**Which improves market efficiency of ETFs: Active or passive management?#**

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**Abstract:** This paper extends the debate over the benefits of active versus passive management by investigating their impact on market efficiency using data from available ETFs traded on the U.S. market. After accounting for a variety of empirical methodologies with respect to random walks, profits of trading strategies, and transaction costs, our findings reveal that active management matters to the improvement of market efficiency and helps information being incorporated into prices. One practical implication of this study is that fund managers should employ more active strategies in designing and managing their ETFs.

**Keywords:** Market Efficiency; Exchange-Traded Funds; Active Management

**JEL Classification:**G11, G14

**1. Introduction**

As indicated by Investment Company Institute Fact Book (2011)[[2]](#footnote-2), the total number of passively- and actively-managed ETFs had grown to 923, and total net assets were $992 billion by the end of 2010. According to the Efficient Market Hypothesis (EMH), financial markets are assumed to be efficient in terms of information environment. Consequently, fund managers fail to consistently achieve abnormal returns in excess of average market returns conditional on the available information. This logic pushes fund managers to employ passive instead of active management strategies to construct their portfolios. In practice, passive investment plays a dominant role so that the asset managed by this investing style accounts for nearly 40 percent among large-blended domestic equity funds.[[3]](#footnote-3)

A variety of previous literature finds a price-pressure impact of index funds based on passive management skill on the stock market. Keim and Madhavan (1997) show that passive-fund traders could result in a greater price influence at short horizons in comparison to active-fund traders. Moreover, the price impact is observed by examining the daily flows of three Fidelity index funds (Goetzmann and Massa, 2003). By the same token, Madhavan (2003) attributes the price-pressure effect triggered by reconstituting Russell 2000 stock index to the liquidity demand from index funds. The above empirical evidence seems to suggest that the passive management employed by index funds matters market liquidity. In contrast, little study so far has been conducted to evaluate the effect of active or passive management on market efficiency.

Even though prior theoretical work seldom answers the question what is the optimal proportion of active or passive element in managing index funds, it allows us to gain some useful insights based on a belief that 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 under the market equilibrium (Grossman and Stiglitz, 1980). Therefore, mispricings generated by excessive trading from noise (passive) traders could lead to the involvement of informed (active) traders into the market, which helps to attain price efficiency. Following the prediction of Grossman and Stiglitz (1980) model, active management may be conducive to including information into prices and therefore enhancing market efficiency. However, Admati and Pfleiderer (1988) document that uninformed (passive) traders refrain from participating into the market when there is evidence for informed trading by active traders. Their findings indicate that excessive trading from informed (active) traders is likely to cause a market failure, resulting in an inefficient price discovery. If this perception is true to some extent, active management seems to prevent price from achieving market efficiency. Such ambiguous impact of management skill on market efficiency sparks my interest in exploring this issue in a different angle and context. Specifically, I empirical examine whether active management contributes to achieving price efficiency in the Exchange-Traded Funds (ETFs) market.

With the identification flag of the Center for Research in Security Prices (CRSP) survivor-bias-free U.S. mutual fund database, it is comparatively easy to differentiate active ETFs from the passive ETFs. What becomes more important is to quantify measures of market efficiency. In order to draw a robust and reliable conclusion, our paper conduct a comprehensive investigation based on multiple efficiency measures in terms of random walks, profits from trading strategies, and transaction costs. Overall, our analysis presents a consistent picture of less deviation from efficiency in actively-managed ETFs using various empirical methods and over a number of time horizons. These findings are consistent with Grossman and Stiglitz (1980), who predict that prices in active funds incorporate information more swiftly than those in passive funds.

This paper proceeds as follows. Section 2 presents a host of market efficiency measures following related literature. Section 3 describes ETFs sample and basic summary statistics. Section 4 examines the effect of active and passive management on market efficiency based on measures developed in Section 2. Section 5 concludes.

**2. Market Efficiency Measures**

Market 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 theoretically efficient market is not present in reality due to market frictions, which drive a temporary wedge between traded prices and efficient ones. If the academic concept of efficiency is mapped to practitioners’ perception, inefficiency represents an arbitrage opportunity that traders can exploit. In the view of a large empirical literature, we measure market efficiency in three dimensions: 1) random walks; 2) trading strategies; and 3) transaction costs.

2.1 Random walks

Efficiency refers to how closely prices resemble a random walk over different time horizons. In this sense, multiple efficiency measures are developed to reflect the deviation of traded prices from the efficient price. For consistency with a variety of prior studies, we focus on four commonly-adopted measures to evaluate how quickly information is included into prices, namely, autocorrelations; variance ratios; delay coefficients; and pricing errors.

2.1.1 Autocorrelations

Earlier literature of weak-form market efficiency employs autocorrelations based on returns to assess whether prices look close to a random walk (Solnik, 1973). A random walk indicates that return autocorrelations should be equal to zero at all horizons. Because we are just concerned with departures from a random walk in either direction, we calculate the absolute value of return autocorrelations. In order to minimize the impact of time horizon, autocorrelation coefficients of order 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10 for both daily and weekly return series are estimated. In addition, data at the weekly frequency allows us to control for autocorrelations induced by microstructure effects (Griffin et al., 2010).

