active management is in place, as they increase the speed of adjustment to private information. Our following analysis would test this argument by a formal empirical investigation in the ETFs market.

3. Measures of Price Efficiency

Price efficiency describes the degree to which all available information is impounded into prices accurately and quickly. If a market is fully efficient, prices should follow a random walk and thus be unpredictable. In addition, investors fail to earn abnormal returns in the absence of trading costs regardless of trading strategies. However, such theoretical efficiency does not exist in reality due to market frictions, which drive a temporary wedge between the traded prices and the efficient ones. In the view of prior literature, we measure price efficiency in three categories: 1) random walks; 2) trading strategies; and 3) transaction costs.

3.1 Random walk

Earlier literature develops return correlation to measure price efficiency and assess whether prices look close to a random walk. Specifically, one measure of price efficiency follows Saffi and Sigurdsson (2014) to define the correlation as the cross-correlation (*CC*) between the ETF return and its net asset value (NAV)[2]. Because we are just concerned

2 Net asset value of the ETF is calculated by dividing the total asset value in the fund portfolio, less its liabilities, by the number of fund shares outstanding.

with departures from a random walk in either direction, the absolute value of correlation is calculated. To minimize the impact of time horizon, correlation coefficients of order 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10 for daily return are estimated.

The nonparametric run test is the second empirical method to examine price efficiency. Concretely, the main idea is to look into whether successive ETF price changes (autocorrelations) are random. The null hypothesis of independence can be assessed by probing the relationship between the total number of runs and the expected number of runs (Ho *et al*., 2013). Consistently with before, we also perform run tests on autocorrelations (*AR*) of order ranging from 1 to 10 to mitigate the time effect.

As suggested by Wright (2000), price efficiency can be evaluated by the variance ratio (*VR*) test using ranks. Two potential advantages are associated with this test. On the one hand, the size distortions can be avoided since the asymptotic approximation is not required. On the other hand, this test still works even though the normal distribution is violated. We first perform a simple linear transformation of the ranks on the time series of ETF returns. Next, the ratio of long-term return variances to short-term return variances, divided by unit time, would be constructed for hypothesis testing. As above, we just calculate the absolute deviations from one for variance ratios ($|VR(m,n)-1|$), where $VR(m,n)$ represents the return variance over *m* periods to the return variance over *n* period, both adjusted by the length of the period. For reliability, tests based on *VR* of (2,1), (3,1), (4,1), (5,1), (6,1), (7,1), (8,1), (9,1), and (10,1) is conducted to alleviate the influence of time horizon.

The transaction-cost model (Mech, 1993) indicates that delays occur between the arrival of information and its inclusion into prices, which is not captured by return correlations and variance ratios. Hence, we employ the following method to capture the average delay with which a ETF's price responds to market information. The NAV return is viewed as the relevant news to which ETFs respond. For each ETF, we run the unrestricted and the restricted models over the entire sample period. The model involving *n* lags of NAV returns is given as follows:

$$NR_{i,t} = \alpha_i + \sum\nolimits_{j=0}^{n} \beta_{j,i} IR_{i,t-j} + \varepsilon_{i,t} \tag{1}$$

Where $IR_{i,t}$ is the return on ETF *i*'s NAV on day *t*, and $NR_{i,t}$ is the return on ETF *i* on day *t*. If all β_j ($j\neq 0$) are equal to zero, the above specification is the restricted model. Otherwise, it is the unrestricted model. Next, we compute delay measures for individual ETFs relying on the R^2 from unrestricted and restricted regressions. This measure is proposed by Hou and Moskowitz (2005) and defined as:

$$\text{Delay} = 1 - \frac{R^2_{restricted}}{R^2_{unrestricted}} \tag{2}$$

The next method is based on the stochastic dominance (*SD*) theory and later used by various studies to investigate price efficiency (Chan *et al*., 2012). *X* and *Y* are return series from two assets with a common support of $\Omega = [a, b]$. In this paper, X represents the ETF and Y represents the NAV of the ETF. Given $\{X_i\}$ and $\{Y_i\}$ are subject to i.i.d. and withdrawn from their probability density functions (f, g), their cumulative distribution functions (F, G) can be estimated by:

$$\hat{F}_j(x) = \frac{1}{N(j-1)!}\sum_{i=1}^{N}(x - z_i)_+^{j-1}, \ \hat{G}_j(y) = \frac{1}{N(j-1)!}\sum_{i=1}^{N}(y - z_i)_+^{j-1} \tag{3}$$

