ETFs and Information Transfer Across Firms

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Abstract: This paper examines the role that exchange-traded funds (ETFs) play in information transfer/dissemination across firms. Using earnings announcements as a source of information, we examine how ETF ownership influences the flow of information between firms. We focus on the largest constituents of ETFs and separate them into lead announcers and followers. Consistent with a factor-investing role, sector ETFs have improved information transfer around earnings announcements, with greater followers' reaction to the leaders' announcements and lower subsequent reversals. In this setting, non-sector ETFs are not particularly effective in facilitating information transfer, with the reversal effect observed in the overall sample being driven primarily by the non-sector ETFs. We also show that ETF ownership at the firm level is associated with lower levels of post-earnings announcement drift, but only when the ETF ownership is sectoral. In general, we find that sector ETFs are effective at transmitting factor (industry) information impounded in earnings news but general broad market ETFs are not very useful (and potentially detrimental). Our results highlighting the role of sector ETFs help reconcile conflicting results in the prior research as to whether ETFs foster greater market efficiency.

Keywords: ETF, Information transfer, Post earnings announcement drift, sector ETF

JEL Classification: G12, G14, M41, D53

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Abstract: This paper examines the role that exchange-traded funds (ETFs) play in information transfer/dissemination across firms. Using earnings announcements as a source of information, we examine how ETF ownership influences the flow of information between firms. We focus on the largest constituents of ETFs and separate them into lead announcers and followers. Consistent with a factor-investing role, sector ETFs have improved information transfer around earnings announcements, with greater followers' reaction to the leaders' announcements and lower subsequent reversals. In this setting, non-sector ETFs are not particularly effective in facilitating information transfer, with the reversal effect observed in the overall sample being driven primarily by the non-sector ETFs. We also show that ETF ownership at the firm level is associated with lower levels of post-earnings announcement drift, but only when the ETF ownership is sectoral. In general, we find that sector ETFs are effective at transmitting factor (industry) information impounded in earnings news but general broad market ETFs are not very useful (and potentially detrimental). Our results highlighting the role of sector ETFs help reconcile conflicting results in the prior research as to whether ETFs foster greater market efficiency.

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1. Introduction

In this paper, we examine the role that exchange-traded funds (henceforth ETFs) play in information transfer/dissemination across firms. The last decade has seen a significant shift in the asset management landscape with the growth of ETFs. As of the end of 2015, the ETF industry had assets under management (AUM) of roughly $2.9 trillion of which nearly $2 trillion was in the US (ICI Factbook 2016). In the 10 years ending 2015, ETFs have seen inflows of nearly $1.6 trillion. ETFs play a significant role in financial markets, particularly equity markets, constituting roughly 30 percent of US market trading by value and 23 percent of trading by volume.[1] Therefore, given the size of the AUM and the proportion of trading volume they represent, understanding the relation between ETFs and its constituents is important to gain insight into the benefits and costs of these instruments. In this paper, we address this issue by focusing on role of ETFs in facilitating or inhibiting the information transfer between constituents of the ETFs. We do this by using earnings announcement as an identifiable and significant source of information and examine the effect of different types of ETFs on flow of information between the ETF constituents.

Ex-ante, the impact of ETFs on information transfer between its constituents is unclear. Information is comprised in varying degrees, of idiosyncratic components, industry level information and information about the economy or market level information. One of the biggest benefits of ETFs is that they allow for trading a large number of stocks in a cost-efficient manner. This feature of ETFs can allow commonality in information (like industry information or market level information) to quickly percolate through to all the constituents of the ETF. In modeling composite securities like ETFs, Subrahmanyam (1991) and Cong and Xu (2017) argue that these

[1] https://www.ft.com/content/6dabad28-e19c-11e6-9645-c9357a75844a

securities attract factor-informed traders. Trading using ETFs can be a more efficient mechanism to capture industry level information or market level information incorporated in any information source.[2] This would suggest that ETFs would make stocks prices of its constituents more efficient.

On the other hand, ETFs could be limited in their ability to effectively transfer information across firms. This is because they are baskets created based on fixed rules (e.g., market capitalization weighted) and therefore ETF trading forces information to be impounded at the proportion determined by the rules rather than based on the value of the information to each of the constituents. This can result in the constituents being potentially mispriced, subsequent to an earnings announcement, unless another group of investors (active managers or arbitragers) trading in the individual constituents quickly correct this mispricing. For example, ETF trading that is driven by earnings news that is idiosyncratic and therefore has no relevance to constituents other than the announcing firm can cause a mispricing in the other firms.[3] This will have to be corrected by investors trading the other constituents.[4] In addition, Israeli, Lee and Sridharan (2017) argue that increased ETF ownership may dis-incentivize traders from acquiring information of individual stocks, leading to fewer firm-specific informed traders and potential pricing inefficiency.

The above discussion suggests that the ability of ETFs to facilitate information flow should be vary by the type of ETFs, with ETFs that allow for factor information to be better expressed having a greater impact on the underlying constituents. While prior studies have viewed ETFs as

[2] Market participants use ETFs to achieve exactly this outcome.

[3] While this is an extreme case and raises the question of why investors would trade ETFs around earnings that is purely idiosyncratic, the more likely scenario is one where the earnings has some systematic information that is not properly weighted given the composition of the existing ETFs.

[4] Another approach would be to have a large number of ETFs with different weights that allow investors to trade the right instrument based on the information in the earnings announced. This would require ETFs with fewer constituents that allow for a more focused expression of the underlying information. At the extreme, this approach simply devolves into each firm being its own ETF.

a homogenous group, in reality ETFs can be broadly partitioned into at least two distinctly different groups: market level ETFs (e.g., SPY, S&P 500 SPDR Fund and VOO, Vanguard S&P 500 Index fund) and sector or industry level ETFs (e.g., XLK, Technology Select Sector SPDR Fund and XLY, Consumer Discretionary Select Sector SPDR Fund). Subrahmanyam (1991) and Cong and Xu (2017) suggest that creating composite security designs that deviate from market weights or expressing factor weights that are different from market weights allows for better factor investing. These securities could result in greater efficiency compared to market weighted ETFs, as the increases in factor-informed traders may offset the decreases in firm-specific informed traders. In this paper, we investigate the role of ETFs in disseminating relevant information contained in the earnings of a firm to other constituent firms. We also examine if the role that ETFs play in facilitating earnings related information flow, and therefore the underlying pricing efficiency of the constituents, is influenced by the type of ETF (sector and non-sector ETFs). In doing so, we also help reconcile some of the conflicting results in the existing literature.

We carry out our analysis at two levels: at the ETF level and at the firm level, using a large sample of ETFs from 2002-2015. Our first approach is an ETF level analysis wherein we identify the five largest holdings within each ETF.[5] Limiting to the top five holdings allows us to identify firms where liquidity, and therefore limited arbitrage opportunities at the individual stock level, is less likely to be an issue.[6] Using this sample, we examine the stock price return behavior of the first firm to announce earnings (the leader) and the other four firms (followers). We analyze the

[5] This distinguishes us from the extant literature on ETFs that has largely conducted analysis at the firm level.

[6] In a recent working paper Pan and Zeng (2017) find mispricing that occurs because of a liquidity mismatch between liquid bond ETFs and illiquid underlying bond instruments. In a related paper Bhattacharya and O'Hara (2017) examine the informational efficiency of underlying markets when the constituents underlying ETFs are illiquid. Focusing on the top five ETF constituents helps avoid this issue.

returns to the leader around its own earnings announcement (LRET) and the returns to the follower across two windows – around the leader's earnings announcement ($FRET_{ANNC}$) and between the leader and the followers' earnings announcements ($FRET_{BETW}$). We then parse ETFs into two groups based on their type. We identify each ETF as a sector or non-sector. As the top five firms in sector level ETFs are more likely to comprise of firms that more closely related to each other, sector ETFs could potentially be more effective in transmitting industry level information. Conversely, the top five firms in non-sector ETFs (e.g., S&P 500 tracking ETFs) are more likely to be from different industries and any information flow between these constituents should be limited to macro level data. Both kinds of ETFs are limited in their ability to transmit firm level idiosyncratic information. We therefore expect to find that more information flows through constituents of sector ETFs and it does so more efficiently as compared with non-sector ETFs.

We find that, on average, follower returns are positively associated with leader returns around the leader's earnings announcement. While this effect is driven by sector and non-sector ETFs, the effect is three times larger for sector ETFs i.e., followers in sector ETFs experience a much larger response to the leader's earnings announcement return.[7] To ensure that our results are driven by ETF membership rather by any alternative explanations including direct intra-industry information transfers, we carry out two additional analyses. First, we examine our results over two sample periods: before and after the introduction of sector ETFs (pre-ETF and ETF periods). Using the same pairs as in the ETF period we find that in the pre-ETF period, non-sector ETF followers did not experience an earnings response to the leader's earnings announcement returns, while sector ETF followers did respond. This has changed in the ETF period with both groups

[7] Good news for the leader does not automatically imply that it is good news for the followers. For example, if the lead announcer has positive earnings surprise arising out of greater market share, it could signal bad news for the follower competitor firms. Our results suggest that on average the information that this being transferred within sector firms is positive.

experiencing a positive response, albeit with a much a stronger response for sector ETF follower firms. The findings on non-sector ETFs is very interesting in that it suggests that ETF membership is causing co-movement of firm returns in the ETF period. The lack of evidence of an association in the pre-ETF period suggests that this co-movement is potentially not warranted and is consistent with the increase in pernicious return co-movement that has been documented in the prior literature on ETFs (Da and Shive, 2018; Leippold, Su and Zeigler 2016; Israeli, Lee and Sridharan 2017). As a second test, we partition the lead-follower pairs into two groups based on whether the underlying ETF trading volume is high or low and expect to see high-volume ETFs to be more effective in transmitting information. Consistent with this, we find that the results pertaining to sector ETFs are primarily driven by high-volume ETFs.