2.1.2 Variance ratios

With respect to variance ratios (VRs), we follow Lo and MacKinlay (1988) and Campbell et al. (1997) to look into market efficiency. If returns are uncorrelated and unforeseeable over time, the ratio of long-term to short-term return variances, divided by unit time, should equal to one. Otherwise, significant VRs greater (less) than one imply a positive (negative) serial correlation. Similar to the method applied to autocorrelations, we calculate the absolute deviations from one for variance ratios (|VR(*m*,*n*)-1|) to compare relative efficiency between actively- and passively-managed ETFs, 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. As before, we construct VR statistics based on ratios of (2,1), (3,1), (4,1), (5,1), (6,1), (7,1), (8,1), (9,1), and (10,1) days and weeks to mitigate the influence of time horizon.

2.1.3 Delay measures

In accordance with the transaction-cost model suggested by Mech (1993), delays occur between the arrival of information and its inclusion into market prices. Because delays affect the adjustment of prices to market information, they are usually regarded as a good indicator to evaluate market quality. We employ two empirical methods 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 unrestricted model involves n lags of NAV returns and is specified as follows:

(1)

Where IRi,t is the return on ETF *i*’s NAV in day (week) *t*, and NRi,t is the return on ETF *i* in day (week) *t*. If the ETF responds immediately to market information, then all βj (j≠0) will be equal to zero. Consequently, the restricted model uses the contemporaneous return of NAV and is:

(2)

Using the estimated results from the above regression, we compute delay measures for individual ETFs. Consistent with Griffin et al. (2010), the first measure is the difference in the R2 from regression without restrictions and with restrictions.

(3)

In order to examine the robustness of our finding, we also follow Hou and Moskowitz (2005) to define delay as one minus the ratio of R2 from the restricted model over the R2 from the unrestricted model. Therefore, such measure based on the scaled version can better reflect the fraction of contemporaneous individual EFT returns explained by lagged NAV returns.

(4)

2.1.4 Pricing errors

Our next measure of market efficiency is in light with Hasbrouck (1993), who decomposes the observed transaction price at time *t*, pt, into the sum of two components:

(5)

One (mt) is the efficient price, representing the expectation of security value conditional on all public available information at time *t*. The other (st) is termed the transitory price error, defined as the departure of the actual transaction price from the efficient price. Intuitively, the standard deviation of the pricing error, σs, measures how closely the transaction price tracks the efficient price, and thus can be interpreted as a summary proxy for market quality.

Because of the economic interpretation and importance, we now turn to estimation of the pricing error. Similar to Hasbrouck (1993), we build up a vector autoregression (VAR) model to allow general serial correlations in the returns between ETFs and their NAV. A representative bivariate VAR system including ETFs’ returns and their NAV returns is specified as follows:

(5)

where IRi,t is the return on ETF *i*’s NAV in day *t*, and NRi,t is the return on ETF *i* in day *t*. The innovations are zero-mean, serially uncorrelated disturbances. The vector moving average (VMA) representation, obtained from the above VAR system, can express the variables in terms of current and lagged disturbances (Judge et al., 1985).

(6)

An expanded representation for the pricing error of the underlying efficient price decomposition model (1) is given:

(7)

The variance of the efficient price component, a slightly different from Hasbrouck (1993), may be estimated as

(8)

After imposing the identification restriction that st must be correlated with {NRt, IRt}, the α’s and β’s in (7) may be computed:

(9)

Based on these coefficients used in (7), the pricing error variance may be estimated by

(10)

In the next session, we use σs to refer to the pricing error. In order to make a meaningful comparison, we employ the standard deviation of prices to normalize σs. As long as the price is efficient, normalized pricing error should approximate to zero.

2.2 Trading strategies

There is another strand of literature examining market efficiency by looking into whether any profitable trading strategies exist. In a fully efficient and frictionless market, prices neither overreact nor underreact to information, and thus forming portfolios that group stocks according to their past returns cannot bring any profits to investors. Since the return difference between high and low-return portfolios has an intuitive economic interpretation, we could investigate market efficiency of ETFs by evaluating the profitability of a number of trading strategies, namely, contrarian and momentum.

2.2.1 Contrarian strategies

The first portfolio trading strategy that might earn abnormal returns by taking short positions in securities that underwent recent price increases and long positions in those that suffered recent prices declines is called the contrarian strategy. As explained by Jegadeesh (1990) and Lehmann (1990), stocks tend to revert if their prices are pushed in a certain direction attributable to either pressure or overreaction. In order to test the market efficiency hypothesis based on this trading strategy, how to form portfolios to measure abnormal returns reveals crucial.

According to similar procedures by Jegadeesh (1990) and Lehmann (1990), we consider the following strategies involving a given set of *N* ETFs over *T* time 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 labeled as portfolio *P1* (winners), and ETFs in the bottom decile are labeled 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.

Next, we estimate abnormal returns on the portfolios formed under the above two strategies formulated on the basis of one-week and four-week past returns. If long positions for winners (*P1*) and short positions for losers (*P10*) are taken simultaneous, abnormal returns are computed over different holding horizons of one and four weeks. As suggested by Griffin et al. (2010), we follow 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. To the best of our knowledge, this strategy, while widely employed to measure inefficiencies for stocks, has not been tested across ETFs.