Where $(x - z_i)_+ = \max(x - z_i, 0)$ and $(y - z_i)_+ = \max(y - z_i, 0)$ for $j = 1, 2, 3$. The SD rule dictates that higher expected utility would be assigned to risk-averse investors if acquiring the dominant asset rather than the dominated asset. In this sense, the following hypotheses are developed based on the first-order, second-order, and third-order stochastic dominance:

H_0: $F_j(x_i) = G_j(y_i)$, for all x_i and y_i, $i = 1, 2, ..., k$;
H_A: $F_j(x_i) \neq G_j(y_i)$, for some x_i and y_i;
H_{A1}: $F_j(x_i) \leq G_j(y_i)$, for all x_i and y_i, $F_j(x_i) < G_j(y_i)$, for some x_i and y_i;
H_{A2}: $F_j(x_i) \geq G_j(y_i)$, for all x_i and y_i, $F_j(x_i) > G_j(y_i)$, for some x_i and y_i.

In order to perform the hypothesis testing, the modified Davidson and Duclos (2000) statistic is constructed to examine the SD relationship.

$$DD^j(z) = \frac{\hat{F}_j(x) - \hat{G}_j(y)}{\sqrt{\hat{V}_j(z)}} \tag{4}$$

where $\hat{V}_j(z) = \hat{V}_X^j(x) + \hat{V}_Y^j(y) - 2\hat{V}_{X,Y}^j(z)$,

$$\hat{V}_H^j(z) = \frac{1}{N}\left[\frac{1}{N\left((j-1)!\right)^2}\sum_{i=1}^{N}(z-h_i)_+^{2(j-1)} - \left(\frac{1}{N(j-1)!}\sum_{i=1}^{N}(z-h_i)_+^{j-1}\right)^2\right], H = F, G; z = x, y$$

$$\hat{V}_{X,Y}^j(z) = \frac{1}{N}\left[\frac{1}{N\left((j-1)!\right)^2}\sum_{i=1}^{N}(z-x_i)_+^{(j-1)}(z-y_i)_+^{(j-1)} - \hat{F}_j(x)\hat{G}_j(y)\right]$$

Based on this statistic, the decision rule is also modified by Bai *et al.* (2011) as follows:

$\max_{l \leq k \leq K} \left|DD^j(\mathrm{X_k})\right| >$ accept $\mathrm{H}_0 : X =_j Y$

$\max_{l \leq k \leq K} DD^j(x_k) > M_\alpha^j$ and $\min_{l \leq k \leq K} DD^j(x_k) < -M_\alpha^j$, accept H_A: $X \neq_j Y$

$\max_{l \leq k \leq K} DD^j(x_k) > M_\alpha^j$ and $\min_{l \leq k \leq K} DD^j(x_k) < -M_\alpha^j$, accept H_{A1}: $X \geq_j Y$

$\max_{l \leq k \leq K} DD^j(x_k) > M_\alpha^j$ and $\min_{l \leq k \leq K} DD^j(x_k) > -M_\alpha^j$, accept H_{A2}: $X \leq_j Y$

where M_α^j is the critical value of *j* order *DD* statistic by the bootstrapping technique.

The final measure of testing the random walk is in the view of Hasbrouck (1993), who decomposes the observed transaction price at time t, p_t, into the sum of the efficient price (m_t) and the pricing error (s_t).

$$p_t = m_t + s_t \tag{5}$$

Intuitively, the standard deviation of the pricing error, σ_s, measures how closely the transaction price tracks the efficient price, and thus can be interpreted as a proxy for price efficiency. We next turn to estimation of the pricing error. Similar to Hasbrouck (1993), a vector autoregression (VAR) model is specified to allow for general serial correlations in the returns between ETFs and their NAV.