The next question is whether the ETF associated market reaction experienced by follower firms around the leader's earnings announcement is efficient or not. We find that followers in non-sector ETFs experience a larger reversal as compared with followers in sector ETFs. This suggests that the follower constituents of non-sector ETFs are likely to experience an overreaction around the leader's earning announcement and is consistent with the return co-movement discussed earlier. Sector ETF followers experience a more muted reversal suggesting a more efficient price response around the leader's earnings announcement. When examining the pre-ETF period, we find distinctly different results with sector ETF pairs experience a strongly reversal as compared with the non-sector ETFs. The finding of strong sector reversals in the pre-ETF period is consistent with Thomas and Zhang (2008). Partitioning the sample based on the underlying ETF trading volume shows evidence consistent with the reversal being driven by high-volume ETFs.

Taken together, the ETF level results suggest that while sector ETFs have facilitated the flow of information and greater market efficiency, non-sector ETFs have likely increased return co-movement and are therefore ineffective or even potentially detrimental to market efficiency. These findings are consistent with Subrahmanyam (1991) and Cong and Xu (2017), in that they suggest that trading earnings information through more factor specific ETFs can result in more efficient pricing of the constituents as compared with broader market ETFs.

As an alternative approach to addressing our research question, we use firm level analyses. Specifically, we use the research design in Thomas and Zhang (2008) that examines the intra-industry transfer of information around earnings announcements. They find that markets overestimate the industry level information of early announcers' earnings for late announcers' earnings (within the same industry), and correct this overestimation when late announcers disclose their earnings. Using their research design, we examine whether the introduction of ETFs (particularly sector ETFs) has affected this overreaction by making it better or worse. We alter their research design to account for introduction of ETFs, using a set of firms within a sector that eventually entered a sector ETF. We examine the intra-industry information transfer for this set of firms, during the period prior to their inclusion into an ETF and compare it to the period after their inclusion. We find that the inclusion in sector ETFs moderates the return reversal for these firms, suggesting that sector ETFs facilitate more efficient information transfer. These results taken together are consistent with the ETF level results and are consistent with sector ETFs improving the information efficiency of the underlying constituents.

To further support our findings from the ETF and firm level analyses, we delve deeper into the returns correlation by carrying out a path analysis that separates the overall correlation between the constituents into a direct correlation between the constituents and an indirect effect that flows through ETFs. The path analysis shows that ETFs play a significant role in facilitating the flow of information between their constituents. The results are particularly strong for sector ETFs, which show that the mediation effect is roughly 48 percent of the overall effect as compared with only 14 percent for non-sector ETFs.

Having documented that ETFs, specifically sector ETFs, can facilitate the transfer of information among individual constituents, we turn our attention to whether these information transfers promote longer-term market efficiency. We study the impact of ETF membership on the post-earnings announcement drift (PEAD), a well-established anomaly that shows that markets are slow to respond to information in earnings announcements. Given our emphasis on earnings announcements, the PEAD is a natural anomaly for us to analyze. Using the overall sample, we find that ETF ownership mitigates the drift – i.e. financial information is impounded into prices earlier for firms with greater ETF ownership. Crucially, this effect is driven entirely by sector ETF ownership. For non-sector ETF ownership, we see limited impact of ETF ownership on the drift.

This paper is related to a recent working paper by Huang, O'Hara and Zhong (2018) who examine the role of industry ETFs in facilitating the hedging of industry specific risks. They posit that ETFs allow traders to take long positions in individual stocks and short industry ETFs to offset industry exposure. They examine sector ETF short-selling behavior before earnings announcements, and find that pre-emptive trading prior to earnings announcements by industry participants (particularly hedge funds) reduces market reaction to earnings surprises. While our focus is on a different channel, in that we examine the role that ETFs (particularly industry or sector ETFs) play in information transfer, the overall message of the papers complement each other - industry ETFs facilitate greater market efficiency.

Our paper bridges the seemingly inconsistent results in the prior academic literature regarding the impact of ETFs on market efficiency. One stream of work finds that ETFs can adversely affect the trading environment as well as the market efficiency of their constituents. Da and Shive (2018) document that ETF activity leads to an anomalous increase in return co-movement leading to future stock price reversals. Ben-David, Franzoni and Moussawi (2017) find that stocks with higher ETF ownership display greater stock price volatility, which increases undiversifiable or idiosyncratic risk. Additionally, Israeli, Lee and Sridharan (2017) show that increases in ETF ownership are associated with higher bid-ask spreads, lower future earnings response coefficients and declines in analyst coverage. In contrast, Glosten, Nallareddy and Zou (2017) find that increases in ETF activity result in the timelier incorporation of systematic earnings information, especially for firms in weak information environments.

These seemingly inconsistent results can be reconciled as they pertain to different aspects of information. The first set of studies indicate that ETFs can increase idiosyncratic risk, while the latter paper shows that ETFs can improve the pricing of systematic risk. By separating ETFs into sector ETFs and non-sector ETFs, we can compare ETFs that are better designed to impound industry level information in earnings to other kinds of ETFs. Non-sector ETFs can cause ETF constituents react to information that may not be relevant, causing anomalous return co-movement and future reversals, leading to increased return volatility. While sector ETFs also increase return co-movement, this is driven by the relevance of common information, leading to earlier impounding of news pertinent to future earnings, which in turn reduces earnings drift. The results hence corroborate the theoretical framework in Subrahmanyam (1991) and Cong and Xu (2017) which suggests that composite securities, such as ETFs, are investing vehicles that facilitate efficient impounding of factor information.

This paper also contributes to the literature on intra-information industry transfer (Freeman and Tse, 1992). Thomas and Zhang (2008) find evidence that late announcers overreact to the earnings release of the early announcers. Our paper contributes to this literature by showing that sector ETFs can facilitate the transfer of information from one firm to another. We find that late announcers that are large constituents of sector ETFs react appropriately to the leader's earnings announcement and exhibit much more muted subsequent reversals, suggesting that ETFs have reduced the intra-industry over-reaction documented in prior work.

The rest of the paper is organized as follows. Section 2 briefly describes the background of ETFs. Section 3 discusses the sample. In section 4, we carry out the analysis at the ETF level while section 5 describes and discusses the firm level analysis. Section 6 focuses on ETFs and Post earnings announcement drift and section 7 concludes the paper.

2. Institutional Background on ETFs

Exchange-traded funds (ETFs) are investment companies classified as open-ended companies or unit investment trusts (UITs). The first U.S ETF began trading in 1993 (SPY, S&P 500 SPDR) but they became very popular after 2000. ETFs assets in 1993 were 464 million dollars and grew to about 33 billion dollars by the end of 1999. ETF assets experience significant growth from 2000 to 2011 rising to about one trillion dollars. In the four years from 2012 to 2015, these assets experienced phenomenal growth by doubling in size to two trillion dollars. As of the end of 2015 there were 1500 ETFs, up from about 80 in 2000. ETFs historically have tracked indices but more recently (starting in 2008), ETFs also include actively managed vehicles.[8]

[8] While ETFs cover a wide spectrum of asset classes, they are predominantly equity focused. Of the approximately two trillion dollars in ETF assets as of the end of 2015, equity ETFs accounted for approximately 82 percent, bond and hybrid ETFs accounted for about 16 percent, and commodities for the remaining 2 percent. While most ETFs are passive vehicles that track an index active ETFs are gaining in popularity, though these are still tiny with an AUM of approximately $27 billion as of the end of 2015 (2016 ICI Factbook).

ETFs are unique investing vehicles that share some similarities and differences from open-ended mutual funds. On the one hand, ETFs are similar to other open-ended funds because ETFs own the underlying assets (stocks, bonds, commodities, futures, foreign currency, etc.) and divide ownership of those assets into shares. On the other hand, unlike open-ended funds which are priced at the end of trading day, ETFs are traded on stock exchanges and priced throughout the day (though the NAV for the ETF is struck only once at the end of the day, like a mutual fund).

An ETF is created by a sponsor who chooses the investment objective and benchmark for the ETF. This could be a market weighted index or other indices created using alternative techniques like equal weighting or factors such as value, growth etc. Index based ETFs could perfectly mimic the underlying index or choose a representative sample of stocks. For example, SPDR S&P 500 ETF Trust (SPY), which is the largest ETF, tracks the S&P 500 which is a float weighted index. Other ETFs could use alternative methods – e.g. First Dow Jones Internet Index Fund (FDN) tracks the Dow Jones Internet Index which is float and volume weighted, while the PowerShares Value with Momentum ETF is a factor-based ETF.

