ETF Trading and Informational Efficiency of Underlying Securities

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October 2015

Very preliminary. Please do not share or quote without permission.

We would like to thank Dan Amiram, Jonathan Glover, Trevor Harris, Alon Kalay, Sharon Katz, Urooj Khan, Nan Li, Doron Nissim, Stephen Penman, Shiva Rajgopal, Gil Sadka, Tanos Santos, and participants of the brownbag seminar at Columbia University for their helpful comments and suggestions. Any remaining errors are our own.

Abstract

We investigate the effect of ETF trading activity on the informational efficiency of underlying securities. We find that ETF trading increases informational efficiency for small stocks and stocks with imperfectly competitive equity markets. Increase in informational efficiency is attributable to timely incorporation of aggregate earnings information. In contrast, we find no such effect for big stocks and stocks with perfectly competitive equity markets. ETF trading increases co-movement and synchronicity, and these increases are partly attributable to timely incorporation of aggregate earnings information. Using S&P 500 index additions and deletions as a setting, we corroborate our main findings.

1. Introduction

The asset management industry has witnessed a tremendous growth in exchange-traded funds (ETFs). As a result, roughly 30% of U.S. equity trading volume is attributable to ETFs (Boroujerdi and Fogertey, 2015).[1] Regulators and academicians have found evidence that ETFs have distorted the capital markets as a whole (e.g., ETFs lead to increased volatility, co-movement, systemic risk, effect real managerial decisions, etc.) (see Wurgler (2010) for a review). Despite this, there is scant systematic evidence on the relation between ETF trading activity and the informational efficiency of underlying securities. We find that ETF trading increases the informational efficiency of underlying securities by improving the link between fundamentals and stock prices. Specifically, firms with more ETF trading reflect incrementally more earnings news in their current stock returns.

In the absence of ETFs, as information arrives investors have to assess the implications of information for each security. As a result, information might not be reflected in some segments of the market (e.g. firms with low liquidity, short sale constraints, etc.) on a timely basis. However, in the presence of ETFs, since investors have ability to trade a basket of securities as oppose to individual stocks, information could be reflected in a more timely manner for a broader cross-section of stocks, resulting in an improved link between fundamentals and stock prices, particularly for stocks that are difficult to trade. For example, during the recent financial crisis (September and October in 2008), the SEC banned short selling for 797 financial stocks. However, all ETFs were explicitly exempted from the ban (Karmaziene and Sokolovski, 2014).

[1] For example, the assets under management by ETFs have grown from a total value of $416 billion in 2005 to $2.5 trillion as of September 2014 (*Economist,* 2014). Further, during the last decade, ETF inflows grew by more than 25% per year. In contrast, traditional mutual funds grew by -3% per year (Boroujerdi and Fogertey 2015).

On the other hand, since an ETF's weights on individual stocks are mechanically determined, information might not be reflected accurately: The sensitivity of each stock to the information could be different from the weight of the each stock in the ETF. Further, ETF trading could also transmit potential non-fundamental shocks (e.g., sentiment related mispricing) resulting in a delink between fundamentals and stock returns (Da and Shive, 2014; Ben-David, Franzoni and Moussawi, 2014). For example, a large liquidity sell order of ETF shares would lead to downward price pressure for the underlying securities for non-fundamental reasons, resulting in a delink between fundamentals and stock prices. Therefore, the effect of ETF trading on information efficiency of the underlying securities is ultimately an empirical question.

Using a large cross-section of ETF holdings data from January 2004 to December 2013, we document that an increase in ETF trading is accompanied by an increase in price informational efficiency of the underlying stocks, as reflected in the increase in the relation between stock returns and earnings news.[2] The effect of ETF trading on information efficiency should be conditional on the information environment and the degree of capital market competition. Consistent with expectations, when we conduct the information efficiency tests within sub categories, we find significant and improved informational efficiency among small firms (firms with market capitalization below NYSE 50^{th} percentile) and stocks with imperfectly competitive equity markets (number of shareholders below 75^{th} percentile). In contrast, we are unable to document such improvement for big firms and also for stocks with perfectly competitive equity markets.

Next, systematic information that affects a basket of securities should result in ETF trading as traders have little benefit to trade on firm-specific information by buying an ETF. Therefore, if ETF

[2] ETF trading could be a result of excess demand and supply from the investors or could be result of ETF arbitrage (Abner, 2010). In this paper we do not make a distinction between these two channels. We define ETF trading for a stock as the quarterly change in ETF ownership.

trading results in increased informational efficiency for underlying stocks then the increase in informational efficiency should be attributable to systematic information rather than idiosyncratic information. We find evidence consistent with this conjecture. We decompose earnings into its systematic and firm-specific components, and find that the commonality component of earnings explains the increase in information efficiency but not the idiosyncratic firm-level earnings. This evidence is consistent with the conjecture that ETF trading results in prices that reflect aggregate information quickly, resulting in increased informational efficiency.

The literature finds that ETF membership increases the co-movement, and this increase is driven by non-fundamental factors (Vijh, 1994; Harris and Gurel, 1986; Barberis, Shleifer, and Wurgler, 2005; Peng and Xiong, 2006; Da and Shive, 2014). However, by making it easier to trade stocks with similar characteristics, ETF trading could potentially move prices to reflect more systematic information and could contribute to higher co-movement. Therefore, increases in co-movement could also be driven by fundamental information. Consistent with expectations, we find that the increase in return co-movement is partially explained by systematic earnings information.

In a recent paper, Israeli, Lee, and Sridharan (2015) documents a positive relation between level of ETF ownership and return synchronicity. The authors conclude that higher ETF ownership reduces the extent to which stock prices reflect firm-specific information. However, higher return synchronicity also indicates that more market and industry information is reflected on a timely manner (Crawford, Roulstone, and So, 2012). Therefore, ETF trading could increase return synchronicity, as systematic information is incorporated into stock prices. After controlling for ETF ownership, we find that greater ETF trading is associated with greater return synchronicity, and the increased return synchronicity can be partially explained by systematic fundamental information.

Finally, using S&P 500 index additions and deletions as a setting, we corroborate our main findings. Standard and Poor's states that stocks are added to the index to make the index representative of the U.S. economy, and inclusion cannot be attributable to firm fundamentals. However, in reality, some of the inclusions and deletions are related to information events that could affect the information efficiency. To address this concern, we carefully exclude the inclusion and exclusion events if the firm is engaged in a merger or takeover, bankruptcy, liquidation, change in listing exchanges 10 trading days around the inclusions, or deletions by checking the CRSP events data. Using this setting, we document that information efficiency increases for small firms that are added to the index relative to those small firms that are deleted from the index. Similarly, we document increases in informational efficiency for firms with imperfect competitive capital markets when they are added to the index relative to those that are deleted from the index.

This paper makes several contributions to the literature. First, our paper contributes to the growing debate on the consequences of index-linked products on the stock market. Specifically, we document whether, how, and when ETF trading increases informational efficiency of underlying stocks. ETF trading increases the information efficiency for small firms and firms with imperfect competitive capital markets by incorporating aggregating accounting information into stock prices in a timely manner. In contrast, we find no such effect for big stocks and stocks with perfectly competitive equity markets. Second, prior literature documents that ETFs increase co-movement (Barberis, Shleifer, and Wurgler, 2004; Da and Shive, 2014) and increase synchronicity (Israeli, Lee, and Sridharan, 2015). Our findings document that these increases are partly attributable to timely incorporation of fundamental information into stock prices and not fully driven by non-fundamental factors. Third, by documenting the effect of ETF trading on informational efficiency of the underlying stocks, we provide evidence in support of the long-standing prediction that policies that stimulate liquidity and ameliorate trading costs improve market efficiency (Chordia, Subrahmanyam and Tong, 2014). Finally, financial regulators are concerned with the impact of ETF trading activities on liquidity, volatility, and information efficiency. We provide evidence in response to regulators' concerns of the potential consequences of ETFs on the capital markets and provide evidence that ETF trading, in fact, increases the informational efficiency for some segments of the equity markets.

This paper is organized as follows. Section 2 provides institutional details. Section 3 describes the data and main variable construction. Section 4 presents the empirical results. Section 5 offers concluding remarks.

2. Institutional Details and Related Literature

2.1 Institutional Details

ETFs are a hybrid of the two antecedents, mutual funds and investment trusts. Like mutual funds, ETFs are open-ended funds, which can create and redeem shares at any time. Like investment trusts but unlike mutual funds, ETFs are traded on organized stock exchanges throughout the day, while open-ended mutual funds can only be bought or sold at the end of the day for net asset value (NAV). ETFs provide investors access to diversified portfolios in a less expensive and convenient way. For example, the average expense ratio is around 0.25% per year for ETFs, while it is around 2% for mutual funds.[3]

The unique creation/redemption mechanism associated with ETFs ensures that ETF shares will expand or contract based on demand from investors. In the primary market, only authorized participants (APs), who are large broker-dealers, buy from and sell to the ETF sponsor large blocks of ETF shares. In the secondary market, investors can then buy and sell ETF shares just like common

[3] See the article on *Economist*: http://www.economist.com/news/finance-and-economics/21627717-regulators-are-worried-trendy-new-product-will-sow-instability-emerging

stocks. Since the price of ETF shares is determined by the demand and supply on the secondary market, the price is not always equal to the NAV. APs try to ensure that intraday prices approximate the NAV of the underlying assets through creation/redemption of ETF shares. For example, if there is an increased demand for the ETF shares, the APs can buy a block of new shares of the ETF, called "creation units," from the ETF sponsor by transferring the basket of the securities to the sponsor, and then sell the new ETF shares on the secondary market.[4] Importantly, the creation/redemption mechanism of ETFs on the primary market indicates excess demand from investors. In other words, an increase in the shares of an ETF implies an increase in excess demand from investors. This implication helps us to build our proxy for ETF trading activity.