$$NR_t = \sum_{i=1}^{n} a_i NR_{t-i} + \sum_{j=1}^{m} b_j IR_{t-j} + \varepsilon_{1,t}$$
$$IR_t = \sum_{i=1}^{n} c_i NR_{t-i} + \sum_{j=1}^{m} d_j IR_{t-j} + \varepsilon_{2,t} \tag{6}$$

where $IR_{i,t}$ is the return on ETF i's NAV on day t, and $NR_{i,t}$ is the return on ETF i on day t. The vector moving average (VMA) representation, obtained from the VAR system, can express the variables in terms of current and lagged disturbances (Judge *et al*., 1985).

$$NR_t = \sum_{j=1}^{\infty} a_i^{*} \varepsilon_{1,t-i} + \sum_{j=1}^{\infty} b_j^{*} \varepsilon_{2,t-j} \tag{7}$$
$$IR_t = \sum_{j=1}^{\infty} c_i^{*} \varepsilon_{1,t-i} + \sum_{j=1}^{\infty} d_j^{*} \varepsilon_{2,t-j}$$

An expanded representation for the pricing error of the underlying efficient price decomposition model (5) is derived in equation (8):

$$s_t = \sum_{i=1}^{\infty} \alpha_i \varepsilon_{1,\, t-i} + \sum_{j=1}^{\infty} \beta_j \varepsilon_{2,\, t-j} + \sum_{k=1}^{\infty} \gamma_k \varepsilon_{t-k} \tag{8}$$

After imposing the identification restriction that s_t must be correlated with $\{NR_t, IR_t\}$, the α*'s* and β's in (8) can be computed:

$$\alpha_i = -\sum_{i=k+1}^{\infty} a_i^{*} \quad \beta_j = -\sum_{j=k+1}^{\infty} b_j^{*} \tag{9}$$

Based on these coefficients used in (9), the pricing error variance is estimated by

$$\sigma_s^2 = \sum_{j=0}^{\infty} \left| [\alpha_j \;\; \beta_j] \mathrm{Cov}\,(\varepsilon) \begin{bmatrix} \alpha_j \\ \beta_j{}' \end{bmatrix} \right. \tag{10}$$

In order to make a meaningful comparison, pricing error (σ_s) should be normalized by the standard deviation of ETFs prices (σ) in the empirical section.

3.2 Trading strategy

There is another line of literature examining price efficiency by looking into whether any profitable trading strategies for a particular asset survive in the market. In a frictionless market, prices neither overreact nor underreact to information, and thus forming portfolios that group assets according to their past returns fails to generate any profits. In this sense, we could assess price efficiency of ETFs by evaluating the profitability of two distinct trading strategies, namely, contrarian and momentum. To the best of our knowledge, these strategies, while widely employed to measure price efficiency of stocks, have not been applied to ETFs so far.

The contrarian strategy might earn abnormal returns by taking short positions in assets that underwent recent price increases and long positions in those that suffered recent prices declines. As explained by Jegadeesh (1990), asset prices tend to revert if the prices are pushed in a certain direction attributable to either pressure or overreaction. How to form portfolios to measure abnormal returns is crucial to test the price efficiency based on the contrarian strategy.

Similar to Jegadeesh (1990), we consider the following strategies involving a given set of N ETFs over T periods. At the beginning of each period t, ETFs are ranked in descending order on the basis of one-week (four-week) past returns, and then ten portfolios are formed. Concretely, ETFs in the top decile are labelled as portfolio *P1* (winners), and ETFs in the bottom decile are labelled as portfolio *P10* (losers). In addition, each ETF in a portfolio is assumed to carry an equal weight when calculating the average return. This procedure is applied to every day to update the portfolio. If long positions for winners (*P1*) and short positions for losers (*P10*) are taken simultaneously after portfolio formation, abnormal returns are calculated over different holding horizons spanning from 1 to 4 weeks. Following Griffin *et al*. (2010), we take the convention of skipping a week between the portfolio formation and the holding periods. Doing so allows us to reduce the adverse effect of distortions by market microstructure.

Even though contrarian strategies have attracted a lot of attention in the literature, recent studies (Jegadeesh and Titman, 1993) on price efficiency concentrate on relative strength of momentum strategies. Such strategy is totally different from the contrarian strategy, because buying past winners and selling past losers with a longer formation and holding horizon are its conspicuous characteristics. In light of Griffin *et al*. (2010), we focus on four momentum strategies. Specifically, they are constructed over the 13-week or 26-week portfolio formation and 13-week or 26-week holding period, respectively. Consistent with prior work, skipping a week between the portfolio formation and holding period is used to calculate abnormal returns for these four momentum strategies.