The sponsor manages the process of creating and redeeming ETFs which is key to ensuring intra-day liquidity. This is achieved through a group of intermediary financial institutions called authorized participants (AP). If the demand for ETFs exceeds the available shares, an AP can buy the underlying constituent portfolio and deposit it with the sponsor in exchange for shares in the ETF (ETF creation). Similarly, if the supply of ETFs in the market exceeds the demand, an AP can buy ETFs in the open market and give them to the sponsor in exchange for shares in the underlying constituents (ETF redemption). This ensures that the market price of the ETF closely tracks its NAV. To facilitate this process, an estimate of the underlying value of the ETF (called the intra-day indicative value) is provided by various parties or calculated by the AP. It is worth noting that on average 90 percent of the daily ETF volume occurs in the secondary market. Thus, while the creation/redemption process is key to a functioning ETF market, it is not often needed.

This process results in ETFs being traded like ordinary stocks that can be bought and sold throughout the trading day. Investors can purchase ETF shares on margin, short sell shares, or hold for the long term. The ability to trade easily, overlaid with low fees and diversification, results in ETFs being very popular and having high trading volume. ETFs on average represent roughly 30 percent of daily market volume. In 2016, the top twelve most traded securities were all ETFs, ahead of the most traded individual security (AAPL). Since high trading volumes mean high liquidity, ETFs are an attractive venue for informed investors as well as noise traders. In summary, the liquidity of ETFs, along with their low cost, tax advantages and diversification have made them attractive to investors who would otherwise have to trade the underlying securities. Our paper aims to better understand the effect of ETFs on market efficiency of their underlying securities.

3. ETF Sample Construction

Our sample selection procedure is outlined in Table 1. Panel A describes how we arrive at the sample of ETFs for our analysis. As discussed in section 2, an ETF is a type of fund that owns the underlying assets (stocks, bonds, commodities, futures, foreign currency, etc.) and divides ownership of those assets into shares. For our study, we focus on ETFs with underlying assets in shares of stocks (i.e., equity ETFs). First, we use CRSP to identify ETFs traded on major US exchanges (CRSP historical code of 73). ETFs are required to disclose their portfolio holdings at the end of each quarter on SEC forms N-CSR and N-Q. We hence merge the names of the ETFs with Thomson-Reuters Mutual Fund Holding (S12) database to construct ETF holdings for each stock at the end of each quarter. This process yields 487 ETFs in the period from 2002 to 2015,[9] which is similar to the number of ETFs from the literature (Israeli, Lee and Sridharan 2017, Glosten, Nallareddy and Zou 2017).

In this study we are also interested in distinguishing between sector and non-sector ETFs. Sector ETFs target various industries and sectors in U.S. and international equity markets, typically identified in the fund title. NYSE, NASDAQ and some popular ETF websites, such as ETF.com and ETFdb.com give a comprehensive list of the names of sector ETFs. We first rely on these names to code our ETFs and also conduct a final check by reading the name of each ETF to prevent miscoding. Of these 487 ETFs, 214 were sector ETFs while 273 were broader non-sector ETFs. For comparison, Huang, O'Hara and Zhong (2018) identify 217 industry ETFs before narrowing their sample down based on additional screens.

Panel B displays the sample distribution across time. The sample has noticeably fewer observations in the early years, with 106 distinct ETFs in 2002. This increases sharply to 413 distinct ETFs by 2007 and 473 distinct ETFs in 2008, declining slightly after that. Overall, there is little evidence of time clustering in our sample. Panel C presents the distribution of the different sectors that the sector ETFs in our sample focus on. The 214 sector ETFs can be classified into 32 distinct sectors or subsectors. While many sectors have only a handful of ETFs, a few sectors have a large number of competing ETFs - e.g. Consumer Products (21), Energy (10), Financial Services (15), Healthcare (29), Real Estate (20) and Technology (18).

[9] We start our analysis from 2002 since ETF ownership was low before 2002. In addition, SEC proposed to require funds to file their complete portfolio holdings schedules with the Commission on a quarterly basis, rather than semi-annually in 2002. This rule was finalized in 2004. Our results remain the same if we start from 2004.

4. ETF Level Analyses

4.1 Research Design

4.1.1 Identifying Leader-Follower pairs

Exchange-traded funds often contain a large number of stocks, including some small capitalization stocks which can be illiquid and thinly traded. Given our interest in the pricing of earnings related information, we focus our attention on the five largest holdings in a given ETF based on dollar value weights.[10] Our analysis is focused around the release of quarterly earnings information. In a given fiscal quarter, the five chosen firms in the ETF are ordered on the basis of their earnings release date. The firm which is first to release quarterly information is referred to as the leader, while the other four are referred to as followers.[11] In all of our analyses, we focus on the overall sample of ETFs as well as sector and non-sector subsamples. A pair can appear only once in a quarter in our data selection process in order to avoid repetitive pairs. If a pair appears in both sector and non-sector subsamples in a given quarter, only the pair from sector ETFs is kept.

Panel A of Table 2 outlines how we generate the sample of leaders and followers for our analysis around earnings announcements. The sample of 487 ETFs correspond to 16,707 distinct ETF-quarters from 2002 to 2015.[12] We begin by identifying the top 5 holdings of each ETF by dollar value weight of each constituent at the end of each quarter. Of these, the firm that releases earnings the first in a given quarter is referred to as the leader, which is paired with four followers.

[10] We also limit our analysis to the two largest holdings, i.e. with one leader and one follower, with similar findings.

[11] As an alternative approach we also identify leaders as the largest market capitalization firm from among the five stocks and followers as subsequent announcers. The results are similar to those discussed using the main sample.

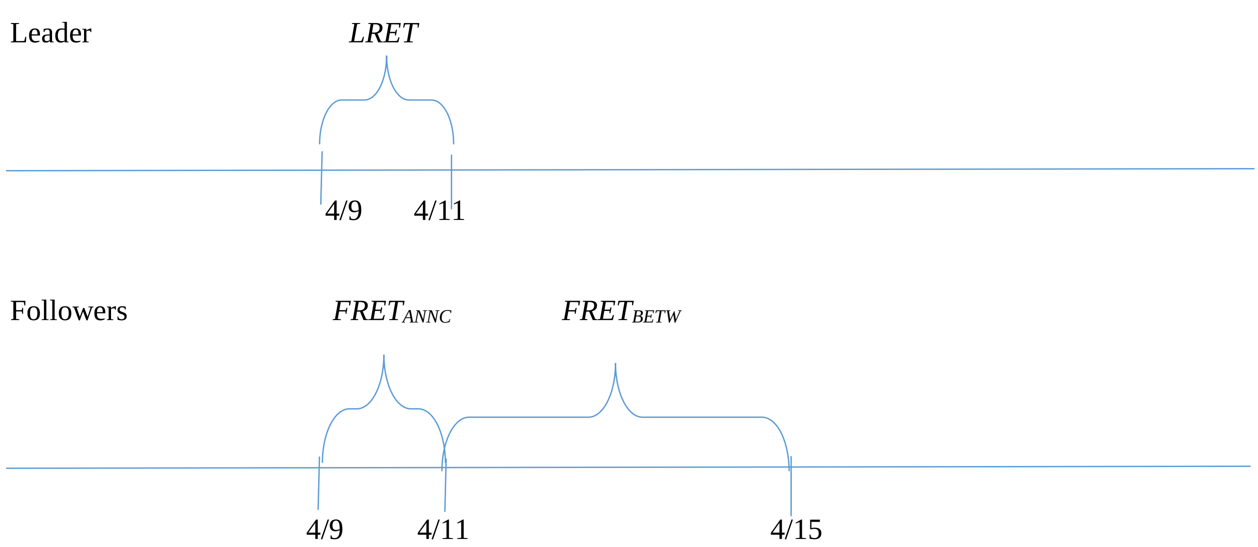
[12] While the first market ETF was launched in 1993 and the first sector ETF in 1999, ETFs were relatively small till their explosive growth starting in 2002. In addition, quarterly reporting data on ETF holding starts in 2002.

We start with these 16,707 distinct ETF-quarters and only keep firms with fiscal ending aligned with calendar ending and no missing underlying ETF trading volume information. We are left with 15,116 distinct ETF-quarters hence corresponding to a theoretical maximum of 60,464 pairs of leader-followers. We delete observations where the follower's announcement was within two days of the leader, as well as observations with missing earnings announcement date and timestamps on IBES. We adjust the earnings announcement date of the firms that announce earnings after market closes to next trading day, following the recent study by McNichols, Beaver and Wang (2017). We then collect ETF average daily trading volume in the quarter before earnings season starts. For example, for firms that announce earnings starting from April, the ETF average daily trading volume is calculated from January 1st through March 31st. We also collect ETF's average trading volume around leader's earnings announcement date window [-1,1]. We define a leader-follower pair as high-volume if underlying ETF's 3-day trading volume around leader's earnings announcement is above the median ETF daily trading volume in the prior quarter. We apply two-step screens to delete repeated leader-follower pairs in any given quarter. If a pair of leader-follower appears multiple times in a given quarter within sector or non-sector ETFs, we keep the pair that is classified as high-volume. If a pair appears in both sector and non-sector subsamples in a given quarter, we keep the pair that is from a sector ETF. The final sample has 31,992 leader-follower pairs from 9,851 distinct ETF-quarters.

4.1.2 Construction of key variables

In this section, we describe how we measure key variables, including investors' response to the leaders and followers at various event windows and earnings surprises. For each ETF-quarter, we first sort the top 5 firms by earnings announcement dates. The firms that is the first among these 5 firms to make earnings announcement is coded as the leader. The remaining 4 firms are coded as follower firms. Therefore, for each ETF quarter, we can form 4 lead-follower pairs.