2.2.2 Momentum strategies

Even though contrarian strategies have attracted a lot of attention in the recent academic literature, earlier studies (Jegadeesh and Titman, 1993) on market efficiency concentrate on relative strength of momentum strategies. Such strategy is totally different from the prior discussed contrarian strategy, because buying past winners and selling past losers with a longer formation and holding horizon is its conspicuous feature. Therefore, many quantitative investment strategies based on the momentum effect would generate significantly abnormal returns if inefficiencies are present in the market.

In the view of the common practice in the academic literature (Griffin et al., 2010), we focus on the following two strategies. One is constructed over the 26-week portfolio ranking and 26-week holding period, and the other is over the 1-week portfolio ranking and 52-week holding period. The same as before, skipping a week between the portfolio formation and holding period is used to examined abnormal returns to momentum strategies.

2.3 Transaction costs

Transaction costs are one of the important analyses on market efficiency in most previous literature. In spite of not a direct measure, transaction costs are usually viewed as a friction to prevent information from being impounded into security prices. However, transaction costs estimates are not always available, or where available, are cumbersome to use. In this paper, we measure transaction costs in light of the method developed by Bekaert, Harvey, and Lundblad (2007) (BHL) and Lesmond Ogden, and Trzcinka (1999) (LOT), respectively.

2.3.1 BHL measures

Our first BHL measure of transaction costs relies on the incidence of observed zero daily return, averaged over the month. The advantage of this measure is that it requires only a time-series of daily equity returns. In accordance with Kyle (1985), the BHL measure is an attractive empirical alternative compared to the paucity of time-series data on preferred measures such as bid-ask spreads or bona-fide order flow.

2.3.2 LOT measures

Another LOT measure infers transaction costs from the limited dependent variable model of Tobin (1958) and Rosett (1959), which assumes that informed investors will trade if the value of information exceeds transaction costs. The limited dependent variable model built on the relationship between measured returns, NRi,t , and true returns, nri,t, is specified as follows:

(11)

where

(12)

For ETF *i*, the threshold to trigger trades in negative and positive information is αi,1 and αi,2 respectively. If the true return lie between αi,1 and αi,2, the measured return will equal to zero since transaction costs are greater than the trading profit. The difference between αi,1 and αi,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 cost such as opportunity costs.

**3. Data and Summary Descriptive**

We retreat data from the Center for Research in Security Prices (CRSP) survivor-bias-free U.S. 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.

In accordance with 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 distinct ETFs on average across every quarter. The number of ETFs per quarter increases from about 29 in 1999 to about 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 remaining 13% are classified as actively-managed ETFs (index-enhanced ETFs).

**[Insert Table 1]**

Table 2 shows the basic descriptive statistics of EFTs’ returns during 1999-2011, grouped by the management style and separated into each year. The mean return suggests that actively-managed ETFs on average perform better than passively-managed ones, even though it is not the case in year 2007 and 2008. In addition, actively-managed ETFs persistently possess larger volatility relative to passively-managed ones. This result is consistent with the finding in Charupat and Miu (2011). It makes sense because actively-managed ETFs’ managers employ derivatives and leverage in their portfolios. However, passively-managed ETFs just hold virtually all securities in the noted index with weightings equal to those in the index.

**[Insert Table 2]**

**4. Empirical Analysis**

4.1 Results from random walks

In general, the concept of market efficiency is described by the extent to which prices contain all available information. To make this concept operational for empirical tests, preceding literature proposes a variety of measures to quantify efficiency. We now turn to common and formal analysis by examining traditional measures with respect to departures from random-walk pricing. In this subsection, we look into four measures: autocorrelations, variance ratios, delay in terms of market prices, and pricing errors. Our results are presented in two groups classified by passively- and actively-managed ETFs to allow for clear comparison.

4.1.1 Autocorrelations

Autocorrelations for daily and weekly returns are computed for each individual ETF, which is advantageous in that one can allow correlations to alter sign across ETFs. As a random walk would dictate a bell-shaped distribution around zero, either positive or negative autocorrelations denote deviations from a random walk. Therefore, we estimate the absolute value of the autocorrelation as an indicator of relative efficiency for each ETF return series in Table 3. Overall, both passively- and actively-managed ETFs depart from a random walk regardless of daily or weekly data. However, it appears that active management seems to mitigate such inefficiency because the deviation from the random walk gets less significant for actively-managed ETFs relative to passively-managed EFTs. This is in line with the prediction of Grossman and Stiglitz (1980). Even though an opposite pattern is observed over certain horizons (i.e. AR(6) and AR(7) using daily data), yet it is statistically insignificant.

**[Insert Table 3]**

4.1.2 Variance ratios

In order to avoid the potential impact from non-trading and bid-ask bounce, it is necessary to repeat the above analysis by means of variance ratios. Similar to autocorrelations, variance ratios are computed at the daily and at the weekly frequency. In most of our analysis, we employ the absolute value of the variance ratio statistic minus one to make comparison. Table 4 presents average variance ratio statistics over various horizons across passively- and actively-managed ETFs, differences between the two averages, and the t statistic from a difference-in-mean test. The result based on the daily data indicates a greater (smaller) deviation from one in passively (actively) managed ETFs, which draws similar inferences to the previous findings. If looking at the ratios computed from weekly returns, it is still true that, as what we found in Table 3, autocorrelations are lower in actively managed ETFs, with the insignificant exception of the short horizons.