3.3 Transaction cost

Transaction costs are one of the important analyses on price efficiency. In spite of not a direct measure, transaction costs are usually viewed as a friction to prevent information from being impounded into asset prices. However, transaction costs estimates are not always available, or where available, are cumbersome to use. In this paper, we measure transaction costs in accordance with Bekaert *et al.* (2007) and Lesmond *et al*. (1999).

Our first BHL measure (Bekaert, Harvey, and Lundblad, 2007) of transaction costs relies on the incidence of observed zero daily return, averaged over the month. The merit of the BHL measure is that it just requires a time-series of daily asset returns. As pointed out by Kyle (1985), this measure is an attractive empirical alternative in comparison to the paucity of time-series data on preferred measures such as bid-ask spreads or bona-fide order flow.

Our second LOT measure (Lesmond, Ogden, and Trzcinka, 1999) infers trading costs from the limited dependent variable model developed by Tobin (1958) who assumes informed investors engage in trading if the value of information exceeds its transaction costs. The limited dependent variable model built on the relationship between observed returns and true returns is specified as follows:

$$nr_{i,t} = \beta_i IR_{i,t} + \varepsilon_{i,t} \tag{11}$$

$$\begin{aligned} NR_{i,t} &= nr_{i,t} - \alpha_{i,1} && \text{if } nr_{i,t} < \alpha_{i,1} \\ NR_{i,t} &= 0 && \text{if } \alpha_{i,1} < nr_{i,t} < \alpha_{i,2} \\ NR_{i,t} &= nr_{i,t} - \alpha_{i,2} && \text{if } \alpha_{i,2} < nr_{i,t} \end{aligned}$$

where $nr_{i,t}$ is the true return on ETF i on day t, $NR_{i,t}$ is the observed return on ETF i on day t, and $IR_{i,t}$ is the observed return on ETF i's NAV on day t. For ETF i, the threshold to trigger trades in negative and positive information is $\alpha_{i,1}$ and $\alpha_{i,2}$, respectively. If the true return lies between $\alpha_{i,1}$ and $\alpha_{i,2}$, the observed return will be equal to zero since transaction costs are greater than the trading profit. The difference between $\alpha_{i,1}$ and $\alpha_{i,2}$ may be interpreted as the round-trip transaction costs, which captures not only direct costs such as bid-ask spreads and commissions, but also indirect costs such as opportunity costs.

4. Data and Summary Descriptive

We retreat data from the Center for Research in Security Prices (CRSP) survivor-bias-free US mutual fund database, which collects a history of each mutual fund's name, investment style, fee structure, holdings, asset allocation, daily total returns, daily net asset values, and dividends. In addition, schedules of rear and front load fees, asset class codes, and management company contact information are provided. The resulting complete data set on ETFs is available only since 1999.

Table 1 | Breakdown of ETFs Sample

Year	All	Passively managed ETFs	Actively managed ETFs
1998	29	29	0
1999	30	30	0
2000	75	75	0
2001	97	97	0
2002	107	107	0
2003	119	119	0
2004	152	152	0
2005	202	202	0
2006	338	334	4
2007	551	526	25
2008	681	632	49
2009	743	683	60
2010	838	759	79
2011	821	749	72
All	369	321	48

Note: Table 1 reports the breakdown of our exchange-traded funds sample each year by the self-reported investment objectives. According to CRSP mutual fund database, exchange-traded funds are classified as passively managed ETFs (pure index ETFs) and actively managed ETFs (index-enhanced ETFs).

In accordance with the index fund flag, ETFs are classified into index-based funds, pure index funds, and index-enhanced funds. Because of both active and passive management used simultaneously in the index-based funds, these samples are removed firstly. Overall, the remaining number of ETFs is 944 in our sample during the period from 1999 to 2011.