Let us assume in a hypothetical example, the leader announces its earnings before market opens on April 10 and a follower firm announces its earnings before market opens on April 17. We define *LRET* as the size-adjusted returns accumulated over 3 trading days starting from the day before leader's announcement date (in this example, starting from April 9). For each follower, we compute market responses over 2 windows. $FRET_{ANNC}$ measures follower's response to leader earnings announcement, computed as the size-adjusted returns accumulated over 3 trading days starting from the leader's announcement date (in this example, starting from April 9). $FRET_{BETW}$ measures follower's size-adjusted stock returns over the period between the earnings release of the leader and the earnings release of the follower firms (in this example, for follower that announces earnings on April 17, the window for $FRET_{BETW}$ starts from April 12 and ends on April 15).[13]



[13] Size-adjusted returns are the daily stock return in excess of the return on a value weighted portfolio of firms having similar market values. The size portfolios are formed by CRSP and are based on size deciles of NYSE and AMEX firms. Membership in a particular portfolio is determined using the market value of equity at the beginning of the calendar year.

4.2 Correlation between key variables

Table 2 presents summary statistics and correlations between our key analysis variables. Panel A of Table 2 shows that, on average, the investors' response to earnings news is zero. Interestingly, though only 214 of the 487 ETFs are sector ETFs, almost half the leader-follower pairs come from sector ETFs, as such pairs are far less likely to be duplicates across multiple ETFs and if a pair appears in both sector and non-sector subsamples in a given quarter, we keep the pair that is from a sector ETF. As expected, the mean returns and news variables are close to zero.

We present correlations separately for the subsamples of sector ETFs and non-sector ETFs in panel B of Table 2. Returns to the leader firms (*LRET*) and the follower firms ($FRET_{ANNC}$) are strongly positively correlated (0.149 Pearson and 0.167 Spearman). When we look at the returns to the follower firms in the in-between window ($FRET_{BETW}$), we see some evidence of a reversal in the negative correlation between $FRET_{BETW}$ and $FRET_{ANNC}$ (-0.028 Pearson, -0.031 Spearman).

Panel C of Table 2 presents correlations for non-sector ETFs. It is interesting to observe the differences in the correlations for non-sector ETFs. While $FRET_{ANNC}$ is still positively correlated with *LRET*, the correlation appears to be significantly weaker (0.050 Pearson, 0.034 Spearman). Further, the reversal in the in-between period appears to be stronger, with a greater negative correlation between $FRET_{BETW}$ and $FRET_{ANNC}$ (-0.074 Pearson, -0.049 Spearman). These results provide preliminary evidence that constituents of sector and non-sector ETFs behave differently, with the earnings of sector ETF leaders being more value relevant to follower firms.

4.3 Analysis of returns around leader's earnings announcement

We begin our analysis by studying the investor response to event window around the leader's earnings announcement. The results are presented in Table 3. In all our regressions, the t-statistics control for two-way clustering at the leader and leader's earnings announcement date level, because the same leader may be paired with multiple followers.

Panel A of Table 3 examines the relationship between the leader's stock returns (*LRET*) and the follower firms' stock returns ($FRET_{ANNC}$).[14] For all firms, the coefficient on *LRET* is 0.049 (t-stat 8.51), which increases to 0.085 (t-stat 7.95) for sector ETF pairs and decreases to 0.023 (t-stat 3.69) for non-sector ETFs. It is interesting to note that follower firms in non-sector ETFs also show a response to the leader's earnings announcement even though there is no industry connection between the two. It is possible that this reaction is driven by market level factor information in the leader's earnings news. We examine this in more detail later in the paper. These results suggest that follower firm's stock returns are associated with the leader firm's stock returns and that this relationship is stronger for sector ETFs.

To gain a better understanding on the role of ETFs in the flow of information, we carry out falsification tests using the period before sector ETFs were created (pre-ETF period).[15] We group firms into sector and non-sector firms based on their ultimate membership in sector ETFs. More specifically, if a pair at any point is included in a sector ETF, it is included in the sector group during the pre-ETF period. Similarly, if a pair is in a non-sector ETF, it is included in a non-sector group. We then carry out analyses similar to that in panel A of Table 3 and provide the results in

[14] The results on the relationship between returns and news are not tabulated in the interest of brevity. Consistent with prior research, we find a significant positive correlation between returns (*LRET*) and earnings news (*LNEWS*) when leader firms release earnings. We also analyze the relationship between the earnings surprise for the leader (*LNEWS*) and the stock returns for follower stocks ($FRET_{ANNC}$) to test whether follower stocks respond to earnings information for the leader. We find that the relationship is significant only for sector ETFs (0.1923, t-statistic 3.31) and insignificant for non-sector ETFs (0.0217, t-statistic 0.49), with the difference between the two coefficients being highly significant at 0.1706 (t-statistic 2.34). This suggests that the information contained in the leader's earnings release is important only for sector ETFs, which generally consist of firms in the same or related industries.

[15] For our pre-sector ETF analysis we focus on the period from 1985 to 1998. This gives us the same number of years as the post period. We end our pre-ETF sample period in 1998 because that is when the first sector ETF was launched in 1999. Our results are not sensitive to extending the pre-ETF period to 2001 and using shorter sample periods.

panel B. The results using all pairs show a more muted follower response to the leader's earnings announcement returns as compared with the ETF period (0.019 vs. 0.049). Sector pair followers show a response to the leader's returns of 0.056 (t-stat 6.28) consistent with prior work on intra-industry information transfer (e.g., Thomas and Zhang, 2008). However, this response is weaker than the response observed during the ETF period (0.056 vs. 0.085). Untabulated results show that interaction term assessing the difference in coefficients between the periods is significant. It is interesting that non-sector pairs do not show a discernible response in the pre-ETF period, which significantly is different from the observed response during the ETF period (-0.004 vs 0.023). Non-sector ETF constituents that were not discernibly sensitive to the earnings announcements in pre-ETF period become sensitive subsequent to their membership in ETFs. The increased response observed for both sector and non-sector pairs is consistent with prior work that finds increased co-movement resulting from ETF membership.

In addition to examining the pre-ETF period, we also carry out cross-sectional analysis during the ETF period by partitioning ETFs into above and below median groups based on their trading volume over the 3 trading days around leader's earnings announcement date [-1,1]. We define a leader-follower pair to be high-volume if the average trading volume of the underlying ETF over the 3 trading days around leader's earnings announcement date [-1,1] is above the median ETF average daily trading volume in the quarter before earnings season starts. If ETFs do play a role in the response of follower firms to the leader's earnings announcement, we expect to see follower-leader pairs with high ETF trading volume to have a greater impact as compared with the pairs with low ETF trading volume. The results are provided in panel C of Table 3. The coefficient on *LRET* is similar for high volume and low volume ETFs suggesting that the response of non-sector followers to the leader's announcement is not determined by ETF trading volume.

However, Columns 2 and 3 of the panel C of Table 3 show that the sector ETF pair results seen in panel A of Table 3 are primarily driven by high volume ETFs. The coefficient on the interaction term *LRET*SEC* is large and highly significant for high volume ETFs (0.103, t-stat 5.46) and insignificant for low volume ETFs (0.017, t-stat 1.21). Column 4 repeats the analysis and shows that the difference between low and high volume groups is significant (0.086, t-stat 3.68).

Overall, the results in Table 3 suggest that while ETF membership seems to have changed the extent to which firms react to other firm's earnings announcement for sector and non-sector ETFs, this effect is particularly strong for sector ETF firms. The results are also consistent with the increased co-movement documented in prior work (e.g., Da and Shive 2018, Israeli, Lee and Sridharan 2017).

4.4 Analysis of returns between leader's and followers' earnings announcement

The results in Table 3 suggest that ETFs play a role in disseminating information stock returns for follower firms in an ETF react to earnings news for the leader firm. We next examine the market's adjustment in the period between the leader's and the followers' earnings announcement. We measure the size-adjusted returns ($FRET_{BETW}$) for follower firms in the time period between the leader's earnings announcement and the follower firm's own earnings announcement. We regress $FRET_{BETW}$ on $FRET_{ANNC}$ for sector and non-sector pairs as well as for the combined sample.

The results are presented in panel A of Table 4. The first column presents the results for the entire sample. We find a significant negative coefficient on $FRET_{ANNC}$ (-0.071, t-stat -3.89). This suggests that the markets correct their initial reaction to the leader's earnings announcement. However, this reversal is primarily driven by non-sector ETFs with the coefficient on $FRET_{ANNC}$

of -0.109 (t-stat -3.54). For sector ETFs, the evidence of a reversal is much weaker, as the coefficient on $FRET_{ANNC}$ is lower in magnitude at -0.037 (t-stat -1.89). The difference in reversal between the two groups is statistically significant (t-stat 1.99). These results are interesting in that they suggest a nuanced picture of the pro and cons of ETFs at least relating to short-term returns. Sector ETFs which are generally more focused on stocks with common factors are likely to be more efficient in transmitting information to its constituents (as observed by the greater reaction around the leader's earnings announcement return and the weaker reversal in subsequent days). Non-sector ETFs on the other hand seem to cause an overreaction in follower returns consistent with trading in these ETFs weakly consistent with a mispricing of the underlying follower stocks.