In addition, ETFs provide investors access to stocks that were previously hard to trade. For example, a popular small-cap ETF, IWM, is based on the Russell 2000 index, for which the underlying stocks are less liquid. However, IWM itself holds more than $26 billion in assets and trades at very low costs (Israeli, Lee and Sridharan, 2015). Such huge benefits of trading ETFs attract traders in the secondary market.

2.2 Literature Review

A number of studies document negative effects of ETFs. Ramaswamy (2011) links the rise of ETFs to greater systemic risk. Hamm (2011) documents that ETF ownership is positively related to a stock's illiquidity. Ben-David, Franzoni and Moussawi (2014) provide evidence that the arbitrage activity between ETFs and the underlying stocks leads to an increase in intraday and daily stock volatility because of the transmission of liquidity shock from ETFs to the underlying stocks. Da and Shive (2014) extend Barberis et al. (2004) and provide empirical evidence that higher ETF arbitrage activity contributes to return co-movement at both the fund and the stock levels. The main conclusion

[4] See the article for the creation/redemption mechanism (http://www.etf.com/etf-education-center/21014-what-is-the-creationredemption-mechanism.html) for details.

that can be drawn from this literature is that non-fundamental demand shocks would be transferred from the ETFs and to the underlying securities. Our paper is most closely related to Israeli, Lee, and Sridharan (2015). Like this study, Israeli, Lee, and Sridharan (2015) directly examines the effect of ETFs on the underlying assets from an information perspective. However, our paper is different from Israeli, Lee, and Sridharan (2015) because that paper examines the effect of the level of ETF ownership on trading costs, analyst following, and future annual returns-earnings relations, while we focus on the implication of ETF trading, rather than ETF ownership level itself. Our empirical results are robust to the inclusion of the level of ETF ownership as a control variable. In addition, Israeli, Lee, and Sridharan (2015) document that level of ETF ownership causes deterioration of a firm's information environment, whereas we find that ETF trading activity increases the information efficiency of underlying stocks.

A number of studies also highlight the positive effects of ETF activity. Hasbrouck (2003) documents that ETFs improve intraday price discovery for the underlying stocks during the sample period March 2000 and May 2000. Boehmer and Boehmer (2003) documents that the initiation of three ETFs increased liquidity and market quality. In contrast to the intraday studies, our paper covers a much broader cross-section ETFs and stocks, and has a longer time period, which allows us to examine broader consequences of ETF trading, particularly given the increasing popularity of ETFs since 2000. To the best of our knowledge, our paper is the first to directly document the positive implication of ETF trading on the incorporation of accounting information into stock prices.

3. Data and Variable Construction

3.1 Data

We obtain ETF data from the CRSP daily stock file, using share code of 73, which uniquely identifies ETFs in the CRSP universe.[5] Quarterly ETF holdings data are from the Thomson-Reuters Mutual Fund holding database (S12). We merge the holding data with the ETF data using the MFLINKS tables. This procedure yields the final sample of 447 ETFs, where each ETF has the holdings data for each stock for the quarters from 2004 to 2013.[6] Stock return and accounting data are from the intersection of the CRSP and Compustat datasets from 2004 to 2013. Our sample includes firms listed on the NYSE, AMEX, or NASDAQ that have CRSP share codes 10 or 11. To align ETF holding data with firm-level accounting data, we include only firms with fiscal-year ends in March, June, September, or December. Further, we exclude stocks with prices less than $2. To alleviate the effects of outliers, we winsorize all independent variables at 1 and 99 percent levels. The final sample contains 109,130 firm-quarters.

3.2 ETF Trading Activity

We use change in ETF ownership for a stock as a proxy for ETF trading activity for each stock. We use change in ETF ownership since it is a direct measure that aggregates the net demand of the stock from different ETFs. ETF ownership is calculated as the proportion of shares owned by all the ETFs in the stock's total shares outstanding. Specifically, the ETF ownership for each stock and quarter, $ETF_{i,t}$, is calculated as

$$ETF_{i,t} = \frac{\sum_{j=1}^{J} SHARES_{j,t}}{Total\ Shares\ Outstanding_{i,t}}, \quad (1)$$

[5] We double check our sample of ETFs using the CRSP mutual fund database. Specifically, we only include an ETF in our sample only if *etf_flag* is equal to "F" in the CRSP mutual fund database.
[6] We start our analyses from 2004, since the average ETF ownership is below 1% before 2004.

where j is the set of ETFs holding stock i, $SHARES_{j,t}$ is the number of stock i's shares held by ETF j at the end of quarter *t*. $Total\ Shares\ Outstanding_{i,t}$ is the total shares outstanding for stock i at the end of quarter t. All the variables are measured at the end of each quarter. The change in ETF ownership is calculated as the quarterly difference in $ETF_{i,t}$. To mitigate the concerns of outliers and also to interpret coefficient estimates, we convert the change in $ETF_{i,t}$ into a rank variable. Specifically, for each quarter, we sort stocks based on change in $ETF_{i,t}$ and rank this variable into 10 groups [0, 9]. We then divide the rank variables by 9, such that the ETF trading activity covering stock i, $\Delta ETF_{i,t}$, is between 0 and 1. Thus, $\Delta ETF_{i,t}$=0 indicates the greatest decrease in ETF ownership in magnitude, while $\Delta ETF_{i,t}$=1 indicates the greatest increase in ETF ownership.

Table 1 presents descriptive statistics. Both the number of ETFs and ETF ownership per stock have increased over time. The average stock in our sample is held by 19.32 ETFs as of last quarter of 2013. The ETF ownership per stock has increased from 1.22% in 2004 to 4.93% in 2013. Mean (median) ETF ownership is 3.20.

3.3 Earnings Information

We use seasonal adjusted earnings deflated by beginning of quarter price as a measure for the fundamental information. Specifically, seasonally adjusted earnings in quarter *t* is measured as:

$$EARN_{i,t} = \frac{(X_{it} - X_{it-4})}{P_{it-1}}, \tag{2}$$

where X_{it} is earnings per share excluding extraordinary items for firm *i* in quarter *t*, and P_{it-1} is price per share for firm *i* at the end of quarter *t-1*. Earnings information for quarter *t* is released in quarter *t+1,* and it is unavailable at the end of quarter *t*.

4. Empirical Analyses

4.1 ETF trading and Contemporaneous Returns-Earnings Relation

In this section, we examine how ETF trading activity affects the extent to which fundamental earnings information is incorporated into underlying stock prices. To do so, we estimate the following Fama-MacBeth (1973) regression:

$$\begin{aligned} Ret_{i,t} = {} & b_{0,t} + b_{1,t}Earn_{i,t} + b_{2,t}\Delta ETF_{i,t} + b_{3,t}Earn_{i,t} * \Delta ETF_{i,t} + b_{4,t}Earn_{i,t-1} \\ & + b_{5,t}Earn_{i,t-1} * \Delta ETF_{i,t} + b_{6,t}Earn_{i,t+1} + b_{7,t}Earn_{i,t+1} * \Delta ETF_{i,t} \\ & + b_{8,t}Size_{i,t-1} + b_{9,t}MTB_{i,t-1} + b_{10,t}Std_{i,t-1} + b_{11,t}Loss_{i,t} \\ & + b_{12,t}Earn_{i,t} * Loss_{i,t} + b_{13,t}ETF_{i,t-1} + \varepsilon_{i,t} \end{aligned} \quad (3)$$

where $Ret_{i,t}$ is the stock return for stock i during quarter t, and $Earn_{i,t}$ is the seasonally adjusted earnings deflated by beginning-quarter price; $\Delta ETF_{i,t}$ is the within-quarter rank for quarterly change in ETF ownership, scaled to [0,1]. $Earn_{i,t}$ is the seasonally-adjusted quarter earnings. Earnings information is realized after the quarter-end and hence unavailable in real-time. The objective of using unavailable earnings information is to investigate whether ETF trading incorporates information about current quarter's earnings that can be inferred from alternative information sources before management announces them. The coefficient b_1 measures the relation between current returns and current earnings. b_3 captures the effect of ETF trading on the informational efficiency. A positive b_3 would indicate that ETF trading pushes prices to reflect more fundamental information. To the extent that ETF trading would impact the incorporation of past and future earnings information, we also include $Earn_{i,t-1}$ and $Earn_{i,t+1}$, and the interactions with the change in ETF ownership.

We control for other characteristics that are related to either stock returns or shown to affect the earnings-return relation. Namely, $Size_{i,t-1}$, the natural logarithm of the market value of equity at the beginning of the quarter; $MTB_{i,t-1}$ (market-to-book ratio), the market value of equity to the book value of equity; $LOSS_{i,t}$, an indicator variable equals one if quarterly earnings for firm *i* are negative, and zero otherwise; the interaction of $Earn_{i,t}$ and $LOSS_{i,t}$; $STD_{i,t-1}$, the standard deviation of earnings during the past 20 quarters (5 years) preceding the quarter *t*. We also control for the effect of the level of ETF ownership, $ETF_{i,t-1}$, in our regressions, as literature documents that it affects volatility and bid-ask spreads of the underlying stocks (Da and Shive, 2014; Ben-David et al. 2014; Israeli, Lee and Sridharan, 2015).

Table 2 presents the time-series average coefficients of the cross-sectional regression of returns on contemporaneous earnings. The evidence from Table 2 suggests that ETF trading incorporates contemporaneous earnings information into stock prices, thereby increasing informational efficiency. In contrast, ETF trading does not increase informational efficiency related to lagged or quarter-ahead accounting information. Specifically, as shown in columns (1) to (4) of Table 2, the interaction between ETF trading and earnings information is significant in explaining stock returns, whereas the interaction between lagged earnings and ETF trading, as well as quarter-ahead earnings and ETF trading, are not significantly related to stock returns. Next, we find that ETF trading activity and stock returns are contemporaneously related.[7] Also, consistent with expectations and prior literature, past, contemporaneous, and future earnings are related to quarter *t* stock returns. The coefficients on control variables are all consistent with expectation and prior literature. The negative coefficients on $Size_{i,t-1}$ and $MTB_{i,t-1}$ are consistent with the size effect (Banz, 1981) and growth effect (Chan, Hamao, and Lakonishok, 1981; Lakonishok, Shleifer and Vishny, 1994). Negative coefficients on loss and the interaction between loss and earnings are also consistent with

[7] In untabulated results, we find that ETF trading activity does not predict stock returns.

prior literature (Hayn, 1995; Basu, 1997). The insignificant coefficient on $ETF_{i,t-1}$ is consistent with Israeli, Lee, and Sridharan (2015).