**[Insert Table 4]**

4.1.3 Delay measures

In light of Griffin et al. (2010), delay is used to describe the degree to which current returns represent past market-wide information. In the next discussion, we let the return on ETFs’ NAV (Net Asset Value) proxy for market-wide information. Hence, delay in relation to past daily and weekly returns is estimated over the entire sample period. As defined in the same manner as Griffin et al. (2010), Table 5 reports the magnitude of the delay measure averaged over actively-managed ETFs and, separately, over passively-managed ETFs in Panel A. Two important findings emerge. First, delay is universally lower among actively-managed ETFs, which suggests a positive role played by active management. Second, as the horizon increases, the efficiency-enhancing effect of actively-managed ETFs exhibits an inverse U shape. To verify the robustness, we examine the sensitivity of these findings by calculating another delay measure developed by How and Moskowitz (2005). However, the results shown in Panel B of Table 5 are qualitatively consistent with those in Panel A.

**[Insert Table 5]**

4.1.4 Pricing errors

As suggested by Boehmer and Kelly (2009), the pricing error is better than other traditional measures of random walks. It is because that permanent and transitory price changes can be isolated by this method. In this sense, we easily attribute only non-information-based (temporary) price changes to deviations from a random walk. However, other measures, based on autocorrelations, variance ratios, and delay, are likely to reflect either inefficiency pricing or efficient pricing discovery when capturing departures from a random walk.

Table 6 provides results on the main relative efficiency measures estimated in accordance with the methodology developed by Hasbrouck (1993). The mean pricing errors, σs, the mean standard deviations of closing prices, σ, and the mean standardized pricing errors, σs/σ, are presented based on the management style. The standardized pricing errors generally tally with the following interpretation: more active management is associated with higher market efficiency. Specifically, the estimated coefficients of σs/σ for actively-managed EFTs are significantly smaller than those for passively-managed EFTs. Because of the involvement of financial derivatives into actively-managed ETFs, it still makes sense that this category has a larger pricing error and a standard deviation of closing prices. In a nutshell, all conventional efficiency measures related to random walks imply that active management matters to better incorporation of information into prices.

**[Insert Table 6]**

4.2 Results from trading strategies

In the following, we further analyze this issue by looking at the returns to two common trading strategies described in Section 2.2: 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 as Griffin et al. (2010). The results are shown in Table 7.

Panel A of Table 7 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-four, four-by-one, and four-by-four-week strategies earn an insignificantly different 0.889, 1.641, 0.596, and 1.302 bps per week, respectively. On the contrary, the same strategy applied to passively-managed ETFs yet generates a lower but significant return. In addition, the differences are economically and statistically negligible. Evidence so far has showed that active management could somewhat mitigate market inefficiency. Due to considering the effect of bid-ask bounce, we repeat identical strategies with a week skipped between the formation and investment period. In spite of smaller values observed in these returns, the conclusion retain consistent with before.

In Panel B, we document the returns for two horizons of long-term momentum strategies. For the no-skip results, the strategy that buys past 26-week winners and sells past 26-week losers on average earns a significantly different 0.016 bps per week in passively-managed ETFs and 0.193 bps per week in actively-managed ETFs. The one-week by 52-week strategy with a week between the formation and holding period has profits of 0.017 bps per week in passively-managed ETFs and 0.179 bps per week in actively-managed ETFs. If the long-lasting momentum return is constructed following Gutierrez and Kelley (2007), the same pattern is found. Overall, our main inference is that active management is conducive to reducing the abnormal returns regardless of trading with contrarian and momentum strategies.

**[Insert Table 7]**

4.3 Results from transaction costs

If weak-form and semi-strong-form efficiency conceptually insufficient to measure a salient feature in the ETFs market, the validity of our prior discussion relying on random walks and trading profits is likely to be suspected. To overcome these limitations, it is useful to re-examine one potential source of efficiency related to transaction costs. Because bid-ask spreads and trading commission could prevent arbitrageurs from taking advantage of deviations from efficient pricing, it is impossible for a market with high transaction costs to share the efficiency with another one with low costs. In this subsection, we make our inferences with two alternative transaction costs measures. One is used by Bekaert, Harvey, and Lundblad (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, Ogden, and Trzcinka (1999). If these impediments to market efficiency present a picture in line with our previous findings, then it supports the notion that active management helps to attain market efficiency.

Panel A in Table 8 shows the proportion of observations with a zero return. The result indicates that passively-managed ETFs (0.009) generally have more zero return days relative to actively-managed ETFs (0.005). Such difference is economically and statistically significant. If examining the time-series changes, a decrease (increase) seems to be found in passively-managed ETFs (actively-managed ETFs). Similar finding is obtained from Panel B in Table 8 when turning to the LOT measure, which is less subject to problems in estimation. In sum, using two prevailing approaches for estimating transaction costs, we observe that transaction costs are persistently lower in actively-managed ETFs. This provides strong evidence to confirm the reliability of our preceding conclusion.