We replicate this reversal analysis for the pre-ETF period (as defined earlier) using the same method as in panel B of Table 3. The results are provided in panel B of Table 4. We find that the reversal in returns subsequent to the leader's earnings announcement for lead-follower pairs in the pre-ETF period, as shown by the negative coefficients for $FRET_{ANNC}$. However, unlike the results in panel A the reversals observed in the pre-ETF period is larger for sector ETFs as compared with non-sector ETFs (-0.100 vs -0.070) although the difference is not significant (t-stat -1.42).[16] However, in comparing the results in panels A and B we find that there is a striking diversion in terms of the changes in reversal in returns subsequent to the leader's earnings announcement for lead-follower pairs from the pre-ETF period to ETF period. The reversals for sector constituents, as shown by the negative coefficients for $FRET_{ANNC}$, has been significantly reduced by two thirds (from -0.100 to -0.037), whereas the reversals for non-sector constituents have increased (from -0.072 to -0.109). Taken together, comparing the pre-ETF period and the

[16] While the reversals observed in the pre-ETF period for non-sector pairs is puzzling (given that there is no reaction observed in panel B of Table 3), one explanation is that it could be result of the short-term reversal pattern documented in prior work (e.g., Jegadeesh, 1990; Lehmann, 1990; Da, Liu and Schaumberg, 2014)

ETF period, we find that sector ETFs have likely enhanced the pricing efficiency of the constituents.

In panel C of Table 4 we provide results for an ETF volume-based analysis similar to the one carried out in panel C of Table 3. If ETFs are playing a role in the return reversals of follower firms subsequent to the leader's earnings announcement, we expect to see a stronger effect on follower-leader pairs with high ETF trading volume. The results are provided in panel C of Table 4. The coefficient on $FRET_{ANNC}$ is larger for high volume than low volume pairs suggesting that the response of non-sector followers to the leader's announcement is determined by ETF trading volume (column 1 of panel C of Table 4). More importantly, Columns 2 and 3 of the panel C of Table 4 show that the sector ETF pair results seen in panel A of Table 4 are primarily driven by high volume ETFs. The coefficient on the interaction term $FRET_{ANNC}*SEC$ is large and statistically significant for high volume ETFs (t-stat 1.83) and insignificant for low volume ETFs (t-stat 0.99) albeit a test of the difference between these two coefficients is not statistically significant as shown under column 4 of panel C of Table 4. If the findings in panel A of Table 4 were simply related to intra-industry information transfer and not ETF membership, we would expect both groups to have the same response. This finding is consistent with the idea that sector ETFs have facilitated factor investing and resulted in smaller return reversal after leader's earnings announcement.

Together these results are consistent with the general message that results on ETFs are contextual to the nature of information and the kinds of ETFs examined. Sector ETFs have improved the information environment by facilitating flow of industry information while non-sector ETFs appear to cause a mispricing in the underlying securities.

5. Firm Level Analyses

5.1 Analysis using the approach in Thomas and Zhang (2008)

As an alternative research design, we use the approach developed in Thomas and Zhang (2008), who document that the existence of investors' overestimation of the intra-industry implications of early announcers' earnings for late announcers' earnings and that overestimation is corrected when late announcers disclose their earnings. We carry out analyses similar to Thomas and Zhang (2008) and expect that this overestimation pattern should be weakened after the introduction of sector ETFs. This analysis is limited to sector ETFs. The regression specification is as follows:

$$ARET = \alpha + \beta_1 * RESP + \beta_2 * POST + \beta_3 * RESP * POST + \varepsilon \qquad (1)$$

Thomas and Zhang (2008) define peer firms (early announcers) for any particular firm i as the firms in the same industry (defined by the four-digit Standard Industrial Classification) that report earnings at least 5 days precede firm i's earnings announcement date. Variable *ARET* represent the excess return around late announcer firm i's own earnings announcement. Since there is typically more than one peer firm for each firm i, variable *RESP* is the average excess return of firm i around its peer firms' earning announcement dates. Firms' quarterly earnings announcement dates are from quarterly Compustat files. Both *ARET* and *RESP* measure excess returns accumulated over 3 trading days starting from the trading day before earnings announcement date. All excess returns are computed as raw returns minus the returns from the same NYSE/AMEX/NASDAQ size decile firms over the same event window.

A key variable for this analysis is the extent of ETF ownership, which we measure by summing up the total ownership by all sector ETFs to construct the percentage of shares owned by sector ETFs at the end of each firm quarter. This approach is similar to the approach used in prior work in this area, albeit in the context of all ETFs.[17] The sample of firms consists of firms which have at some point been included in a sector ETF and therefore have sector ETF ownership exceeding zero. For these firms the *POST* variable takes on a value of 1 during the period when these firms have ownership exceeding zero and takes on a value of zero in the pre-ETF period.

If sector ETFs foster effective and efficient intra-industry information transfers, we expect that the overestimation pattern as documented in Thomas and Zhang (2008) should weaken after the introduction of sector ETFs. Table 5 reports the results of the above analysis. Column 1 of Table 5 presents the results for pre-ETF period. Consistent with Thomas and Zhang (2008), the coefficient for *RESP* is negative and significant, suggesting that in the period prior to introduction of ETFs investor indeed overestimate the intra-industry implications of early announcers' earnings for late announcers' earnings and this overestimation is corrected when late announcers disclose their earnings. More importantly, column 2 of Table 5 shows that the overestimation has been corrected in the ETF period when firms become constituents of a sector ETF. Comparing the coefficients for *RESP*, we find that the coefficient for *RESP*POST* is positive and significant. If we divide the absolute value of the coefficient for *RESP*POST* by the absolute value of the coefficient for *RESP*, we find that sector ETFs assist investors to reduce the overestimation of the intra-industry information transfer by approximately 92 percent. These results reinforce the findings on sector ETFs using ETF level analyses.

[17] Since ETFs only report their holdings at the end of March, June, September, and December, for firms with fiscal quarter ending not aligned with calendar quarter, we use the most recent calendar quarter filing to substitute the holdings at the end of fiscal quarter.

5.2 Path Analysis of the mediation effects of ETFs

We attempt to isolate the role of ETFs in the flow of information between the constituent firms by carrying out path analysis. Using an approach similar to Bhattacharya, Ecker, Olsson, and Schipper (2012), we decompose the association between leader and follower returns into direct effect and mediated effect components.[18] Path analysis allows us to decompose the correlation between the source variable (returns to the leader around its own earnings announcement, *LRET*) and the outcome variable (returns to the follower around the leader's earnings announcement, $FRET_{ANNC}$) into two paths, direct path and mediated path. Our specification of these two paths is guided by existing literature of the co-movement of different stocks. The co-movement between the leader and followers could come directly from the leader firm (direct path or direct correlation between leader and follower returns) or could be mediated by the existence of ETFs (indirect path through ETF returns). Therefore, evidence of a mediated path supports the idea of ETFs being a contributory mechanism for the observed results in Tables 3 and 4. In Figure 1 we provide the diagram showing the two paths. We use a recursive approach where all paths flow in one direction i.e., from the leader to the follower either directly or through the mediating influence of the ETF. This approach is appropriate given the event study nature of the analysis and the timeline involved.

The results from this analysis are provided in Table 6. Using the entire sample of ETFs, we find that they play a significant role in the relationship between leader and follower returns. Panel A of Table 6 provides information on the total effect and the breakup between the mediated effect and the direct effect. The total correlation is 0.097, which can be parsed out into a direct effect of 0.055 and a mediated effect of 0.042 (a product of the correlation between the leader return and ETF return (0.170) and the correlation between ETF return and follower return (0.245). Thus about

[18] For a more detailed description of path analysis please see Asher (1983).

40 percent of the total correlation between the returns is through ETFs while the rest is through a direct effect of leader on follower returns.

Parsing out the sample into sector and non-sector ETFs yields insights consistent with our findings in prior tables. Sector ETFs are particularly effective in facilitating the flow of information between the constituents. The total correlation between leader and follower returns is 0.149, which is much higher than the correlation using the overall sample. What is more interesting is that a larger piece of this correlation can be attributed to the mediating effect of ETFs. 61 percent of the overall effect is mediated by the ETFs which the rest is through direct effect. These results should be contrasted with the overall correlation for non-sector ETFs which is only about 0.050 of which only 16 percent is affected through ETFs. These results are consistent with sector ETFs being more effective in transmitting information to its constituents as compared with non-sector ETFs.

6. Exchange-Traded Funds and the Post-Earnings Announcement Drift

The results thus far suggest that ETFs have a significant short-term impact on the processing of accounting information by capital markets. However, the impact on longer term market efficiency is not very clear. To examine this issue further, we study the impact of ETF ownership on a well-known and often studied market anomaly – the post earnings announcement drift or PEAD (Bernard and Thomas, 1989, 1990). PEAD refers to the positive correlation between the returns in the period after earnings are announced and the earnings surprise. This is considered an anomaly because the return drift persists for a considerable period of time – as long as sixty days after earnings release. The most commonly accepted wisdom about this anomaly is that it represents the delayed processing of earnings information by capital market participants.