Overall, Table 2 provides evidence that ETF trading increases the returns-earnings relation, suggesting that informational efficiency is improved. Our conjecture is that since ETFs enable investors to trade a basket of securities, ETF trading reflects accounting information into a broader cross-section of stocks. In contrast, in the absence of ETF trading, as information arrives, investors have to assess the implications of information for each security. As a result, information might not be reflected in some segments of the market (e.g., firms with low liquidity, short sale constraint, etc.) on a timely basis.

To provide further evidence in support of our conjecture, we perform additional tests. Specifically, we examine the effect of ETF trading on informational efficiency conditional on (1) firm size, and (2) market competition. We use firm size to capture the information environment. Big firms are typically well-followed by analysts and sophisticated investors. As a result, information should be reflected on a timely basis for big firms compared to small firms. Further, limits to arbitrages should be greater for small firms compared to big firms, thereby reducing information efficiency for small firms. Therefore, if our conjecture is correct, we should observe greater increases in informational efficiency for small firms relative to big firms.

At the beginning of each quarter, we classify the full sample into big and small stocks using NYSE median breakpoints. We would expect that the effect of ETF trading on the returns-earnings relation is stronger for small stocks than for big stocks. To test this conjecture, we redo the Fama-MacBeth (1973) regression as in equation (3) for big and small stocks, respectively.

Similarly, if our conjecture is right, we should observe greater increases in informational efficiency for imperfect competition relative to perfect competition. Namely, when equity markets are perfectly competitive, investors are price takers, and their demand has no effect on stock prices (Shleifer, 1986; Hellwig, 1980). Therefore, ETF trading should not increase informational efficiency.

When equity markets are imperfectly competitive, each investor recognizes the price impact of his or her trades, which reduces the capability and incentive to trade on individual stocks. However, in the presence of ETFs, since investors are trading on a basket of securities, their ability to trade stocks with imperfect competition increases as ETFs have higher liquidity compared to stocks with imperfect competition (for example, the unique creation/redemption mechanism by APs in response to investors' demand could make ETFs more liquid than underlying stocks). Therefore, ETF trading should reflect information in a timely manner for these stocks. Following Armstrong, Core, Taylor and Verrecchia (2011), we use the number of investors in a firm as the proxy for the level of competition for a firm's shares. Data is available only at the annual frequency, and we assume that the measure is constant during the fiscal year. Each year, a firm is classified with perfect (imperfect) competition if number of investors for a firm is greater (less) than the 75th percentile. The number of investors is highly skewed for the cross-section of stocks. For example, during the first quarter of 2013, the median number of investors is 804, while the mean is 20,018. We therefore adopt the 75th percentile as the breakpoint — roughly 5,552 shareholders during that quarter — which we believe is a more reasonable classification. We expect the effect of ETF trading on informational efficiency is stronger for imperfect competition stocks than perfect competition stocks. To test this conjecture, we redo the Fama-MacBeth (1973) regression as in equation (1) for these partitions.

Table 3 presents the evidence. Consistent with the expectations, ETF trading increases informational efficiency for small firms and firms with imperfect competition. In contrast, we are unable to document such improvements for big firms and for firms with perfectly competitive equity markets. Specifically, as documented in Columns (1-4), ETF trading increases the earnings-return relation for small firms but not for big firms. Ben-David et al. (2014) finds that ETF arbitrage activity increases intraday and daily volatility and concludes that these results are consistent with ETF arbitrage propagating non-fundamental shocks to the underlying stocks. However, this effect is only significant for big firms. Thus, our results, rather than contradicting Ben-David et al. (2014), complement our understanding about how ETF activity affects small firms and big firms differently. Similarly, as documented in columns (5-8), ETF trading increases the earnings-return relation only for firms with imperfect equity market competition, and not for firms with perfect equity market competition.

In summary, results presented in Table 2 and Table 3 suggest that ETF trading increases informational efficiency of contemporaneous accounting information because ETF trading reflects information for a broader section of stocks on a timely manner. Further, informational efficiency increases for small firms and firms with imperfectly competitive equity markets. In contrast, we are unable to document such improvement for big firms and also for firms with perfectly competitive equity markets.

4.2 ETF trading and incorporation of components of earnings information

In this section, we investigate the channel through which ETF trading increases the information efficiency of underlying stocks. Common information that effects a basket of securities should result in ETF trading as traders have little benefit to trade on idiosyncratic firm-specific information by buying an ETF. Therefore, if ETF trading results in an increase in informational efficiency for the underlying stocks, then such improvement should be attributable to systematic information rather than idiosyncratic information. We test this conjecture in this section. We decompose $Earn_{i,t}$ into two components: systematic and firm-specific earnings news, and regress

$Ret_{i,t}$ on these two components and their interactions with $\Delta ETF_{i,t}$. To do so, we estimate the following Fama-MacBeth (1973) specification:

$$Ret_{i,t} = b_{0,t} + b_{1,t}Earn\_Sys_{i,t} + b_{2,t}Earn\_Firm_{i,t} + b_{3,t}\Delta ETF_{i,t} + b_{4,t}Earn\_Sys_{i,t} * \Delta ETF_{i,t} + b_{5,t}Earn\_Firm_{i,t} * \Delta ETF_{i,t} + b_{6,t}Size_{i,t-1} + b_{7,t}MTB_{i,t-1} + b_{8,t}Std_{i,t-1} + b_{9,t}ETF_{i,t-1} + \varepsilon_{i,t}, \quad (4)$$

where $Earn\_Sys_{i,t}$ is the systematic earnings news, and $Earn\_Firm_{i,t}$ is firm-specific earnings news. All the other variables are defined as above.

The systematic earnings news is calculated as the fitted value from the quarterly regression for each stock *i*:

$$Earn_{i,t} = \beta_{0,i} + \beta_{1,i}Earn\_mkt_t + \beta_{2,i}Earn\_ind_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $Earn\_mkt_t$ is the weighted average of seasonal adjusted earnings of all firms where earnings information is available in Compustat, and $Earn\_ind_{i,t}$ is the weighted average of seasonal adjusted earnings of all firms in the same two-digit SIC code as firm *i*. Firm-specific earnings news is obtained as the residuals of regression (5).

Table 4 presents the evidence. We conduct the analysis for the full sample, as well as for partitions based on firm size and market competition. The evidence from Table 4 suggests that increase in informational efficiency is attributable to contemporaneous aggregate accounting information. Specifically, in columns (1) and (2), the coefficient on the interaction of systematic earnings news and $\Delta ETF_{i,t}$ is positive and significant, implying that an increase in ETF trading pushes prices to reflect more systematic fundamental information. The coefficient on the interaction of firm-specific earnings news and $\Delta ETF_{i,t}$ is insignificant, indicating that the ETF trading does not increase informational efficiency related to the firm-specific earnings news. Results are also consistent for different partitions. Specifically, for the small firms — columns (3) and (4) — the coefficient on $Earn\_Sys_{i,t} * \Delta ETF_{i,t}$ is significant and positive at 0.10 level, indicating that prices reflect more systematic earnings for small firm. Similarly, for the imperfect competition partition — columns (7) and (8) — the coefficients on $Earn\_Sys_{i,t} * \Delta ETF_{i,t}$ are statistically significant at 0.05 level. Consistent with expectations, we do not find improvement in informational efficiency for big and perfect competitive partitions even after we split the earnings into aggregate and firm-level earnings news.

Overall, the evidence suggests increases in informational efficiency because of ETF trading are attributable to timely incorporation of aggregate accounting information.

4.3 ETF Trading and Co-movement

In this section, we examine the link between ETF trading and market beta. The literature finds that ETF membership increases co-movement, and this increase is driven by non-fundamental factors (Vijh, 1994; Harris and Gurel, 1986; Barberis, Shleifer, and Wurgler, 2005; Peng and Xiong, 2006; Da and Shive, 2014). However, the evidence so far from the paper suggests that ETF trading increases informational efficiency of underlying stocks by incorporating aggregate accounting information into prices for a broader cross-section of stocks. Therefore, increase in co-movement could also be driven by timely incorporation of aggregate accounting information (i.e., fundamental factors) into stocks.

We investigate the relation between ETF trading and co-movement in two steps. In step 1, we estimate the increase in co-movement that is attributable to ETF trading. Specifically, we estimate the following Fama-MacBeth (1973) regression:

$$\beta_{i,t} = b_{0,t} + b_{1,t}|\Delta ETF_t| + b_{2,t}Size_{i,t-1} + b_{3,t}MTB_{i,t-1} + \ b_{4,t}Std_{i,t-1} + \ b_{5,t}ETF_{i,t-1} + \varepsilon_{i,t}. \tag{6}$$

where $\beta_{i,t}$ is the coefficient from the regression of stock i's daily excess return on the market daily return in quarter t; $|\Delta ETF_{i,t}|$ is the scaled absolute change in ETF holdings. All other variables are as defined above. In the above specification, we use the absolute change in ETF holdings to capture trading activity because both buying and selling activity would push up return co-movement. For example, facing positive economic news, traders would buy ETF shares and push stock prices to reflect positive news. Similarly, facing negative economic news, traders would sell ETF shares and push stock prices to reflect negative news. Both directions would increase stocks' return co-movement. The absolute value of ETF ownership change captures the strength of ETF trading, and more trading of ETFs should be positively associated with return co-movement.