**[Insert Table 8]**

**5. Conclusion**

Actively-managed ETFs has grown so fast that they are widely believed to be venues of substantial trading profits. Under this context, market efficiencies of these innovative products gradually enter researchers’ eyesight in comparison to traditional passively-managed ETFs. In this paper, we evaluate whether active management matters to the extent of information incorporation into prices by various empirical measures, namely random walks, profits of trading strategies, and transaction costs. Overall, actively-managed ETFs deviate less from a random walk, earn lower returns based on contrarian and momentum strategies, and incur smaller transaction costs relative to passively-managed ETFs. This finding motivates us to believe the significance of active management in the improvement of market efficiency. In addition, such result sends a useful message to practitioners, as they should add more active-management element when designing, establishing, and managing respective ETFs. However, the biggest limitation of this study is to measure market efficiency accurately although a variety of methodologies are employed. We hope to see more and more future researches analyzing market efficiency from a broader perspective rather than only focusing on the information arbitrage component in returns across ETFs markets.

**Reference:**

Admati, A. R. and P. Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies* 1, 3-40.

Bekaert, G., C. R. Harvey, and C. Lundblad, 2007, Liquidity and expected returns: Lessons from emerging markets, *Review of Financial Studies* 20, 1783-1831.

Beveridge, S., and C. Nelson, 1981, A new approach to the decomposition of economics time series into permanent and transitory components with particular attention to the measurement of the “business cycle”, *Journal of Monetary Economics* 7, 151-174.

Boehmer, E., and E. K. Kelley, 2009, Institutional investors and the informational efficiency of prices, *Review of Financial Studies* 22, 3563-3594.

Charupat, N., and P. Miu, 2011, The pricing and performance of leveraged exchanged-traded funds, *Journal of Banking and Finance* 35, 966-977.

Goetzmann, W. and M. Massa, 2003, Index funds and stock market growth, *Journal of Business* 76, 1-27.

Griffin, J. M., P. J. Kelly, and F. Nardari, 2010, Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets, *Review of Financial Studies* 23, 3225-3277.

Grossman, S. J. and J. E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *American Economic Review* 70, 393-408.

Gutierrez, R. C. and E. K. Kelley, 2007, The long-lasting momentum in weekly returns, *Journal of Finance* 63: 415-447.

Hasbrouck, J., 1993, Assessing the quality of a security market: A new approach to transaction-cost measurement, *Review of Financial Studies* 6, 191-212.

Hou, K., and T. J. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *Review of Financial Studies* 18, 981-1020.

Jegadeesh, N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Judge, G. G., W. E. Griffiths, R. C. Hall, H. Lutkepol, and T. C. Lee, 1985, *The Theory and Practice of Econometrics* (2d ed.), Wiley, New York.

Keim, D. B. and A. Madhavan, 1997, Transactions costs and investment style: An inter-exchange analysis of institutional equity trades, *Journal of Financial Economics* 46, 265-292.

Kyle, A. P., 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Lehmann, B. N., 1990, Fads, martingales, and market efficiency, *Quarterly Journal of Economics* 105, 1-28.

Lesmond, D. A., J. P. Ogden, and C. A. Trzcinka, 1999, A new estimate of transaction costs, *Review of Financial Studies* 12, 1113-1141.

Madhavan, A., 2003, The Russell reconstitution effect, *Financial Analysts Journal* 59, 51-64.

Mech, T., 1993, Portfolio return autocorrelation, *Journal of Financial Economics* 34, 307-344.

Rosett, R., 1959, A statistical model of friction in economics, *Econometrica* 27, 263-267.

Solnik, B. H., 1973, Note on the validity of the random walk for European stock prices, *Journal of Finance* 28, 1151-1159.

Tobin, J., 1958, Estimation of relationships for limited dependent variables, *Econometrica* 26, 24-36.

Wermers, R. and T. Yao, Active vs. passive investing and the efficiency of individual stock prices, *Working Paper*, University of Iowa and University of Maryland.

**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).

**Table 2 Descriptive statistics of ETFs’ returns**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Year | Passively-managed ETFs | |  | Actively-managed ETFs | |
| Mean | S.D. |  | Mean | S.D. |
| 1998 | 0.285 | 2.204 |  | - | - |
| 1999 | 0.095 | 1.422 |  | - | - |
| 2000 | -0.027 | 1.761 |  | - | - |
| 2001 | -0.026 | 1.748 |  | - | - |
| 2002 | -0.071 | 1.824 |  | - | - |
| 2003 | 0.131 | 1.194 |  | - | - |
| 2004 | 0.064 | 0.963 |  | - | - |
| 2005 | 0.041 | 0.855 |  | - | - |
| 2006 | 0.071 | 1.021 |  | 0.174 | 1.538 |
| 2007 | 0.031 | 1.215 |  | 0.018 | 2.431 |
| 2008 | -0.157 | 2.821 |  | -0.273 | 6.255 |
| 2009 | 0.132 | 2.052 |  | 0.252 | 4.623 |
| 2010 | 0.067 | 1.282 |  | 0.154 | 3.082 |
| 2011 | 0.071 | 1.060 |  | 0.181 | 2.479 |
| All | 0.030 | 1.761 |  | 0.099 | 4.114 |

Note: Table 2 reports the descriptive statistics of ETFs’ returns each year grouped by passively-managed ETFs and actively-managed ETFs. For each year, both the mean and the standard deviation of returns are tabulated.