As our results thus far indicate, the presence of ETFs changes the processing of information by capital markets. Stock price relevant information arrives constantly, not just when the firm announces earnings, but when any ETF component announces earnings. This may have the potential to reduce PEAD, as a proportion of the earnings information may have already been impounded into prices by the time earnings are announced.[19] However, the results in Tables 3 and 4 are also consistent with the irrational pricing of information that may not be relevant, especially for non-sector ETFs. This suggests that ETF ownership might exacerbate PEAD.

In our analysis, we analyze the impact of the extent of ETF ownership on PEAD. Unlike in section 4 where we focus on follower-leader pair based on each ETF, we examine PEAD at the firm level. Panel A of Table 7 outlines how we construct the sample for the PEAD analysis. As discussed in section 3, the merging of equity ETFs with Thompson-Reuters Mutual Fund Holding (S12) yields 487 equity ETFs in the period from 2002 to 2015 and we are able to compute shares owned by each of these 487 ETFs at the end of each quarter. We then sum the total ownership by all ETFs to construct the percentage of shares owned by ETFs at the end of quarter for each firm quarter. After requiring non-missing values for firm characteristics that have found to be related to PEAD, we have 136,508 firm quarter observations over 2002 to 2015 period.

Earnings surprises (SUE) are calculated as I/B/E/S actual earnings per share minus the last mean analyst consensus forecast before the earnings-announcement dates, scaled by the stock price at the start of the quarter. We obtain our daily stock returns and daily stock prices from CRSP. To calculate the cumulated size-adjusted returns following earnings announcements (*POST60*), we

[19] Consistent with this, in untabulated results we find that follower firms have lower earnings response coefficients compared to leader firms, and this declines when the lag between the leader's earnings announcement and follower's earnings announcement increases (i.e. when it is more likely that many other ETF firms have also released potentially correlated earnings information)

require a firm to have a minimum of 40 days during the 60 trading days following the quarterly earnings announcements. We adjust the earnings announcement date of the firms that announce earnings after market closes to the next trading day, following the recent study by McNichols, Beaver and Wang (2017). The size portfolios are formed by CRSP and are based on size deciles of NYSE/NASDQ/AMEX firms. Membership in a particular portfolio is determined using the market value of equity at the beginning of the calendar year.

Panel B of Table 7 presents some summary statistics related to ETF ownership. The average firm in our sample has a mean 4.4% (median 3.7%) of shares outstanding owned by ETFs. The percentage of shares owned by sector ETF has a mean of 0.5% (median 0.1%). Figure 2 graphically presents the ownership by ETFs over time – for both ETF ownership in general and sector ETF ownership, one can observe a steady increase in ownership. Interestingly, we see a slight increase in the relative proportion of sector ETFs in recent years.

Panel C of Table 7 presents the average returns in the 60 days after earnings announcement (*POST60*) for deciles formed on the basis of the earnings surprise (*SUE*). The first column presents results for all firms. We see a monotonic increase in *POST60* across deciles of *SUE*, from -1.37% for the lowest SUE group to +3.81% for the highest *SUE* group, a spread of 5.18% that is significant at the 1% level, corroborating the evidence from the long-standing literature on PEAD (Bernard and Thomas, 1989, 1990). The next two columns consider sub-samples partitioned on the basis of ETF ownership. For the subset with lower than median ETF ownership, the spread increases to 5.44%, while for the subset with above median ETF ownership, the spread is 4.73%. This provides preliminary evidence that greater ETF ownership is associated with lower drift, though this difference in spread of -0.89% is not significant (t-stat -0.89). However, when we partition our sample on the basis of sector ETF ownership, we find that the subset with above median sector ETF ownership has significantly lower drift at 2.93% versus the subset with below median sector ETF ownership at 6.57% (significant difference of -3.63%, t-stat -4.56).

To better test the association between PEAD and ETF ownership, we examine this in a multivariate regression setting, controlling for other known determinants of PEAD including size (*SIZE*), market to book ratio (*MTB*), risk (*BETA*), and momentum (*PRERET*).

$$POST60 = \alpha + \beta_1*RSUE + \beta_2*ETF\% + \beta_3*SIZE + \beta_4*BETA + \beta_5*MTB + \beta_6*PRERET + \beta_7*RSUE*ETF\% + \beta_8*RSUE*SIZE + \beta_9*RSUE*BETA + \beta_{10}*RSUE*MTB + \beta_{11}*RSUE*PRERET \quad (2)$$

For easier interpretation the coefficient on earnings surprise, we construct variable *RSUE*, where the 10th decile *RSUE* equals 1 and the 1st decile *RSUE* equals 0 (2^{nd} decile RSUE=0.111, 3^{rd} decile RSUE=0.222 etc). Thus, the coefficient for *RSUE* can be interpreted as the difference in PEAD between decile 10 and decile 1. A positive coefficient for *RSUE* suggests that PEAD increases with *SUE*. ETF% is the percentage of shares outstanding owned by ETFs. Our key variable of interest is the interaction, *RSUE*ETF%*. A positive coefficient indicates a worsening of the drift with ETF ownership while a negative coefficient indicates a mitigation in the drift.

Based on Huang, Li and Wang (2015), we control for the other firm characteristics that have been shown in prior research to be associated with the level of the drift.[20] We run the above regression model using two procedures – a pooled panel regression with two-way clustered t-statistics (clustered by ETF and year), and annual regressions summarized using the Fama and MacBeth (1973) procedure. In the first set of regression, we consider the total level of ETF

[20] The control variables are as follows. SIZE is the log of total assets at the end of the fiscal quarter. MTB is the market-to-book ratio measured at the end of fiscal quarter. BETA is the estimated coefficient for market returns in the market model regression of a firm's daily returns on value-weighted market returns from all the trading days in the prior quarter. PRERET is the return momentum measured as the cumulated size-adjusted returns over the 20 trading days [-21,-2] before earnings announcements.

ownership (*ETF%*), while in the next set of regressions, we partition this variable into Sector ETF ownership (*SECT%*) and other remaining ETF ownership (*REST%*).

The results are presented in Table 8. The first column presents the pooled panel regression using *ETF%*. Consistent with the presence of PEAD, we find that *RSUE* has a strong positive association with *POST60* with a coefficient of 0.112 (t-stat 14.70), suggesting the difference in PEAD between the firms with 10th decile of earnings surprises and firms in the 1st decile of earnings surprises is about 11.2 percent. Consistent with ETF ownership being associated with lower drift, we find a significant negative coefficient on the interaction between *RSUE* and *ETF%* (-0.142, t-stat -3.51). Consistent with prior research, we also find that the drift is negatively associated with size, positively associated with systematic risk and momentum and negative associated with the market-to-book ratio. The next column repeats the analysis using annual Fama and MacBeth (1973) regressions and finds similar results.

The next two columns of Table 8 repeat the analysis partitioning *ETF%* into *SECT%* and *REST%*. We find that while sector ETF ownership is strongly associated with lower drift, this effect is insignificant for non-sector ETF ownership. For the pooled specification, the coefficient on *RSUE*SECT%* is -0.516 (t-stat -4.41), while the coefficient on *RSUE*REST%* is -0.066 (t-stat -1.32). For the Fama and MacBeth specification, the coefficient on *RSUE*SECT%* is -0.700 (t-stat -2.63), while coefficient on *RSUE*REST%* is weakly significant at -0.168 (t-stat -1.13). This suggests that the mitigating effect of ETF ownership on PEAD seems to stem entirely from sector ETF ownership. These results are also consistent with our earlier results regarding the evolution of returns over the quarter. They are consistent with the following explanation - with greater sector ETF ownership there is a greater impounding of relevant information in the pre-earnings announcement period, which reduces the extent of PEAD.

7. Conclusion

This paper examines the role of ETFs in facilitating the flow of information between firms. One of the primary advantages of ETFs is that they allow for a basket of shares to be traded in a cost effective and efficient way. This advantage can manifest in information, particularly factor-based information, to flow across firms more efficiently. On the other hand, ETFs composition is generally based on specific rules which can limit the ability of the ETF traders to correctly impound the information into prices resulting in potential mispricing of information, particularly idiosyncratic information and to a lesser degree factor level information. In addition, ETFs may dis-incentivize information intermediaries from acquiring firm-specific information.

Using earnings announcements as our information event, we examine the effect of ETF ownership on the flow of information between firms. Focusing on the largest constituents of ETFs and separating them in the lead announcer and the follower firms, we find that ETFs play a role in transmitting information across firms. For the overall sample, followers experience significant reaction to the earnings news of the leader. However, this reaction is followed by a reversal, consistent with followers overreacting to the leader's earnings news. These results suggest that while ETFs make it easier to impound information across multiple firms, by the very nature of their rigid construction rules, the information transfer is unlikely to occur in an efficient manner. Parsing the sample into sector and non-sector ETFs yields interesting insights. We find that sector ETFs seem to be better at facilitating efficient flow of information between firms. The reversal effect seen in the overall sample is driven primarily by the non-sector ETFs.

To ensure that our results are likely to be driven by the emergence of ETFs and not any other contemporaneous change, we carry out numerous additional analyses including a falsification analysis using pre-ETF data, partition analysis based on ETF trading volume and path analysis. These results confirm our basic finding that ETFs, especially sector ETFs, facilitate the efficient flow of information across firms. In our final tests, we examine whether the presence of ETF ownership mitigates the well-established anomaly associated with earnings announcements – the post-earnings announcement drift and find much lower drift in the presence of ETF ownership, but only for sector ETFs.