In step 2, we examine what fraction of the increase in co-movement is because of ETF trading attributable to fundamental factors such as earnings. To do so, we use the fitted value from step 1 and regress it on earnings and other controls. Specifically, we estimate the following Fama-MacBeth (1973) regression:

$$\widehat{\beta_{i,t}} = b_0 + b_{1,t}|Earn\_Agg_{i,t}| + b_{2,t}|Earn\_Firm_{i,t}| + b_{3,t}Size_{i,t-1} + b_{4,t}MTB_{i,t-1} + b_{5,t}Std_{i,t-1} + \ b_{6,t}ETF_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

where $\widehat{\beta_{i,t}}$ is the fitted value from equation (4) (with only $|\Delta ETF_{i,t}|$ and without control variables). $|Earn\_Agg_{i,t}|$ is the absolute value of the systematic component of aggregate earnings. All other variables are defined above.

Table 5 presents the results. Panel A presents results from step 1. A positive and significant coefficient on $|\Delta ETF_t|$ in both columns (1) and (2) implies that more ETF trading is associated with greater return co-movement. These results are consistent with findings from prior literature (Vijh, 1994; Harris and Gurel, 1986; Barberis, Shleifer, and Wurgler, 2005; Peng and Xiong, 2006; Da and Shive, 2014). However, prior literature attributes the increase in co-movement to non-fundamental factors. The second-step results are reported in Panel B. The positive and significant coefficient on $|Earn\_Agg_{i,t}|$ in columns (1) and (2) implies that the increase in beta can be explained by fundamental aggregate earnings news. This evidence is consistent with our conjecture that ETF trading incorporates aggregate accounting information in a timely manner, resulting in both informational efficiency and return co-movement. Consistent with expectations, fitted beta cannot be explained by firm-specific earnings information. We find similar results for small stocks and stocks in imperfect competition equity markets in columns (3), (4), (7), and (8).

In summary, we find evidence to support the claim that the increase in co-movement because of ETF trading can be partially explained by systematic earnings news.

4.4 ETF Trading and Return Synchronicity

In this section we examine the link between ETF trading and return synchronicity. Israeli, Lee, and Sridharan (2015) documents a positive relation between the level of ETF ownership and return synchronicity, concluding that higher ETF ownership reduces the extent to which stock prices reflect firm-specific information. However, higher return synchronicity also indicates more market and industry information is reflected in a timely manner (Crawford, Roulstone, and So, 2012). Therefore, ETF trading could increase return synchronicity, as systematic earnings information is incorporated into stock prices. We test this conjecture in this section.

Similar to the co-movement tests, we conduct two steps to investigate the relation between ETF trading and return synchronicity. In the first step, we estimate the increase in synchronicity that is attributable to ETF trading. Specifically, we estimate the following Fama-MacBeth (1973) regression in step 1:

$$Sync_{i,t} = b_{0,t} + b_{1,t}|\Delta ETF_t| + b_{2,t}Size_{i,t-1} + b_{3,t}MTB_{i,t-1} + b_{4,t}Std_{i,t-1} + b_{5,t}ETF_{i,t-1} + \varepsilon_{i,t}. \quad (8)$$

where $Sync_{i,t}$ is the return synchronicity measure for stock i during quarter t. To calculate the return synchronicity measure, we adopt the methodology described in Crawford, Roulstone, and So (2012). Specifically, we estimate a firm-level measure of return synchronicity by regressing daily returns on the market return and two-digit SIC industry return for each quarter:

$$Ret_{i,d} = \beta_{0,i} + \beta_{1,i}Mkt_d + \beta_{1,i}Ind_{i,d} + \varepsilon_{i,d} \quad (9)$$

where $RET_{i,d}$ is the stock's return on day d, MKT_d is the market return on day d, and IND_d is the weighted average return of all the firms in the same two-digit SIC code as firm i. The model is estimated using daily returns in quarter t. Following the definition in Morck et al. (2000), we calculate synchronicity as:

$$SYNC_{i,t} = \log(\frac{R_{i,t}^2}{1-R_{i,t}^2}), \quad (10)$$

where $R_{i,t}^2$ is the adjusted R^2 from specification (7). A positive b_1 in equation (6) indicates that an increase in ETF trading is accompanied by an increase in return synchronicity. The results of equation (8) are reported in Panel A of Table 6. The coefficients on $|\Delta ETF_{i,t}|$ are all positive and statistically significant at the 0.01 level except for big firms adding when firm characteristic controls are added to the specification. Thus, ETF trading activity is associated with greater return synchronicity, and the effect is more pronounced for small firms than big firms. Note that the positive and significant coefficient on ETF_{t-1} is consistent with Israeli, Lee, and Sridharan's (2015) finding that the lagged ETF ownership is positively related to return synchronicity.

Like in the co-movement tests, the objective of step 2 is to examine what fraction of the increase in return synchronicity because of ETF trading can be attributable to fundamental factors such as earnings. To do so, we use the fitted value from step 1 and regress it on earnings and other controls. Specifically, we estimate the following use Fama-MacBeth (1973) regression:

$$\widehat{Sync_{i,t}} = b_0 + b_{1,t}\left|Earn\_Agg_{i,t}\right| + b_{2,t}\left|Earn\_Firm_{i,t}\right| + b_{3,t}Size_{i,t-1} + b_{4,t}MTB_{i,t-1} + b_{5,t}Std_{i,t-1} + b_{6,t}ETF_{i,t-1} + \varepsilon_{i,t}, \tag{11}$$

where $\widehat{Sync_{i,t}}$ is the fitted value from equation (8) (with only $|\Delta ETF_{i,t}|$ and without control variables). The results are reported in Panel B of Table 6. Columns (2), (4), and (8) imply that, controlling for firm characteristics, the increase in return synchronicity due to ETF trading can be at least partially explained by systematic-related earnings news for the full sample, small firms and firms facing less competitive equity markets. Therefore, Table 6 indicates that more ETF trading is accompanied by greater return synchronicity, and the increased synchronicity can be attributed to fundamental systematic earnings information.

In summary, we find evidence to support the claim that the increase in return synchronicity because of ETF trading can be partially explained by systematic earnings news.

4.5 Index Inclusion and Deletion

In this section, using S&P 500 index additions and deletions as a setting, we corroborate our main findings. Specifically, we use S&P 500 inclusions and deletions as quasi-experiments to test the informational efficiency before and after these events. Standard and Poor's states that inclusion into the index should not be attributable to fundamental reasons. Instead, the intention of inclusion in the index is to select stocks to make the index representative of the U.S. economy. Therefore, index inclusions and exclusions can be used as an identification strategy to test our conjectures that ETF trading increases informational efficiency. Ex ante, given that the S&P 500 index is widely traded, we should observe that informational efficiency should increase for small firms that are added to the index relative to those small firms that are deleted from the index. Similarly, we should also observe an increase in informational efficiency for firms with imperfect competitive capital markets when they are added to the index relative to those that are deleted from the index. One of the limitations of this approach is that in the sample period, a stock on average is part of 8 ETFs in 2004 and 19 ETFs in 2013. Therefore, even if the stock is added to the S&P 500 index, informational efficiency may not necessarily increase as the stock is part of other ETFs. Therefore, the power of this identification strategy is low, and our empirical tests are likely to detect lower-bound estimates of increases in informational efficiency.

S&P 500 constituents and event dates are obtained from CRSP. The initial sample covers 257 addition and 257 deletion events from January 2004 to December 2014. Some of the inclusions and deletions are related to information events (e.g., mergers and acquisitions), which could affect the informational efficiency. To address this concern, we exclude the inclusion and exclusion event if the firm is engaged in a merger or takeover, bankruptcy, liquidation, or change in listing exchanges 10 trading days around the inclusions and deletions by checking the CRSP events data. Further, our final sample includes only firms with accounting data at least one quarter before and one quarter after the event date. The final sample contains 166 inclusion and 61 deletion events. [8]

We employ a difference-in-difference design. Namely, we compare the informational efficiency pre- and post-addition and deletion events. If additions to the S&P index increase the informational efficiency and deletions from the S&P index decrease informational efficiency, we

[8] Barberis, Shleifer, and Wurgler (2005) use the additions to and deletions from the S&P 500 from 1976 to 2000 to study the effect on return co-movement. Our sample screening procedure yields similar results during that period. The results are available upon request.

should expect the difference in informational efficiency pre- and post- addition events to be larger than the difference between pre- and post- deletion events. Specifically, we adopt a following pooled regression specification:

$$\begin{aligned} Ret_{i,t} = {} & b_1 Earn_{i,t} + b_2 In_{i,t} + b_3 Post_{i,t} + b_4 Earn_{i,t} * In_{i,t} * Post_{i,t} + b_5 In_{i,t} * Post_{i,t} \\ & + b_6 Earn_{i,t} * In_{i,t} + b_7 Earn_{i,t} * Post_{i,t} + b_8 Size_{i,t-1} + b_9 MTB_{i,t-1} + \mu_t + \varepsilon_{i,t}, \end{aligned} \tag{12}$$

where $In_{i,t}$ equals 1 if firm i is added to the S&P 500 index during the sample period, and $In_{i,t}$ equals 0 if firm i is deleted from the S&P500 index. $Post_{i,t}$ equals 1for the event quarter and the quarter ahead, and $Post_{i,t}$ equals 0 for the quarter prior to the event date. The regression also includes time fixed effects, μ_t, to control for time trends in informational efficiency across all firms in our sample. The coefficient on the interaction variable, $Earn_{i,t} * Post_{i,t}$ captures the average change in informational efficiency for deletion events. The main variable of interest, b_4, captures the changes in informational efficiency for inclusion firms relative to changes for deletion firms. A positive b_4 would indicate that informational efficiency increases for inclusion firms after being added relative to deletion firms.

Table 7 presents the results. The results for the full sample are reported in column (1). For the full sample, we do not find that the change (post-event period – pre-event period earnings-return relation) in informational efficiency for inclusion firms is statistically different from the change in informational efficiency for deletion firms. This result could be because, compared with the universe of stocks, S&P 500 stocks are larger, so information is reflected in these stocks on a timely basis.