As indicated in Table 1, there are around 369 ETFs on average across every year. The number of ETFs increases from 29 in 1999 to 821 toward the end of the sample period. About 87% of the ETFs in our sample are classified as passively managed ETFs (pure index ETFs), and the other 13% are classified as actively managed ETFs (index-enhanced ETFs). The purpose of sample categorization is to investigate price efficiency of actively managed ETFs benchmarking with passively managed ETFs.

5. Empirical Finding

5.1 Results from random walk tests

We now turn to common and formal analysis by conducting six tests related to departures from random-walk pricing, including cross-correlation test, run test on autocorrelations, variance ratio test using ranks, delay measure test, stochastic dominance test, and pricing error test. Our results in Table 2 are presented in two groups classified by passively and actively managed ETFs to allow for clear comparison.

Panel A indicates that the absolute value of the cross-correlation is significant for both actively and passively managed ETFs over different time horizons. Overall, active management persistently has a lower CC relative to passive management. Even though an opposite pattern is observed for cross-correlations at certain order such as 7 and 9, yet it is statistically insignificant. In this sense, active management seems to weaken the correlation between ETF returns and its NAV returns, which contributes to the inclusion of information into ETF prices.

Next we focus on run tests on autocorrelations for ETFs with and without active management. As expected, in Panel B we find that prices of active ETFs are independent and random. However, passive management would lead to price inefficiency because of rejecting the null hypothesis. In addition, the value of Z statistic is also improved significantly for active funds in comparison to passive funds across all orders of autocorrelations. This implies that ETFs would enhance their price efficiency after active management is employed, which is in line with the prediction of Grossman and Stiglitz (1980).

In order to avoid the potential impact from non-trading and bid-ask bounce, it is necessary to repeat the analysis by means of variance ratio tests using ranks. Similar to cross-correlations and autocorrelations, variance ratios are computed at the daily frequency. In most of our analysis, we employ the absolute value of the variance ratio statistic minus one to make sensible comparison. From Panel C, the results indicate that the random walk hypothesis is rejected for both active and passive funds. But we can still infer that active management facilitates incorporating information into prices because the value of variance ratio is reduced in actively managed funds at horizons of 2 (0.062) and 3 (0.020). And such significant effect is not detected as the horizon increases over 3 days.

However, the above tests are likely to be biased since they fail to control for potentially omitted variables. The delay measure following Hou and Moskowitz (2005) can alleviate these concerns. Generally, the delay measure describes the degree to which current asset returns represent past market-wide information. In the present study, we let the return on ETFs' NAV proxy for market-wide information. Table 2 reports the magnitude of the delay measure averaged over actively managed ETFs and, separately, over passively managed ETFs in Panel D. Two important findings emerge. First, by contrast with passively managed ETFs, delay is universally higher but insignificant among active funds, suggesting that active management could lead to a random walk.

Table 2 | Random Walk Tests

Panel A: Cross-correlation test

	|CC1|	|CC2|	|CC3|	|CC4|	|CC5|	|CC6|	|CC7|	|CC8|	|CC9|	|CC10|
Passive	0.160**	0.085**	0.110**	0.078**	0.077**	0.095**	0.083**	0.117**	0.073**	0.146**
Active	0.131**	0.084**	0.088**	0.069**	0.062**	0.074**	0.095**	0.088**	0.084**	0.131**
Diff.	0.029*	0.001	0.022**	0.009	0.015**	0.021**	−0.012	0.029**	−0.011	0.014

Panel B: Run test on autocorrelations

	AR1	AR2	AR3	AR4	AR5	AR6	AR7	AR8	AR9	AR10
Passive	−12.418**	−9.220**	−9.298**	−10.810**	−11.259**	−9.507**	−9.169**	−10.268**	−10.005**	−8.867**
Active	−1.924	−1.471	−1.244	−1.244	−0.565	−0.565	0.115	−0.791	−1.924	−2.603**
Diff.	10.494**	7.749**	8.054**	9.565**	10.695**	8.943**	9.283**	9.476**	8.081**	6.264**