**Table 3 Autocorrelations between passively- and actively-managed ETFs**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | |AR(1)| | |AR(2)| | |AR(3)| | |AR(4)| | |AR(5)| | |AR(6)| | |AR(7)| | |AR(8)| | |AR(9)| | |AR(10)| |
| *Daily Data* | | | | | | | | | | |
| Passive | 0.094 | 0.078 | 0.053 | 0.051 | 0.048 | 0.047 | 0.043 | 0.037 | 0.034 | 0.041 |
|  | (29.584) | (33.747) | (34.298) | (30.632) | (28.622) | (29.501) | (28.431) | (28.676) | (26.866) | (27.069) |
| Active | 0.080 | 0.061 | 0.054 | 0.040 | 0.042 | 0.059 | 0.049 | 0.037 | 0.029 | 0.037 |
|  | (14.692) | (12.029) | (12.095) | (11.695) | (11.255) | (10.978) | (12.076) | (11.100) | (9.218) | (9.961) |
| Diff. | 0.014 | 0.017 | -0.001 | 0.011 | 0.006 | -0.011 | -0.006 | 0.000 | 0.005 | 0.004 |
|  | (2.315) | (2.172) | (-0.184) | (2.902) | (2.038) | (-0.062) | (-0.165) | (2.042) | (3.216) | (3.776) |
| *Weekly Data* | | | | | | | | | | |
| Passive | 0.129 | 0.083 | 0.111 | 0.082 | 0.074 | 0.094 | 0.092 | 0.090 | 0.070 | 0.150 |
|  | (40.457) | (24.366) | (36.320) | (20.606) | (22.214) | (25.319) | (19.179) | (22.367) | (20.505) | (36.837) |
| Active | 0.154 | 0.074 | 0.091 | 0.065 | 0.061 | 0.077 | 0.097 | 0.117 | 0.080 | 0.136 |
|  | (13.537) | (7.363) | (11.284) | (10.057) | (9.850) | (8.976) | (9.625) | (11.513) | (8.865) | (17.578) |
| Diff. | -0.025 | 0.009 | 0.020 | 0.017 | 0.013 | 0.017 | -0.004 | -0.026 | -0.010 | 0.014 |
|  | (-0.253) | (2.787) | (2.968) | (2.255) | (2.148) | (2.357) | (-0.262) | (-0.944) | (-0.905) | (2.037) |

Note: Table 3 reports average absolute autocorrelations across passively- and actively-managed ETFs, differences between the two averages, and the t-statistics from a difference-in-means test based on daily (weekly) data. AR(*n*) represents the autocorrelation based on returns between *t* and *t-n*. The t-statistics for hypotheses testing are given in the parentheses.

**Table 4 Variance ratios between passively- and actively-managed ETFs**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | |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| |
| *Daily Data* | | | | | | | | | |
| Passive | 0.095 | 0.156 | 0.183 | 0.202 | 0.218 | 0.233 | 0.245 | 0.255 | 0.264 |
|  | (29.587) | (29.988) | (27.257) | (25.605) | (24.779) | (24.429) | (24.384) | (24.456) | (24.452) |
| Active | 0.082 | 0.139 | 0.157 | 0.178 | 0.203 | 0.229 | 0.245 | 0.263 | 0.271 |
|  | (14.875) | (15.401) | (17.050) | (17.451) | (18.284) | (21.319) | (23.244) | (25.255) | (26.398) |
| Diff. | 0.013 | 0.017 | 0.026 | 0.024 | 0.015 | 0.003 | 0.000 | -0.007 | -0.006 |
|  | (2.183) | (2.978) | (3.172) | (2.902) | (2.525) | (2.107) | (-0.009) | (-0.205) | (-0.175) |
| *Weekly Data* | | | | | | | | | |
| Passive | 0.130 | 0.179 | 0.188 | 0.209 | 0.226 | 0.249 | 0.267 | 0.274 | 0.282 |
|  | (42.550) | (40.210) | (30.720) | (27.928) | (25.835) | (24.191) | (23.280) | (22.037) | (20.961) |
| Active | 0.150 | 0.198 | 0.193 | 0.199 | 0.210 | 0.206 | 0.212 | 0.209 | 0.213 |
|  | (14.210) | (15.925) | (14.137) | (13.451) | (12.678) | (12.051) | (11.498) | (11.214) | (11.112) |
| Diff. | -0.021 | -0.019 | -0.004 | 0.010 | 0.016 | 0.043 | 0.055 | 0.065 | 0.069 |
|  | (-0.942) | (-0.271) | (-0.199) | (2.385) | (2.533) | (3.253) | (3.428) | (3.572) | (3.556) |

Note: Table 4 reports average absolute deviations from one for variance ratios across passively- and actively-managed ETFs, differences between the two averages, and the t-statistics from a difference-in-means test based on daily (weekly) data. VR(*m*,*n*) represents the variance over *m*-day (*m*-week) returns to the variance over *n*-day (*n*-week) returns, both adjusted by the length of the period. The t-statistics for hypotheses testing are given in the parentheses.