We next partition our sample based on firm size and the level of equity market competition to investigate the effect of ETF trading on informational efficiency. We partition the full sample of additions and deletions into two groups based on the NYSE 50$^{\text{th}}$ percentile breakpoints of market capitalization. Firms above (below) median are classified as big (small) firms. We find that the increase in return-earnings is greater after inclusion, on average, among smaller firms.[9] Specifically, as documented in columns (2) and (3), the coefficient on $Earn_{i,t} * In_{i,t} * Post_{i,t}$ is positive and statistically significant at the 10% level for small firms, but insignificant for big firms. This result suggests that the informational efficiency increases for small firms after inclusion relative to deletion firms.

The increase in the informational efficiency is also larger for firms with imperfectly competitive equity markets. Columns (4) and (5) present the results for market competition partition. Firms below (above) the 75th percentile of the number of shareholders during each quarter are classified as imperfectly (perfectly) competitive. The coefficient on $Earn_{i,t} * In_{i,t} * Post_{i,t}$ is positive and statistically significant for firms with imperfectly competitive equity markets but insignificant for firms with perfectly competitive equity markets. This result suggests that the informational efficiency increases for firms with imperfectly competitive equity markets after inclusion relative to deletion.

Overall, the evidence presented in this section corroborates our previous main finding of the impact of ETF trading on informational efficiency. By using the identification of inclusion into and deletion from the S&P 500 index, which is likely information-free, we find that inclusion into the index increases the informational efficiency for small firms and firms with imperfectly competitive equity markets.

[9] To partition firms into small versus big, we use the sample of addition and deletion firms rather than the full CRSP universe. If we use the CRSP universe, we do not find any small firms (firm with market capitalization below NYSE 50th percentile) that are added to the S&P 500 index. However, if we use the CRSP universe to classify firms with perfectly or imperfectly competitive equity markets, the results are stronger for firms with imperfectly competitive equity markets, compared with the results that are presented in Table 7.

5. Conclusions

We find that greater ETF trading activity is associated with improvement in informational efficiency for underlying stocks. Further, we document that the increase in informational efficiency is attributable to incorporation of incrementally more systematic fundamental information, rather than firm-specific fundamental information. However, the improved informational efficiency is confined to firms with less transparent information environment, as reflected among small firms and firms with imperfectly competitive equity markets.

Prior literature finds that ETF membership increases co-movement and return synchronicity, and these increases are driven by non-fundamental factors (Vijh, 1994; Harris and Gurel, 1986; Barberis, Shleifer, and Wurgler, 2005; Peng and Xiong, 2006; Da and Shive, 2014; Israeli, Lee, and Sridharan, 2015). However, if ETF trading is associated with more systematic information being incorporated into prices, that could increase return co-movement and return synchronicity. Consistent with expectations, we find that increases in co-movement and return synchronicity linked to ETF trading can be partially explained by systematic fundamental information. Finally, we corroborate our main findings by using S&P 500 index additions and deletions as a setting.

Collectively, the evidence presented in this paper suggests that ETF trading can improve informational efficiency for underlying stocks. Our evidence does not suggest or claim that ETF trading is completely driven by fundamental information, but our results suggests that ETF trading can be partially explained by systematic fundamental information.

REFERENCE

Abner, D., 2010. The ETF handbook (John Wiley and Sons, Inc., Hoboken, New Jersey.).

Armstrong, C., Core, J., Taylor, D., and Verrecchia, R., 2011. When does information asymmetry affect the cost of capital? Journal of Accounting Research 49, 1-40.

Ball, R., Brown, P., 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6, 159-178.

Barberis, N., Shleifer, A., 2003. Style investing. *Journal of Financial Economics* 68, 161–199.

Barberis, N., Shleifer, A., Wurgler, J., 2005. Comovement. *Journal of Financial Economics* 75, 283–317.

Basu, S., 1997. The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics* 24, 3-37.

Banz, R. W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics* 9(1), 3–18.

Ben-David, I., Franzoni, F., Moussawi, R., 2014. Do ETFs Increase Volatility? Working paper. The Ohio State University.

Bernard L. V., Thomas, J. K.,1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305-340.

Boehmer, B., and Boehmer, E., 2003. Trading your neighbor's ETFs: Competition or fragmentation?, *Journal of Banking and Finance* 27.

Boroujerdi, R., and Fogertey, K., 2015. ETFs: The Rise of the Machines, Goldman Sachs Equity Research., April 10, 2015.

Chan, K., Chan, Y. C., 2014. SEO underpricing, stock price synchronicity and analyst coverage. *Journal of Financial Economics*, forthcoming.

Chan, K. C., Hamao, Y., and Lakonishok, J., 1991. Fundamentals and stock returns in Japan. *Journal of Finance* 46, 1739–1764.

Chordia, T, Subrahmanyam, A., Tong, Q., 2014. Have capital market anomalies attenuated in the recent era of high liquidity and trading activity. Journal of Accounting Economics 58, 41-58.

Crawford, S. S., Roulstone, D. T., So, E. C.,2012. Analyst initiations of coverage and stock return synchronicity. *The Accounting Review* 87: 1527-1553.

Da, Z., Shive, S., 2014. When the bellwether dances to noise: evidence from exchange-traded funds. Working paper. University of Notre Dame.

Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy* 81, 607-636.

Fama, E., French, K., 1992. The cross-section of expected stock returns.*The Journal of Finance* 47, 427-465.

Fang, Y., Sang, G. C. 2012. Index price discovery in the cash market. Working paper. Louisiana State University, January 16th.

Gow, I., Taylor, D. J., 2009. Earnings Volatility and the cross-section of returns. Working Paper. Northwestern University and Stanford University.

Grossman, S., Stiglitz, J., 1980. On the impossibility of informationally efficient markets. *The American Economic Review*, 70(3), 393-408.

Hamm, S., 2011. The effect of ETFs on stock liquidity. Working paper

Harris, L., Gurel., E., 1986. Price and volume effects associated with changes in the S&P 500: new evidence for the existence of price pressures., Journal of Finance 41, 815-829.

Hasbrouck, J., 2003. Intraday price formation in U.S. equity index markets. *The Journal of Finance* 58: 2375-2399

Hayn, C., 1995. The information content of losses. *Journal of Accounting and Economics* 20, 123-153.

Hellwig, M., 1980. On the Aggregation of Information in Competitive Markets." *Journal of Economic Theory* 22, 477–498.

Israeli, D., Lee, C., Sridharan, S., 2015. Is there a dark side to exchange traded funds (ETFs)? An information perspective. Working paper. UCLA and Stanford University.

Karmaziene, E., and Sokolovski, V., 2014. Exchange traded funds and the 2008 short-sale ban. Work paper. Swedish House of Finance Research Paper.

Newey, W., West, K., 1987. A Simple, Positive Definite, Heteroskedasticity and autocorrelation Consistent Covariance Matrix, *Econometrica* 55, 703–708.

Peng, L., Xiong, W., 2006, Investor attention, overcon_dence and category learning, Journal of Financial Economics 80, 563-602.

Ramaswamy, S., 2011. Market structures and systemic risks of exchange-traded funds. Working paper, Bank of International Settlements.

Shleifer, A., 1986. Do Demand Curves for Stocks Slope Down? *Journal of Finance* 41, 579–90.

Shleifer, A., Vishny, R., 1997. The limits of arbitrage, *Journal of Finance* 52, 35-55.

Vijh, A., 1994. S&P 500 trading strategies and stock betas. *Review of Financial Studies* 7, 215–251.

Wugler, J., 2010, *Challenges to Business in the Twenty-First Century: The Way Forward*. Chap. On the Economic Consequences of Index-Linked Investing (American Academy of Arts and Sciences).

Appendix: Variable Definitions

ETF Variables

Variable	Description
$ETF_{i,t}$	The percentage of common shares outstanding of stock *i* held by ETFs at the end of quarter *t*. The data are obtained from Thomson-Reuters and CRSP.
$\Delta ETF_{i,t}$	At the end of each quarter *t*, change in $ETF_{i,t}$ from the end of quarter *t-1* through the end of quarter *t* is ranked from 0 to 9 and scaled by 9. The data are obtained from Thomson-Reuters and CRSP.
$\lvert\Delta ETF_t\rvert$	At the end of each quarter *t*, the absolute value of change in $ETF_{i,t}$ from the end of quarter *t-1* through the end of quarter *t* is ranked from 0 to 9 and scaled by 9. The data are obtained from Thomson-Reuters and CRSP.
$\#ETF_{i,t}$	The number of ETFs holding stock *i* at the end of quarter *t*. The data are obtained from Thomson-Reuters.

Main Variables:

$Return_{i,t}$	The quarterly return for stock *i* in quarter *t*. The data are obtained from CRSP.
$Earn_{i,t}$	Seasonally adjusted earnings innovation, scaled by price: $$Earn_{i,t} = \frac{X_{i,t} - X_{i,t-4}}{P_{i,t-1}}$$ where $X_{i,t}$ denotes firm *i*'s earnings per share excluding extraordinary items form i in quarter *t,* and $P_{i,t-1}$ denotes the price at the beginning of quarter *t*. The data are obtained from COMPUSTAT.
$Earn\_Agg_{i,t}$	Systematic component of the current earnings innovation. It is calculated as the fitted value from the quarterly regression for stock i: $Earn_{i,t} = \beta_{0,i} + \beta_{1,i}Earn\_mkt_t + \beta_{2,i}Earn\_ind_{i,t} + \varepsilon_{i,t}$, where $Earn\_mkt_t$ is the weighted average of seasonal adjusted earnings of all firms with available earnings information in Compustat, and $Earn\_ind_{i,t}$ is the weighted average of seasonal adjusted earnings of all firms in the same two-digit SIC code as firm *i*. The data are obtained from COMPUSTAT.
$Earn\_Firm_{i,t}$	Firm-specific component of the current earnings innovation. It is calculated as the residual from the quarterly regression for stock i: $Earn_{i,t} = \beta_{0,i} + \beta_{1,i}Earn\_mkt_t + \beta_{2,i}Earn\_ind_{i,t} + \varepsilon_{i,t}$, where $Earn\_mkt_t$ is the weighted average of seasonal adjusted earnings of all firms with available earnings information in Compustat, and $Earn\_ind_{i,t}$ is the weighted average of seasonal adjusted earnings of all firms in the same two-digit SIC code as firm *i*. The data are obtained from COMPUSTAT.