Panel C: Variance ratio test using ranks

	|VR(2,1)−1|	|VR(3,1)−1|	|VR(4,1)−1|	|VR(5,1)−1|	|VR(6,1)−1|	|VR(7,1)−1|	|VR(8,1)−1|	|VR(9,1)−1|	|VR(10,1)−1|
Passive	0.475**	0.626**	0.712**	0.770**	0.809**	0.841**	0.866**	0.885**	0.900**
Active	0.413**	0.606**	0.705**	0.770**	0.814**	0.845**	0.868**	0.886**	0.900**
Diff.	0.062*	0.020*	0.007	0.000	−0.005	−0.004	−0.002	−0.001	0.000

Panel D: Delay measure test

	Delay(1)	Delay(2)	Delay(3)	Delay(4)	Delay(5)	Delay(6)	Delay(7)	Delay(8)	Delay(9)	Delay(10)
Passive	0.004**	0.006**	0.008**	0.010**	0.011**	0.011**	0.012**	0.013**	0.014**	0.015**
Active	0.018	0.018	0.020	0.021	0.022	0.022	0.026	0.030	0.031	0.032
Diff.	−0.014	−0.012	−0.012	−0.012	−0.011	−0.011	−0.014	−0.016	−0.017	−0.017

Panel E: Stochastic dominance test

	First-order Stochastic Dominance		**Second-order Stochastic Dominance**		**Third-order Stochastic Dominance**	
	Negative	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**
Passive						
DD>0	0	7.59	0	12.66	0	8.66
DD<0	0	0	0	0	0	0
Active						
DD>0	0	0	0	0	0	0
DD<0	0	0	0	0	0	0

Panel F: Pricing errors test

	σ_s	σ	σ_s/σ
Passive	0.004**	0.016**	0.245**
Active	0.009**	0.037**	0.236**
Diff.	−0.004**	−0.021**	0.008**

Note: Table 2 reports the results of various random walk tests. In Panel A, average absolute cross-correlations across passively and actively managed ETFs, and their differences are tabulated. CC_n represents the cross-correlation between ETFs' returns at time *t* and their net asset values at time *t-n*. In Panel B, run tests for autocorrelations of the premiums/discounts across passively and actively managed ETFs, and their differences are presented. AR(*n*) represents the autocorrelation based on premiums/discounts between *t* and *t-n*. In Panel C, average absolute deviations from one for variance ratios using ranks (Wright, 2000) are reported. VR(*m*,*n*) represents the variance over *m*-week returns to the variance over *n*-week returns, both adjusted by the length of the period. In Panel D, Delay measure ($1- R^2_{restricted} / R^2_{unrestricted}$) following Saffi and Sigurdsson (2014) are shown for passively and actively managed ETFs, and their differences. Delay is constructed by the unrestricted and the restricted R^2 from two variations of a basic model containing contemporaneous and lagged returns on ETFs' net asset value: Unrestricted model to calculate Delay(*n*): $NR_{i,t} = \alpha_i + \sum_{j=0}^{n} \beta_{j,i} IR_{i,t-j} + \varepsilon_{i,t}$; Restricted model to calculate Delay(*n*): $NR_{i,t} = \alpha_i + \beta_{0,i} IR_{i,t} + \varepsilon_{i,t}$. Where $IR_{i,t}$ is the return on ETF *i*'s NAV in week *t*, and $NR_{i,t}$ is the return on ETF *i* in day week *t*. In Panel E, the average percentages of the modified Davidson-Duclos statistics significantly in the negative domain and the positive domain at the 5% level are reported. In Panel F, average pricing errors (σ_s), standard deviations of closing prices (σ), and standardized pricing errors (σ_s/σ) across passively and actively managed ETFs, and their differences are documented. Pricing errors are estimated in light of Hasbrouck (1993).

** and * represent the statistical significance at the 1% and 5% level.

Second, as the horizon increases, delay keeps an increasing momentum for both active and passive ETFs. Considered together, these findings conclude that higher price efficiency, measured by delay, is associated with active management.

In terms of stochastic dominance tests, we tabulate the average percentage of modified DD statistics significant at the 5% level across passive and active ETFs in Panel E. The result is presented based on first, second, and third orders stochastic dominance over the negative and the positive domain, respectively. In terms of passive funds, 7.59% (0%) of first-order stochastic dominance in the positive (negative) domain implies that returns brought by passively managed ETFs stochastically dominate the returns generated by their underlying assets. This seems to be consistent with Petajisto (2013) who finds that the prices of ETFs deviate significantly from their net asset values. In addition, similar finding also holds valid for second- and third-order stochastic dominance. Therefore, we can conclude that passive management would cause price inefficiency of ETFs because there is an arbitrage opportunity between passive funds and their underlying assets. However, there is no significant SD relationship for actively managed ETFs in the view of the first three orders, suggesting that prices of active ETFs are not rejected to be efficient.