These results suggest that the answer to the question of whether ETFs help or hurt the flow of information between firms is contextual. ETFs have a bright side as well as a dark side. Markets seem to effectively use sector ETFs to transmit factor (industry) information impounded in earnings news but general broad market ETFs are not very useful (and potentially detrimental) to this type of information.[21] Our results suggest that the conflicting results documented in prior work might both be right if examined in the right context. Certain types of ETFs might assist in the flow of some types of information while being ineffective or even detrimental to the flow of other types of information.

[21] It is possible that the reason broad market ETFs are not very effective in this context is that earnings announcement might not contain significant macro information. Market ETFs might be effective in settings where macro information is being released and impounded by markets (e.g., GDP, interest rate or inflation data). We do not examine these information events in this paper.

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APPENDIX

Variable Definitions

Variable	Definition
LRET	Size-adjusted returns for the leader firm accumulated over 3 trading days starting from the day before leader's earnings announcement date
$FRET_{ANNC}$	Size-adjusted returns for the follower firm accumulated over 3 trading days starting from the day before leader's earnings announcement date
$FRET_{BETW}$	Size-adjusted returns for the follower firm accumulated starting 2 days after the leader's announcement date until 2 days before the follower's earnings announcement date
SEC	Indicator variable that equals 1 for sector ETFs and 0 for non-sector ETFs
HIGH	Indicator variable that equals 1 for leader-follower pair if the average trading volume over the 3 trading days starting from the day before leader's earnings announcement date exceed the median average daily ETF trading volume in the quarter before earnings season starts and 0 otherwise.
POST	Indicator variable that equals 1 for fiscal quarter ends in years 2002 to 2015 and 0 for fiscal quarter ends in years 1985 to 1998.
RESP	The average of firm's 3-day size-adjusted returns around its peers' earnings announcements, where the earnings announcement dates are at least five days prior to firm I's earnings annocuement date. The peer firm is defined as the firms from the same 4-digit SIC code.
ARET	Size-adjusted returns accumulated over 3 trading days starting from the firm's earnings announcement date.
POST60	Size-adjusted stock returns for the 60 day period after earnings.
ETF%	Percentage of shares outstanding owned by all ETFs
SECT%	Percentage of shares outstanding owned by sector ETFs
REST%	Percentage of shares outstanding owned by ETFs other than sector ETFs
SUE	Unexpected Earnings defined as I/B/E/S actual earnings per share minus the last mean analyst consensus forecast before the earnings-announcement dates, scaled by the stock price at the start of the quarter.
RSUE	Decile rank of SUE
SIZE	Log of total assets at the end of the fiscal quarter
BETA	Estimated coefficient for market returns in the market model regression of a firm's daily returns on value-weighted market returns from all the trading days in the prior quarter.
MTB	Market-to-book ratio measured at the end of fiscal quarter
PRERET	Return momentum measured as the cumulated size-adjusted returns over the 20 trading days [-21,-2] before earnings announcements.

Figure 1: Path Analysis

Figure 1a: Path Analysis for All ETFs

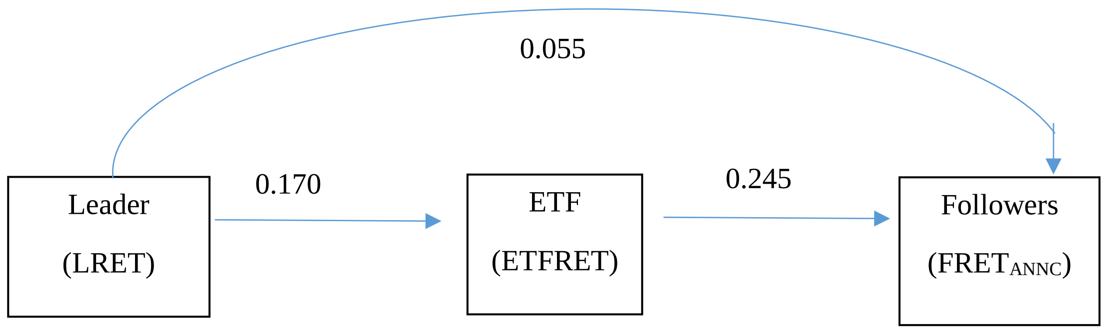

Figure 1b: Path Analysis for sector ETFs

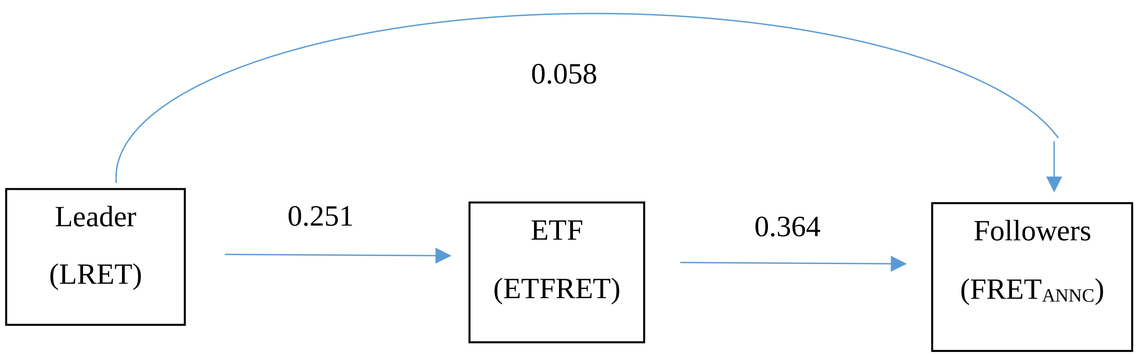

Figure 1c: Path Analysis for non-sector ETFs

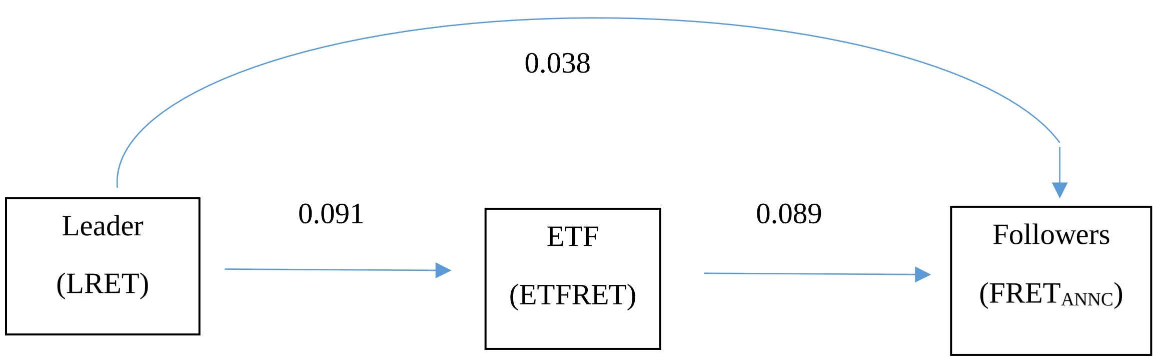

Figure 2: Trends in ETF ownership

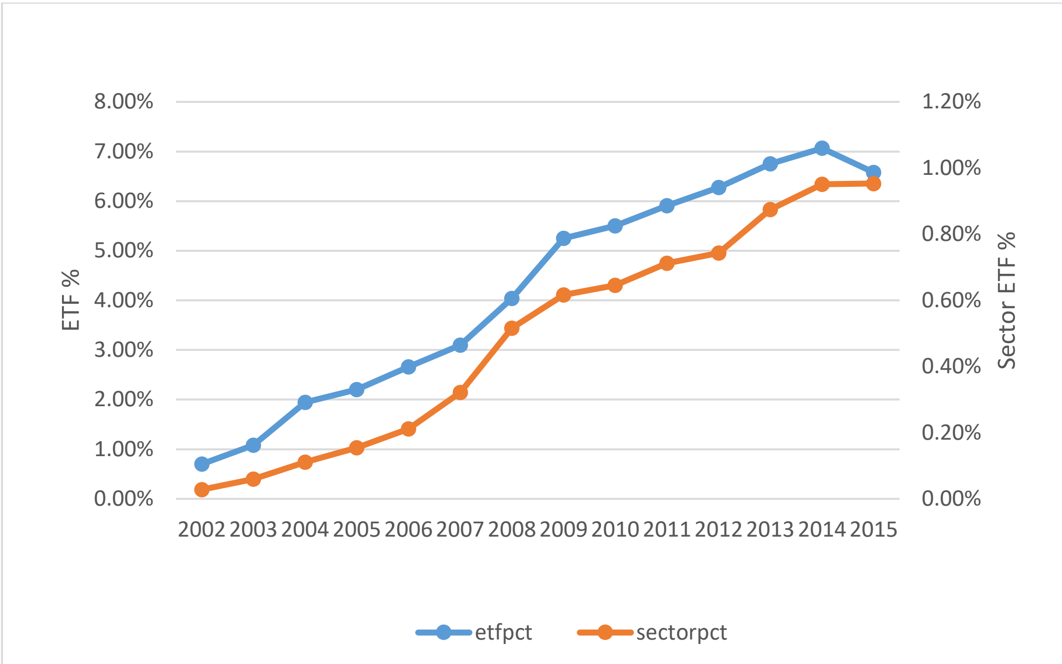

TABLE 1

Sample Selection and Distribution

Panel A: Sample Selection (ETF Level)