$Beta_{i,t}$	The $\beta_{i,t}$ coefficient from firm-quarter estimation of the model: $$RET\_RF_{i,d} = \beta_{0,i} + \beta_{1,i}MKT\_RF_d + \varepsilon_{i,d}$$ where $RET\_RF_{i,d}$ is the stock's excess return on day *d*, and MKT_RF_d is market excess return on day *d*. The model is estimated using daily returns in quarter *t*. The data are obtained from CRSP.
$R^2_{i,t}$	The adjusted $R^2$from the firm-quarter estimation of the model: $$RET_{i,k} = \beta_{0,i} + \beta_{1,i}MKT_k + \beta_{1,i}IND_k + \varepsilon_{i,k}$$ where $RET_{i,d}$ is the stock's return on day *d*, MKT_d is the market return on day *d*, and IND_d is the average return of all the firms in the same two-digit SIC code as firm *i*. The model is estimated using daily returns in quarter *t*. The data are obtained from CRSP.
$SYNC_{i,t}$	Logarithmic transformation of $R^2_{i,t}$, defined as log($R^2_{i,t}/(1 - R^2_{i,t})$) The data are obtained from CRSP.

Control Variables:

$MVE_{i,t}$	The market value of equity at the end of quarter *t.* The data are obtained from CRSP.
$Size_{i,t}$	The logged market capitalization of the stock (in $millions) at the end of quarter *t*. The data are obtained from CRSP.
$BVE_{i,t}$	Book value of equity at the end of quarter *t.* The data are obtained from item #60 from COMPUSTAT.
$MTB_{i,t}$	The ratio of $MVE_{i,t}$ to $BVE_{i,t}$. The data are obtained from CRSP and COMPUSTAT.
$STD_{i,t}$	Standard deviation of firm *i*'s earnings per share excluding extraordinary items, over 20 quarters prior to quarter *t*. The data are obtained from COMPUSTAT.
$LOSS_{i,t}$	Indicator variable equaling 1 if $Earn_{i,t}$ is negative, and equaling 0 otherwise. The data are obtained from COMPUSTAT.

Table 1. Descriptive Statistics

Table 1 presents descriptive statistics of ETF ownership as well as all other variables of interest. The sample spans 40 quarters from Q1:2004 to Q4:2013. Panel A presents ETF ownership over time. $ETF_{i,t}$ is the percentage of a stock held by ETFs, computed for each year and averaged across stocks and quarters. $\# ETF_{i,t}$ is the average number of ETFs that hold the stock. Panel B presents descriptive statistics for other key variables of interest. Variable definitions are in the Appendix.

Panel A. ETF Ownership Over Time

Year	**$ETF_{i,t}$**	**$\# ETF_{i,t}$**
2004	1.22%	8.79
2005	1.61%	9.47
2006	1.92%	8.75
2007	2.22%	13.49
2008	2.72%	17.48
2009	3.00%	15.85
2010	2.49%	11.95
2011	4.32%	19.41
2012	4.54%	17.69
2013	4.93%	19.32

Panel B. Descriptive Statistics of Key Variables of Interest

	N	Mean	Median	Q1	Q3	Std Dev
$\Delta ETF_{i,t}$	109130	0.14%	0.04%	-0.25%	0.52%	1.40%
$ETF_{i,t}$	109130	3.20%	2.49%	0.99%	4.67%	2.80%
$Size_{i,t}$	109130	6.88	6.76	5.63	7.99	1.72
$MTB_{i,t}$	109130	2.70	1.90	1.20	3.16	2.69
$Loss_{i,t}$	109130	0.23	0.00	0.00	0.00	0.42
$STD_{i,t}$	109130	0.00	0.00	0.00	0.00	0.00
$Beta_{i,t}$	109130	1.12	1.08	0.70	1.49	0.66
$Sync_{i,t}$	109130	-1.61	-0.95	-2.11	-0.09	2.60
$\#Shareholders_{i,t}$	109130	21.28	1.23	0.23	6.91	171.41

Table 2. ETF Trading and Informational Efficiency

Table 2 presents associations between returns and earnings using Fama-MacBeth (1973) regressions of returns on contemporaneous earnings that are not available in real-time. The tabulated coefficient estimates are the time-series averages from the following cross-sectional regression:

$$Ret_{i,t} = b_{0,t} + b_{1,t}Earn_{i,t} + b_{2,t}\Delta ETF_{i,t} + b_{3,t}Earn_{i,t} * \Delta ETF_{i,t} + Controls_{i,t} + \varepsilon_{i,t},$$

where $Ret_{i,t}$ is the compounded 3-month return for quarter t. $Earn_{i,t}$ is the seasonally adjusted earnings for quarter t, deflated by the price at the beginning of quarter t. $\Delta ETF_{i,t}$ is the within-quarter decile rank of changes in ETF ownership, scaled to [0,1]. All other variables are as defined in the Appendix. *t*-statistics with Newey-West correction for autocorrelation are reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	1	2	3	4
Intercept	0.02	0.06**	0.02	0.05**
	(1.30)	(2.61)	(1.15)	(2.44)
$Earn_{i,t}$	0.12***	0.19***	0.11***	0.21***
	(3.77)	(5.42)	(3.28)	(4.32)
$\Delta ETF_{i,t}$	0.02***	0.02***	0.02***	0.02***
	(2.99)	(4.02)	(3.43)	(4.64)
$Earn_{i,t}$ * $\Delta ETF_{i,t}$	**0.42*** **	**0.31*** **	**0.30*** **	**0.19** **
	(5.84)	**(4.42)**	**(4.21)**	**(2.49)**
$Earn_{i,t-1}$			0.21***	0.20***
			(4.68)	(4.64)
$Earn_{i,t-1}$* $\Delta ETF_{i,t}$			-0.02	-0.01
			(-0.37)	(-0.12)
$Earn_{i,t+1}$			0.19***	0.19***
			(5.42)	(5.55)
$Earn_{i,t+1}$* $\Delta ETF_{i,t}$			0.09	0.09
			(1.48)	(1.54)
$Size_{i,t-1}$		-0.00**		-0.00*
		(-2.10)		(-1.87)
$MTB_{i,t-1}$		-0.00		-0.00
		(-1.00)		(-1.58)
$STD_{i,t-1}$		-0.39		-0.47
		(-1.06)		(-1.18)
$LOSS_{i,t}$		-0.03***		-0.03***
		(-6.91)		(-7.47)
$Earn_{i,t}$ * $LOSS_{i,t}$		-0.08***		-0.12***
		(-3.23)		(-3.48)
$ETF_{i,t-1}$		-0.10		-0.10
		(-0.88)		(-0.83)
Adj-Rsq	0.01	0.04	0.03	0.06

Table 3. ETF Trading and Informational Efficiency for Alternative Partitions

Table 3 presents associations between returns and earnings using Fama-MacBeth (1973) regressions for alternative subgroups. Small (big) firms are those with market capitalization below (above) the 50th NYSE percentile. Imperfect (perfect) competition firms are those with the number of shareholders below (above) the 75th percentile. For each subgroup, the tabulated coefficient estimates are the time-series averages from the following cross-sectional regression:

$$Ret_{i,t} = b_{0,t} + b_{1,t}Earn_{i,t} + b_{2,t}\Delta ETF_{i,t} + b_{3,t}Earn_{i,t} * \Delta ETF_{i,t} + Controls_{i,t} + \varepsilon_{i,t},$$

where $Ret_{i,t}$ is the compounded 3-month return for quarter t. $Earn_{i,t}$ is the seasonally adjusted earnings for quarter t, deflated by the price at the beginning of quarter t. $\Delta ETF_{i,t}$ is the within-quarter decile rank of changes in ETF ownership, scaled to [0,1]. All other variables are as defined in the Appendix. t-statistics with Newey-West correction for autocorrelation are reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Small Firms		Big Firms		Imperfect Comp		Perfect Comp	
	1	2	3	4	5	6	7	8
Intercept	0.01	0.13***	0.05***	0.26***	0.02	0.07***	0.03*	0.11***
	(0.55)	(5.95)	(3.49)	(6.44)	(1.12)	(2.87)	(1.69)	(3.41)
$Earn_{i,t}$	0.11***	0.22***	0.15***	0.34***	0.10***	0.22***	0.20***	0.38***
	(3.30)	(3.64)	(3.33)	(3.72)	(2.92)	(3.22)	(3.18)	(4.57)
$\Delta ETF_{i,t}$	0.03***	0.04***	-0.00	-0.01*	0.02***	0.02***	0.01**	0.01
	(4.25)	(6.16)	(-0.44)	(-1.72)	(3.79)	(4.31)	(2.11)	(0.80)
$Earn_{i,t}$ * $\Delta ETF_{i,t}$	**0.45***	**0.23***	**0.21**	**-0.03**	**0.48***	**0.25***	**0.19**	**-0.05**
	(6.37)	**(2.93)**	**(1.14)**	**(-0.12)**	**(6.12)**	**(3.26)**	**(1.37)**	**(-0.35)**
$Earn_{i,t-1}$		0.22***		0.15		0.22***		0.20**
		(5.66)		(1.56)		(3.24)		(2.43)
$Earn_{i,t-1}$* $\Delta ETF_{i,t}$		-0.04		0.21**		-0.04		-0.03
		(-0.58)		(2.12)		(-0.45)		(-0.26)
$Earn_{i,t+1}$		0.18***		0.23**		0.22***		0.07
		(4.97)		(2.52)		(6.16)		(1.03)
$Earn_{i,t+1}$* $\Delta ETF_{i,t}$		0.01		0.07		0.02		0.23**
		(1.46)		(0.59)		(0.38)		(2.09)
$Size_{i,t-1}$		-0.02***		-0.02***		-0.01**		-0.01***
		(-5.4)		(-5.87)		(-2.54)		(-3.27)
$MTB_{i,t-1}$		-0.00**		0.00		-0.00		-0.00
		(-2.46)		(0.84)		(-1.70)		(-1.57)
$STD_{i,t-1}$		-0.47		11.04***		-1.16**		-0.34
		(-1.15)		(3.06)		(-2.50)		(-0.20)
$LOSS_{i,t}$		-0.03***		-0.00		-0.03***		-0.03***
		(-8.79)		(-0.45)		(-6.93)		(-4.69)
$Earn_{i,t}$ * $LOSS_{i,t}$		-0.12***		-0.24***		-0.16**		-0.21***
		(-3.41)		(-2.97)		(-2.51)		(-3.05)
$ETF_{i,t-1}$		0.24		-0.19		-0.13		-0.27*
		(1.61)		(-0.82)		(-1.04)		(-1.87)
Adj-Rsq	0.02	0.07	0.01	0.08	0.01	0.05	0.02	0.08