As the last test for price efficiency, Boehmer and Kelly (2009) indicate that the pricing error is better than other traditional measures of random walks. Panel F provides the results on the main relative efficiency measures estimated in accordance with the methodology developed by Hasbrouck (1993). The mean pricing errors, σ_s, the mean standard deviations of closing prices, σ, and the mean standardized pricing errors, σ_s/σ, are presented for passive and active ETFs, respectively. As anticipated, more active management is associated with higher price efficiency. Specifically, the estimated coefficient of σ_s/σ for actively managed EFTs (0.236) is significantly smaller than that for passively managed EFTs (0.245). Due to the adoption of financial derivatives by actively managed ETFs, it is likely that active funds have a larger pricing error (σ_s) and a larger standard deviation of closing prices (σ). In a nutshell, the finding based on all tests related to random walks implies that active management plays a positive role in accelerating incorporation of information into prices.

5.2 Results from trading strategy tests

In the following, we further analyse the impact of active management on price efficiency by looking into the returns of two common trading strategies described in Section 3.2: contrarian and momentum. In order to prevent our results from being driven by infrequently traded ETFs, we require individual ETFs to be traded on at least 30% of trading days in the year ending in the December prior to portfolio formation following Griffin *et al.* (2010). The results are documented in Table 3.

Panel A of Table 3 reports descriptive statistics for contrarian returns and indicates that the contrarian strategy persistently seems to yield larger returns in actively managed ETFs. Concretely, the one-by-one, one-by-two, one-by-three, one-by-four, four-by-one, four-by-two, four-by-three, and four-by-four-week strategies earn an insignificantly different 0.009, 0.012, 0.012, 0.014, 0.005, 0.008, 0.009, and 0.006 bps *per* week, respectively if there is no week skipped between the formation and investment periods. On the contrary, the same strategy applied to passively managed ETFs yet generates a lower but significant return. In addition, the return differential between active and passive funds is negligible from a statistical viewpoint. Evidence so far has showed that active management could somewhat mitigate price inefficiency. After weighing the effect of bid-ask bounce, we repeat identical strategies with a week skipped. In spite of different magnitude, the conclusion qualitatively retains the same as above.

Table 3 | Trading Strategy Tests

Panel A: Contrarian Strategy	[1x1]	[1x2]	[1x3]	[1x4]	[4x1]	[4x2]	[4x3]	[4x4]
No skip								
Passive	0.004**	0.006**	0.004	0.002	0.001	0.002	0.004*	0.005*
Active	0.009	0.012	0.012	0.014	0.005	0.008	0.009	0.006
Diff.	0.004	0.006	0.008	0.012	0.004	0.006	0.005	0.001
Skip–a–week								
Passive	0.001	0.001	0.002	0.004	0.002	0.005**	0.006**	0.007**
Active	0.002	0.002	0.004	0.009	0.003	0.005	0.007	0.008
Diff.	0.001	0.001	0.002	0.05	0.001	0.001	0.001	0.001
Panel B: Momentum Strategy	**[13×13]**		**[13×26]**		**[26×13]**		**[26×26]**	
No skip								
Passive	0.006*		0.012*		0.013**		0.015*	
Active	−0.110**		−0.204**		−0.081**		−0.175**	
Diff.	0.116**		0.216**		0.094**		0.190**	
Skip–a–week								
Passive	0.007*		0.014*		0.013**		0.015*	
Active	−0.094**		−0.192**		−0.074**		−0.167**	
Diff.	0.101**		0.205**		0.087**		0.182**	

Note: Table 3 reports average profits in percentages to trading strategies across passively and actively managed ETFs. In Panel A, contrarian strategies are formulated by forming portfolios based on past 1-week and 4-week returns. In Panel B, momentum strategies are formulated by forming portfolios based on past 13-week and 26-week returns. [m x n] represents a strategy that sorts shares into quintiles in accordance with past returns over *t-m* to *t* and then ships a week (Skip-a-week) or not (No skip) and then holds the shares for *n* weeks. The t-statistics for hypotheses testing that profits are significantly different from zero are given in the parentheses. ** and * represent the statistical significance at the 1% and 5% level.