**Table 5 Delay measures between passively- and actively-managed ETFs**

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Delay(1) | Delay(2) | Delay(3) | Delay(4) | Delay(5) | Delay(6) | Delay(7) | Delay(8) | Delay(9) | Delay(10) |
| **Panel A: Delay Measure 1** | | | | | | | | | | |
| *Daily data* |  |  |  |  |  |  |  |  |  |  |
| Passive | 0.068 | 0.091 | 0.104 | 0.114 | 0.122 | 0.129 | 0.136 | 0.139 | 0.144 | 0.154 |
|  | (2.705) | (2.834) | (2.078) | (2.276) | (2.463) | (2.640) | (2.760) | (2.838) | (2.962) | (3.157) |
| Active | 0.029 | 0.044 | 0.054 | 0.056 | 0.056 | 0.077 | 0.085 | 0.090 | 0.099 | 0.114 |
|  | (2.926) | (2.447) | (2.752) | (2.755) | (2.805) | (3.237) | (3.336) | (3.383) | (3.625) | (3.592) |
| Diff. | 0.039 | 0.048 | 0.050 | 0.059 | 0.066 | 0.051 | 0.051 | 0.049 | 0.045 | 0.040 |
|  | (2.293) | (2.288) | (2.302) | (2.353) | (2.400) | (2.318) | (2.312) | (3.303) | (3.279) | (3.246) |
| *Weekly data* |  |  |  |  |  |  |  |  |  |  |
| Passive | 0.255 | 0.321 | 0.412 | 0.483 | 0.467 | 0.501 | 0.566 | 0.627 | 0.559 | 0.639 |
|  | (5.507) | (5.936) | (6.557) | (6.703) | (7.361) | (7.518) | (7.902) | (7.878) | (8.177) | (7.979) |
| Active | 0.278 | 0.308 | 0.363 | 0.401 | 0.427 | 0.465 | 0.470 | 0.578 | 0.575 | 0.613 |
|  | (5.322) | (5.447) | (5.775) | (5.165) | (5.163) | (5.092) | (4.963) | (4.564) | (4.571) | (4.531) |
| Diff. | -0.023 | 0.012 | 0.049 | 0.082 | 0.039 | 0.036 | 0.096 | 0.049 | -0.017 | 0.026 |
|  | (-0.149) | (2.069) | (3.233) | (3.341) | (2.186) | (2.162) | (3.404) | (2.185) | (-0.073) | (2.098) |
| **Panel B: Delay Measure 2** | | | | | | | | | | |
| *Daily data* |  |  |  |  |  |  |  |  |  |  |
| Passive | 0.514 | 1.465 | 1.506 | 1.457 | 1.307 | 1.141 | 1.171 | 1.162 | 1.123 | 1.107 |
|  | (2.556) | (2.210) | (2.238) | (2.310) | (3.392) | (2.498) | (3.518) | (2.580) | (2.660) | (2.717) |
| Active | 0.114 | 0.182 | 0.200 | 0.190 | 0.198 | 0.241 | 0.265 | 0.290 | 0.319 | 0.404 |
|  | (2.695) | (2.029) | (2.210) | (2.122) | (2.146) | (2.503) | (2.635) | (2.689) | (2.626) | (2.642) |
| Diff. | 0.400 | 1.282 | 1.306 | 1.266 | 1.109 | 0.901 | 0.906 | 0.871 | 0.804 | 0.703 |
|  | (2.366) | (2.320) | (3.324) | (3.344) | (2.357) | (2.357) | (3.355) | (3.358) | (3.359) | (2.329) |
| *Weekly data* |  |  |  |  |  |  |  |  |  |  |
| Passive | 0.522 | 0.731 | 1.049 | 1.161 | 1.166 | 1.243 | 1.410 | 1.505 | 1.447 | 1.593 |
|  | (4.287) | (4.673) | (5.161) | (5.298) | (5.265) | (5.290) | (5.605) | (5.614) | (5.352) | (5.447) |
| Active | 0.460 | 0.510 | 0.744 | 0.890 | 1.114 | 1.158 | 1.110 | 1.490 | 1.487 | 1.643 |
|  | (4.550) | (4.564) | (3.138) | (2.870) | (2.473) | (2.593) | (2.611) | (2.686) | (2.664) | (2.614) |
| Diff. | 0.061 | 0.222 | 0.305 | 0.271 | 0.052 | 0.085 | 0.300 | 0.015 | -0.040 | -0.050 |
|  | (2.152) | (3.427) | (3.451) | (2.370) | (3.070) | (3.108) | (3.357) | (2.017) | (-0.044) | (-0.051) |

Note: Table 5 reports average absolute Delay in percentages across passively- and actively-managed ETFs, differences between the two averages, and the t-statistics from a difference-in-means test based on daily (weekly) data. Delay is constructed by the unrestricted and the restricted R2 from two variations of a basic model containing contemporaneous and lagged returns on ETFs’ net asset value: Unrestricted model to calculate Delay(*n*): ; Restricted model to calculate Delay(*n*): . Where IRi,t is the return on ETF *i*’s NAV in day (week) *t*, and NRi,t is the return on ETF *i* in day (week) *t*. Delay measure 1 in Panel A (R2unrestricted - R2restricted) and Delay measure 2 in Panel B (1 - R2restricted / R2unrestricted) follow Griffin et al. (2010) and How and Moskowitz (2005), respectively. Delay(*n*) represents *n* NAV return lags included in the unrestricted model, but not in the restricted model. The t-statistics for hypotheses testing are given in the parentheses.