Table 4. ETF Trading and Informational Efficiency: Earnings Components

Table 4 presents associations between returns and earnings components using Fama-MacBeth (1973) regressions for alternative subgroups. Small (big) firms are those with market capitalization below (above) the 50th NYSE percentile. Imperfect (perfect) competition firms are those with the number of shareholders below (above) the 75th percentile. For each firm in each quarter t, total earnings are decomposed into aggregate earnings ($Earn\_Agg_{i,t}$) and firm-specific earnings ($Earn\_Firm_{i,t}$). The aggregate earnings news and firm-specific earnings news are calculated as the fitted values and residuals from firm-specific quarterly regressions of earnings on value-weighted market-related earnings and value-weighted industry-related earnings. For each subgroup, the tabulated coefficient estimates are the time-series averages from the following cross-sectional regression:

$$Ret_{i,t} = b_{0,t} + b_{1,t}Earn\_Agg_{i,t} + b_{2,t}Earn\_Firm_{i,t} + b_{3,t}\Delta ETF_{i,t} + b_{4,t}Earn\_Agg_{i,t} * \Delta ETF_{i,t} + b_{5,t}Earn\_Firm_{i,t} * \Delta ETF_{i,t} + Controls_{i,t} + \varepsilon_{i,t},$$

All other variables are as defined in the Appendix. t-statistics with Newey-West correction for autocorrelation are reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Full		**Small Firms**		**Big Firms**		**Imperfect Comp**		**Perfect Comp**	
	1	2	3	4	5	6	7	8	9	10
Intercept	0.02	0.03*	0.01	0.11***	0.05***	0.28***	0.02	0.06*	0.03*	0.09***
	(1.41)	(1.70)	(0.65)	(5.01)	(3.60)	(6.79)	(1.16)	(1.93)	(1.89)	(2.80)
$Earn\_Agg_{i,t}$	0.26***	0.27***	0.27***	0.28***	0.34**	0.38**	0.23***	0.26***	0.31**	0.32***
	(2.91)	(3.12)	(2.97)	(3.11)	(2.31)	(2.37)	(2.83)	(3.25)	(2.68)	(2.79)
$Earn\_Firm_{i,t}$	0.22***	0.22***	0.21***	0.21***	0.24***	0.24***	0.25***	0.25***	0.20**	0.22**
	(5.62)	(5.80)	(5.16)	(5.16)	(4.78)	(4.06)	(6.46)	(6.51)	(2.39)	(2.62)
$\Delta ETF_{i,t}$	0.02***	0.02***	0.03***	0.03***	-0.00	-0.01**	0.02***	0.02***	0.01*	0.01
	(2.94)	(4.41)	(4.09)	(5.60)	(-0.46)	(-2.09)	(3.64)	(4.12)	(1.94)	(0.89)
$Earn\_Agg_{i,t} * \Delta ETF_{i,t}$	**0.31****	**0.31****	**0.30***	**0.29***	**0.42***	**0.34**	**0.28****	**0.27****	**0.16**	**0.18**
	(2.27)	**(2.23)**	**(1.97)**	**(1.95)**	**(1.80)**	**(1.42)**	**(2.67)**	**(2.47)**	**(0.99)**	**(1.04)**
$Earn\_Firm_{i,t} * \Delta ETF_{i,t}$	**-0.00**	**0.00**	**0.02**	**0.02**	**-0.01**	**-0.01**	**-0.05**	**-0.04**	**0.07**	**0.04**
	(-0.02)	**(0.03)**	**(0.29)**	**(0.40)**	**(-0.06)**	**(-0.05)**	**(-0.82)**	**(-0.77)**	**(0.60)**	**(0.32)**
$Size_{i,t-1}$		-0.00		-0.02***		-0.03***		-0.00		-0.01**
		(-1.00)		(-4.96)		(-6.06)		(-1.53)		(-2.57)
$MTB_{i,t-1}$		-0.00		-0.01**		0.00		-0.00*		-0.00
		(-1.47)		(-2.48)		(1.09)		(-1.69)		(-0.92)
$STD_{i,t-1}$		-0.93**		-1.01**		11.67***		-1.47***		-1.95
		(-2.32)		(-2.41)		(3.23)		(-3.22)		(-1.04)
$ETF_{i,t-1}$		-0.11		0.18		-0.24		-0.18		-0.23
		(-1.00)		(1.22)		(-1.09)		(-1.45)		(-1.58)
Adj R-sq	0.02	0.03	0.02	0.03	0.02	0.06	0.02	0.03	0.03	0.05

Table 5. Market Beta and Fundamentals

Table 5 presents associations between market beta ($\beta_{i,t}$) increase linked to ETF trading and aggregate earnings. $\beta_{i,t}$ is the coefficient of the stock's daily excess returns on daily market excess returns in the quarter t. Panel A presents the relation between market beta and ETF trading, and other controls. The tabulated coefficient estimates in Panel A are the time-series averages from the following cross-sectional regression:

$$\beta_{i,t} = b_{0,t} + b_{1,t}|\Delta ETF_{i,t}| + Controls_{i,t} + \varepsilon_{i,t},$$

where $|\Delta ETF_t|$ is the within-quarter decile rank of the absolute value of $\Delta ETF_{i,t}$, scaled to [0, 1].

Panel B presents change in market beta attributable to ETF trading and earnings components. The tabulated coefficient estimates in Panel B are the time-series averages from the following cross-sectional regression:

$$\widehat{\beta_{i,t}} = b_{0,t} + b_{1,t}|Earn\_Agg_{i,t}| + b_{2,t}|Earn\_Firm_{i,t}| + Controls_{i,t} + \varepsilon_{i,t}$$

$\widehat{\beta_{i,t}}$ is the fitted value of $\beta_{i,t}$ obtained from the first-stage regression (Panel A) with no controls. All other variables are as defined in the Appendix. *t*-statistics with Newey-West correction for autocorrelation are reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A: First stage

	Full Sample		Small Firms		Big Firms		Imperfect Comp		Perfect Comp	
	1	2	3	4	5	6	7	8	9	10
Intercept	0.92***	0.64***	0.89***	0.14	1.03***	1.16***	0.96***	0.65***	0.99***	1.28***
	(29.10)	(8.21)	(18.86)	(1.61)	(38.99)	(8.78)	(21.91)	(6.94)	(42.7)	(13.68)
$\lvert\Delta ETF_{i,t}\rvert$	**0.40*** **	**0.22*** **	**0.50*** **	**0.22*** **	**0.10*** **	**0.04**	**0.40*** **	**0.21*** **	**0.25*** **	**0.14*** **
	(8.21)	**(3.07)**	**(8.24)**	**(2.94)**	**(2.82)**	**(1.07)**	**(6.62)**	**(2.78)**	**(6.02)**	**(2.79)**
$Size_{i,t-1}$		0.02***		0.12***		-0.02		0.03***		-0.04***
		(3.07)		(11.87)		(-1.56)		(3.24)		(-4.74)
$MTB_{i,t-1}$		0.00		0.01		-0.00		0.00		-0.00
		(1.23)		(1.54)		(-0.49)		(1.31)		(-0.55)
$STD_{i,t-1}$		4.25*		6.02***		36.10***		-0.21		6.64
		(1.97)		(3.13)		(2.77)		(-0.13)		(1.08)
$ETF_{i,t-1}$		7.97***		7.13***		2.62***		7.88***		4.00***
		(4.61)		(4.14)		(2.93)		(3.89)		(3.94)
Adj R-sq	0.05	0.11	0.07	0.16	0.01	0.04	0.05	0.11	0.03	0.08

Table 5. Continued.