In Panel B, we scrutinize the returns for four horizons of long-term momentum strategies. Regardless of no-skip or skip-a-week results, positive (negative) and significant returns are found in passively managed (actively managed) ETFs, which shows neither active nor passive management would enhance price efficiency. Based on Panel A and B, it is interesting to point out that contrarian (momentum) strategies enable investors of active (passive) ETFs to earn a higher return. Overall, although momentum strategy tests fail to support our argument, contrarian strategy tests still corroborate the positive impact of active management on price efficiency.

5.3 Results from transaction cost tests

If weak-form and semi-strong-form price efficiency are conceptually insufficient to measure a salient feature in the ETFs market, the validity of our prior discussion relying on random walks and trading strategies might be suspected. To overcome these limitations, it is useful to re-examine one potential source of price efficiency related to transaction costs. In this subsection, we make our inferences with two alternative transaction costs measures. One is used by Bekaert *et al*. (2007) to measure the percentage of zero returns. The other has the same intuition as the BHL measure to estimate round-trip transaction costs developed by Lesmond *et al.* (1999). If these impediments to price efficiency present a picture in line with our previous findings, then it supports the notion that active management helps to attain market efficiency.

Table 4 | Transaction Cost Tests

Panel A: BHL measure	2006	2007	2008	2009	2010	2011	Average
Passive	0.016**	0.012**	0.006**	0.005**	0.007**	0.006**	0.009**
Active	0.002	0.002**	0.004**	0.004**	0.006**	0.004**	0.005**
Diff.	0.014*	0.010**	0.002	0.001	0.000	0.003	0.004**

Panel B: LOT measure	α_1	α_2	$\alpha_2 - \alpha_1$
Passive	−0.094	0.150**	0.243**
Active	−0.020**	0.036**	0.056**
Diff.	−0.074**	0.114**	0.187**

Note: Table 4 reports trading costs across passively and actively managed ETFs based on the BHL measure (Bekaert *et al*., 2007) and the LOT measure (Lesmond *et al*., 1999), respectively. In Panel A, the proportion of daily zero returns in each month is calculated and then taken average annually. In Panel B, the LOT model intercept, α_2 and α_1, are estimated by regressing ETFs' returns on their NAV. $\alpha_2 - \alpha_1$ measure the average round-trip transaction cost. ** and * represent the statistical significance at the 1% and 5% level.

Panel A in Table 4 shows the proportion of observations with a zero return. The result indicates that passive ETFs (0.009) generally have more zero return days relative to active ETFs (0.005). Such difference is economically and statistically significant at the 1% level. Roughly speaking, a decrease (increase) is detected in passively managed ETFs (actively managed ETFs) if examining the time-series changes. Similar finding is observed from Panel B in Table 4 when turning to the LOT measure which is less subject to problems in estimation. Trading costs are lower for active funds (0.056) relative to passive funds (0.243), albeit significant for both funds. In sum, using these prevailing approaches for estimating transaction costs, we conclude that active management can effectively and persistently lower transaction costs in comparison with passive management. This reconfirms the reliability of our preceding conclusion.

6. Conclusion

Actively managed ETFs have grown so fast that they are widely believed to be venues of substantial trading profits. Under this context, price efficiencies of these innovative products gradually enter researchers' eyesight. In this paper, we evaluate whether active management matters to the extent of information incorporation into prices by various empirical tests related to random walks, trading strategies, and transaction costs after benchmarking with passive management. Overall, actively managed ETFs deviate less from a random walk, earn insignificant trading returns based on contrarian strategies, and incur smaller transaction costs relative to passively managed ETFs. This finding indicates the important role of active management in the improvement of price efficiency. In addition, such result seem to send a useful message to fund managers, as more active management element should be considered when designing, establishing, and managing respective ETFs. We hope to see more and more future researches analysing price efficiency from a broader perspective rather than only focusing on the information arbitrage component in returns across ETFs markets.

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