**Table 6 Pricing errors between passively- and actively-managed ETFs**

|  |  |  |  |
| --- | --- | --- | --- |
|  | σs | σ | σs/σ |
| Passive | 0.004 | 0.016 | 0.245 |
|  | (44.677) | (63.821) | (47.416) |
| Active | 0.009 | 0.037 | 0.236 |
|  | (14.580) | (21.216) | (28.763) |
| Diff. | -0.005 | -0.021 | 0.008 |
|  | (-16.146) | (-21.463) | (2.494) |

Note: Table 6 reports average pricing errors (σs), standard deviations of closing prices (σ), and standardized pricing errors (σs/σ) across passively- and actively-managed ETFs, differences between the two averages, and the t-statistics from a difference-in-means test based on daily data. Pricing errors are estimated in light of Hasbrouck (1993). The t-statistics for hypotheses testing are given in the parentheses.

**Table 7 Profits to past return between passively- and actively-managed ETFs**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Panel A: Contrarian Strategy** | | | | | | |
| *No Skip* | | *[1x1]* | *[1x4]* | | *[4x1]* | *[4x4]* |
| Passive | | 0.451 | 0.336 | | 0.143 | 0.139 |
|  | | (3.348) | (2.464) | | (3.957) | (2.552) |
| Active | | 0.889 | 1.641 | | 0.596 | 1.302 |
|  | | (1.144) | (1.139) | | (0.717) | (0.883) |
| Diff. | | -0.438 | -1.305 | | -0.453 | -1.163 |
|  | | (-0.954) | (-1.589) | | (-0.908) | (-1.666) |
| *Skip-a-Week* | |  |  | |  |  |
| Passive | | 0.198 | 0.187 | | 0.089 | 0.047 |
|  | | (3.578) | (2.829) | | (3.599) | (3.447) |
| Active | | 0.421 | 0.956 | | 0.270 | 0.976 |
|  | | (0.507) | (0.741) | | (0.316) | (0.691) |
| Diff. | | -0.223 | -0.769 | | -0.181 | -0.929 |
|  | | (-0.480) | (-1.494) | | (-0.712) | (-1.602) |
| **Panel B: Momentum Strategy** | | | | | | |
| *No Skip* | *[26×26]* | | | *[1×52]* | | |
| Passive | 0.016 | | | 0.011 | | |
|  | (2.591) | | | (3.351) | | |
| Active | 0.193 | | | 0.027 | | |
|  | (1.136) | | | (0.360) | | |
| Diff. | -0.177 | | | -0.016 | | |
|  | (-1.521) | | | (-1.083) | | |
| *Skip-a-Week* |  | | |  | | |
| Passive | 0.017 | | | 0.016 | | |
|  | (2.774) | | | (3.956) | | |
| Active | 0.179 | | | 0.021 | | |
|  | (0.960) | | | (0.281) | | |
| Diff. | -0.162 | | | -0.005 | | |
|  | (-1.103) | | | (-1.058) | | |

Note: Table 7 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 or 4-week returns. In Panel C, momentum strategies are formulated by forming portfolios based on past 26-week and 1-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.

**Table 8 Trading costs between passively- and actively-managed ETFs**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Panel A: BHL Measure** | | | | | | | | | |
|  | 2006 | 2007 | 2008 | | 2009 | 2010 | | 2011 | Average |
| Passive | 0.016 | 0.012 | 0.006 | | 0.004 | 0.006 | | 0.006 | 0.009 |
|  | (26.609) | (27.917) | (16.557) | | (20.069) | (21.639) | | (13.781) | (62.207) |
| Active | 0.002 | 0.002 | 0.004 | | 0.005 | 0.007 | | 0.004 | 0.005 |
|  | (1.000) | (3.684) | (2.703) | | (8.424) | (5.221) | | (3.857) | (9.105) |
| Diff. | 0.014 | 0.010 | 0.002 | | -0.001 | -0.001 | | 0.003 | 0.004 |
|  | (2.276) | (4.993) | (1.433) | | (-1.074) | (-0.441) | | (1.772) | (6.486) |
| **Panel B: LOT Measure** | | | | | | | | | |
|  | α1 | | | α2 | | | α2-α1 | | |
| Passive | -0.094 | | | 0.150 | | | 0.243 | | |
|  | (-1.456) | | | (2.777) | | | (2.094) | | |
| Active | -0.020 | | | 0.036 | | | 0.056 | | |
|  | (-3.334) | | | (7.596) | | | (5.294) | | |
| Diff. | -0.074 | | | 0.114 | | | 0.187 | | |
|  | (-2.653) | | | (5.044) | | | (3.788) | | |

Note: Table 8 reports trading costs across passively- and actively-managed ETFs based on the BHL measure (Bekaert, Harvey, and Lundblad, 2007) and the LOT measure (Lesmond, Ogden, and Trzcinka, 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, α2 and α1, are estimated by regressing ETFs’ returns on their NAV. α2-α1 measure the average round-trip transaction cost. The t-statistics for hypotheses testing are given in the parentheses.

1. # We are grateful to Y. K. Ip and Andy C. N. Kan for their constructive insights and encouragement in our paper. We also thank financial support from the Open University of Hong Kong Research & Development Fund for this project. All errors remain our own responsibility.

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2. Refer to the internet resource [www.ici.org](http://www.ici.org). [↑](#footnote-ref-2)
3. See Wermers and Yao (2010). [↑](#footnote-ref-3)