Panel B: Second Stage

	Full Sample		**Small Firms**		**Big Firms**		**Imperfect Comp**		**Perfect Comp**	
	1	2	3	4	5	6	7	8	9	10
Intercept	1.03***	1.03***	1.02***	0.93***	1.05***	1.04***	1.07***	1.05***	1.05***	1.14***
	(46.15)	(38.05)	(31.56)	(22.96)	(54.55)	(43.55)	(36.33)	(33.26)	(67.55)	(44.89)
$\|Earn\_Agg_{i,t}\|$	**0.06***	**0.06****	**0.06***	**0.04****	**0.02**	**0.02**	**0.06***	**0.08****	**0.13*****	**0.06***
	(1.89)	**(2.04)**	**(1.74)**	**(2.08)**	**(1.01)**	**(0.69)**	**(1.83)**	**(2.53)**	**(3.07)**	**(2.00)**
$\|Earn\_Firm_{i,t}\|$	**-0.01**	**-0.01**	**-0.03**	**0.01**	**-0.01**	**-0.00**	**-0.03**	**-0.00**	**0.01**	**-0.01**
	(-0.81)	**(-0.45)**	**(-1.08)**	**-0.56**	**(-0.70)**	**(-0.39)**	**(-1.12)**	**(-0.22)**	**(0.81)**	**(-0.69)**
$Size_{i,t-1}$		-0.00		0.02***		0.00		0.00***		-0.01***
		(-0.23)		(3.55)		(0.49)		(3.02)		(-3.22)
$MTB_{i,t-1}$		0.00		-0.00		0.00**		0.00		-0.00*
		(0.74)		(-0.31)		(2.23)		(0.41)		(-1.80)
$STD_{i,t-1}$		-0.76		-0.16		0.05		-0.86		-2.52**
		(-1.45)		(-0.50)		(0.07)		(-1.95)		(-2.27)
$ETF_{i,t-1}$	3.88***	3.85***	4.96***	3.45***	0.99***	1.00***	3.76***	3.54***	2.38***	2.01***
	(4.47)	(4.41)	(4.55)	(4.81)	(3.46)	(3.56)	(4.00)	(4.02)	(4.04)	(4.20)
Adj R-sq	0.25	0.28	0.28	0.31	0.20	0.26	0.23	0.25	0.20	0.28

Table 6. Synchronicity and Fundamentals

Table 6 reports associations between return synchronicity ($Sync_{i,t}$) increases linked to ETF trading and aggregate earnings. $Sync_{i,t}$ is the stock return synchronicity in quarter t. Panel A presents the relation between return synchronicity and ETF trading, and other controls. The tabulated coefficient estimates in panel A are the time-series averages from the following cross-sectional regression:

$$Sync_{i,t} = b_{0,t} + b_{1,t}|\Delta ETF_t| + Controls_{i,t} + \varepsilon_{i,t}.$$

where $|\Delta ETF_t|$ is the within-quarter decile rank of the absolute value of $\Delta ETF_{i,t}$, scaled to [0, 1].

Panel B presents change in return synchronicity attributable to ETF trading and earnings components. The tabulated coefficient estimates in Panel B are the time-series averages from the following cross-sectional regression:

$$\widehat{Sync}_{i,t} = b_{0,t} + b_{1,t}|Earn\_Agg_{i,t}| + b_{2,t}|Earn\_Firm_{i,t}| + Controls_{i,t} + \varepsilon_{i,t}$$

$\widehat{Sync}_{i,t}$ is the fitted value of $Sync_{i,t}$ obtained from the first-stage regression (panel A) with no controls. All other variables are as defined in the Appendix. *t*-statistics with Newey-West correction for autocorrelation are reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A: First Stage

	Full Sample		**Small Firms**		**Big Firms**		**Imperfect Comp**		**Perfect Comp**	
	1	2	3	4	5	6	7	8	9	10
Intercept	-2.44***	-7.66***	-3.45***	-9.27***	-0.52***	-4.47***	-2.83***	-7.86***	-0.77***	-5.55***
	(-11.54)	(-21.43)	(-13.96)	(-25.96)	(-3.30)	(-11.40)	(-10.89)	(-19.19)	(-4.09)	(-12.50)
$\|\Delta ETF_{i,t}\|$	**1.70*** **	**0.72*** **	**2.58*** **	**0.74*** **	**0.27*** **	**0.10**	**2.02*** **	**0.66*** **	**0.27** **	**0.31** **
	(9.95)	**(3.78)**	**(11.28)**	**(3.79)**	**(3.00)**	**(1.22)**	**(9.53)**	**(3.55)**	**(2.09)**	**(2.20)**
$Size_{i,t-1}$		0.71***		1.02***		0.40***		0.76***		0.51***
		(30.70)		(35.80)		(15.18)		(25.54)		(16.58)
$MTB_{i,t-1}$		-0.01***		-0.01***		-0.02***		-0.02***		-0.02***
		(-4.22)		(-3.70)		(-6.08)		(-5.30)		(-4.30)
$STD_{i,t-1}$		-22.25***		-11.58*		-191.11***		-23.41***		-75.68***
		(-3.69)		(-1.90)		(-7.00)		(-5.25)		(-4.70)
$ETF_{i,t-1}$		33.94***		28.47***		24.95***		32.48***		26.35***
		(7.13)		(6.43)		(4.83)		(5.96)		(6.76)
Adj R-sq	0.07	0.39	0.12	0.36	0.01	0.12	0.08	0.36	0.03	0.31

Table 6. Continued.

Panel B: Second Stage

	Full Sample		Small Firms		Big Firms		Imperfect Comp		Perfect Comp	
	1	2	3	4	5	6	7	8	9	10
Intercept	-1.99***	-2.13***	-2.78***	-3.47***	-0.43***	-0.64***	-2.26***	-2.47***	-0.60***	-0.93***
	(-11.16)	(-11.26)	(-14.07)	(-11.37)	(-3.04)	(-3.80)	(-10.60)	(-10.93)	(-3.86)	(-4.96)
$\lvert Earn\_Agg_{i,t-1} \rvert$	**0.17**	**0.28****	**0.22**	**0.30****	**-0.02**	**0.08**	**0.16**	**0.28****	**-0.33****	**0.00**
	(1.28)	**(2.34)**	**(1.16)**	**(2.08)**	**(-0.32)**	**(1.42)**	**(1.04)**	**(2.11)**	**(-2.23)**	**(0.02)**
$\lvert Earn\_Firm_{i,t-1} \rvert$	**-0.10**	**0.00**	**-0.16**	**0.09**	**-0.11****	**-0.07***	**-0.11**	**0.04**	**-0.14***	**0.02**
	(-1.65)	**(0.03)**	**(-1.20)**	**(1.10)**	**(-2.58)**	**(-1.81)**	**(-1.24)**	**(0.40)**	**(-2.05)**	**(0.38)**
$Size_{i,t-1}$		15.54***		21.40***		2.73***		0.04***		0.04***
		(5.23)		(5.86)		(2.38)		(3.94)		(3.37)
$MTB_{i,t-1}$		0.02*		0.13***		0.00***		0.00		-0.00
		(1.81)		(4.64)		(3.56)		(0.14)		(-1.58)
$STD_{i,t-1}$		0.00		-0.00		-0.00		-3.95*		0.63
		(0.15)		(-0.19)		(-1.24)		(-2.00)		(0.72)
$ETF_{i,t-1}$	15.59***	-2.14	25.87***	-0.56	1.98	-7.41***	19.02***	17.73***	1.15	2.64**
	(5.22)	(-1.05)	(5.32)	(-0.26)	(1.49)	(-2.82)	(4.94)	(4.94)	(0.86)	(2.55)
Adj R-sq	0.25	0.28	0.28	0.31	0.20	0.26	0.23	0.25	0.20	0.28

Table 7. ETF Trading and Informational Efficiency of Stocks Added to and Deleted from the S&P 500 Index

Table 7 presents the association between returns and earnings using the sample comprised of firms that are added to or deleted from S&P 500 index from March 2004 to December 2013. Small (big) firms are those with market capitalization below (above) the 50th NYSE percentile. Imperfect (perfect) competition firms are those with the number of shareholders below (above) the 75th percentile. For each subgroup, the tabulated coefficient estimates are the time-series averages from the following cross-sectional regression:

$Ret_{i,t}=b_1Earn_{i,t}+ b_2In_{i,t} +b_3Post_{i,t}+ b_4\ Earn_{i,t} * In_{i,t} *Post_{i,t}+ b_5\ In_{i,t} *Post_{i,t}+ b_6\ Earn_{i,t} * In_{i,t}+ b_7Earn_{i,t}* Post_{i,t}+Controls+ \mu_t+\varepsilon_{i,t}$

where $In_{i,t}$=1 if firm *i* is added into S&P 500 index during the sample period, and $In_{i,t}$ =0 if firm *i* is deleted from S&P500 index. $Post_{i,t}$=1 if the addition/deletion event happens in quarter *t* or quarter *t-1*, and $Post_{i,t}$=0 if the addition/deletion event happens in quarter t+1. All other variables are as defined in the Appendix. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Full	**Small**	**Big**	**ImPerfect Comp**	**Perfect Comp**
	1	2	3	4	5
Intercept	0.17	1.58***	-0.03	0.08	-0.07
	(1.15)	(4.82)	(-0.14)	(0.62)	(-0.20)
$Earn_{i,t}$	0.41***	0.26*	0.43	0.49*	0.53***
	(3.81)	(2.00)	(1.08)	(1.93)	(2.79)
$Earn_{i,t}$ *$In_{i,t}$ *$Post_{i,t}$	**0.75**	**2.48***	**0.19**	**1.48****	**2.89**
	(1.53)	**(1.77)**	**(0.30)**	**(2.23)**	**(0.96)**
$In_{i,t}$ *$Post_{i,t}$	-0.07**	-0.01	-0.26***	-0.06	-0.23**
	(-1.76)	(-0.09)	(-3.16)	(-1.34)	(-2.10)
$Earn_{i,t}$ *$In_{i,t}$	-0.66	-0.58	-0.56	-0.72	-2.72
	(-1.34)	(-0.52)	(-0.89)	(-1.35)	(-0.90)
$In_{i,t}$	0.19***	0.38***	0.19***	0.17***	0.25**
	(5.39)	(6.37)	(2.63)	(4.40)	(2.61)
$Post_{i,t}$	0.00	-0.07	0.22***	-0.00	0.07
	(0.10)	(-1.41)	(2.78)	(-0.08)	(0.80)
$Earn_{i,t}$ * $Post_{i,t}$	-0.51***	-0.37***	-0.07	-0.57**	-0.71***
	(-4.51)	(-2.73)	(-0.17)	(-2.23)	(-3.35)
$Size_{i,t-1}$	-0.03***	-0.21***	-0.01	-0.02**	-0.03
	(-2.69)	(-2.60)	(-0.71)	(-1.52)	(-0.77)
$MTB_{i,t-1}$	0.00	0.01*	0.00	0.00	0.01
	(0.46)	(2.11)	(0.27)	(0.19)	(1.19)
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	681	336	345	524	157
Adj-Rsq.	0.40	0.49	0.51	0.41	0.53