Sample Selection Criterion	*Observations*
Initial universe of ETF funds from CRSP as of 2015	2,091
Less: ETFs that are invested in stocks with no matches with Thomson-Reuters Mutual Fund Holding (S12) database	(1,604)
Number of distinct Equity ETFs with constituent holding information	487
Number of sector ETFs	214
Number of non-sector ETFs	273

Panel B: Distribution across Time

Year	*# distinct ETFs*
2002	106
2003	109
2004	138
2005	154
2006	177
2007	413
2008	473
2009	426
2010	453
2011	446
2012	434
2013	423
2014	407
2015	409

Panel C: Distribution of Sector ETFs by Sector

Sector	*Number of ETFs*	*% of Sector ETFs*
Aerospace	2	0.93%
Agriculture	1	0.47%
Banks	5	2.34%
Basic Materials	9	4.21%
Biotech	5	2.34%
Chemical	1	0.47%
Construction	3	1.40%
Consumer products	21	9.81%
Energy	10	4.67%
Environmental	2	0.93%
Financial Services	15	7.01%
Healthcare	29	13.55%
Industrials	9	4.21%
Infrastructure	2	0.93%
Internet	7	3.27%
Media	1	0.47%
Medical Devices	1	0.47%
Natural resources	2	0.93%
Nuclear	1	0.47%
Oil & Gas	8	3.74%
Pharmaceutical	4	1.87%
Precious Metals	2	0.93%
Real Estate	20	9.35%
Renewable Energy	4	1.87%
Retail	3	1.40%
Semiconductors	5	2.34%
Steel	1	0.47%
Technology	18	8.41%
Telecommunications	7	3.27%
Timber	1	0.47%
Transportation	1	0.47%
Utilities	10	4.67%
Water	4	1.87%
Total	214	100%

TABLE 2

Summary Statistics and Correlations for Leader-Follower Pairs Analyses

The table below presents sample selection and summary statistics for the variables used in the leader-follower analysis. There are 31,992 distinct leader-follower pairs within ETFs in the 2002-2015 period. See Appendix for variable definitions. In Panel B and C, figures above/below diagonal represent Pearson/Spearman rank-order correlations. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests.

Panel A: Sample Selection (leader-follower pairs)

Sample Selection Criterion	*Observations*
Total Number of ETF-quarters from 2002 to 2015	16,707
Less: Observations deleted for firms with fiscal quarter ending not aligned with calendar quarter ending and missing underlying ETF trading volume	
Total useable number of ETF-quarters from 2002 to 2015	15,116
Times 4 followers equals theoretical maximum number of pairs	60,464
Less: Observations deleted for missing earnings announcement dates or earnings announcement within 2 days of leader's earnings announcement	(9.072)
Leader-follower pairs with appropriately spaced earnings announcements	51,392
Less: duplicates within sector type by underlying ETF trading volume	(18,872)
Less: duplicates from non-sector ETFs	(528)
Final Leader-follower sample	31,992

Panel B: Summary Statistics

Variables	*P25*	*Median*	*Mean*	*P75*	*Std*
LRET	-3.19%	-0.18%	0.07%	3.25%	6,78%
$FRET_{ANNC}$	-1.55%	-0.07%	-0.08%	1.41%	3.47%
$FRET_{BETW}$	-1.75%	-0.04%	-0.01%	1.69%	4.80%
SEC	0	0	0.509	1.000	0.500

Panel C: Correlation Table for Subsample of Firm-quarters from Sector ETFs

	Pearson Correlation			*Spearman Correlation*		
	LRET	$FRET_{ANNC}$	$FRET_{BETW}$	*LRET*	$FRET_{ANNC}$	$FRET_{BETW}$
LRET	1.000	0.149***	-0.002	1.000	0.167***	-0.008
$FRET_{ANNC}$	0.149***	1.000	-0.028***	0.167***	1.0000	-0.031***
$FRET_{BETW}$	-0.002	-0.028***	1.000	-0.008	-0.031***	1.000

Panel D: Correlation Table for Subsample of Firm-quarters from Non-Sector ETFs

	Pearson Correlation			*Spearman Correlation*		
	LRET	$FRET_{ANNC}$	$FRET_{BETW}$	*LRET*	$FRET_{ANNC}$	$FRET_{BETW}$
LRET	1.000	0.050***	-0.011**	1.000	0.034***	-0.005**
$FRET_{ANNC}$	0.050***	1.000	-0.074***	0.034***	1.000	-0.049***
$FRET_{BETW}$	-0.011*	-0.074***	1.000	-0.054*	-0.049***	1.000

TABLE 3

Investors' Reaction to Earnings News for the Leader

The sample consists of leader-follower pairs within ETFs. The ETF period sample covers years from 2002-2015. The same pairs from ETF period during the years 1985 to 1998 are classified in pre-ETF period. See Appendix for variable definitions. t-values are reported below each coefficient. All regressions are clustered at leader and leader's earnings announcement date level. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests.

Panel A: Investors' reaction to follower firms on leader firm's earnings announcement during ETF period
Model: $FRET_{ANNC} = \alpha + \beta_1 {*} LRET + \varepsilon$ *(for columns 1 to 3)*
Model: $FRET_{ANNC} = \alpha + \beta_1 {*} LRET + \beta_2 {*} SEC + \beta_3 {*} FRET_{ANNC} {*} SEC + \varepsilon$ *(for column 4)*

ETF period	1 All ETFs	2 Sector ETFs	3 Non-Sector ETFs	4 All ETFs with interaction
Intercept	-0.001***	0.000	-0.001***	-0.001***
	(3.25)	(0.48)	(4.34)	(4.34)
LRET	**0.049*** **	**0.085*** **	**0.023*** **	**0.026*** **
	(8.51)	**(7.95)**	**(3.69)**	**(3.69)**
SEC				0.001**
				(2.40)
LRET*SEC				**0.062*** **
				(5.12)
# of obs	31,992	16,281	15,711	31,992
Adj R square	0.93%	2.22%	0.25%	1.33%

Panel B: Investors' reaction to follower firms on leader firm's earnings announcement during pre-ETF period

Model: $FRET_{ANNC} = \alpha + \beta_1 {*} LRET + \varepsilon$ *(for columns 1 to 3)*
Model: $FRET_{ANNC} = \alpha + \beta_1 {*} LRET + \beta_2 {*} SEC + \beta_3 {*} FRET_{ANNC} {*} SEC + \varepsilon$ *(for column 4)*

pre-ETF period	1 All ETFs	2 Sector ETFs	3 Non-Sector ETFs	4 All ETFs with interaction
Intercept	0.000**	0.000	-0.001***	-0.001***
	(2.04)	(0.71)	(-2.71)	(-2.71)
LRET	**0.019*** **	**0.056*** **	**-0.004**	**-0.004**
	(4.19)	**(6.28)**	**(-0.83)**	**(-0.83)**
SEC				0.000
				(0.93)
LRET*SEC				**0.060*** **
				(5.94)
# of obs	68,752	29,888	38,864	68,752
Adj R square	0.08%	0.53%	0.00%	0.25%

Panel C: Investors' reaction to ETF follower firms on ETF leader firm's earnings announcement partitioned by ETF Volumes

Model $FRET_{ANNC} = \alpha + \beta_1{*}LRET + \beta_2{*}SEC + \beta_3{*}LRET{*}SEC + \varepsilon$ *(for columns 1 to 3)*

Model $FRET_{ANNC} = \alpha + \beta_1{*}LRET + \beta_2{*}SEC + \beta_3{*}LRET{*}SEC + \beta_4{*}HIGH + \beta_5{*}\ LRET{*}HIGH + \beta_6{*}HIGH{*}SEC + + \beta_7{*}LRET{*}HIGH{*}SEC + \varepsilon$ *(for column 4)*

	1 All pairs	2 High Volume pairs	3 Low Volume pairs	4 All pairs with interaction
Intercept	-0.001***	-0.002***	-0.001***	-0.001***
	(-4.34)	(-3.26)	(-3.05)	(-3.05)
LRET	**0.023*** **	**0.019** **	**0.026*** **	**0.026*** **
	(3.69)	**(2.22)**	**(2.94)**	**(2.94)**
SEC	0.001**	0.001*	0.001	0.001
	(2.40)	(1.82)	(1.64)	(1.64)
LRET*SEC	**0.062*** **	**0.103*** **	**0.017**	**0.017**
	(5.12)	**(5.46)**	**(1.21)**	**(1.21)**
HIGH				0.000
				(0.52)
SEC*HIGH				0.000
				(0.32)
LRET*HIGH				-0.007
				(-0.54)
LRET*SEC*HIGH				**0.086*** **
				(3.68)
# of obs	31,992	16,301	15,691	31,992
Adj R square	1.33%	2.53%	0.50%	1.59%

TABLE 4

Adjustment by Investors between Leader`s and Followers` Earnings Announcements

The sample consists of leader-follower pairs within ETFs. The ETF period sample covers years from 2002-2015. The same pairs from ETF period during the years 1985 to 1998 are classified in pre-ETF period. See Appendix for variable definitions. t-values are reported below each coefficient. All regressions are clustered at leader and leader's earnings announcement date level. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests.

Panel A: Adjustment by Investors between leader's and followers' earnings announcement during ETF period

Model $FRET_{BETW} = \alpha + \beta_1 * FRET_{ANNC} + \varepsilon$ *(for columns 1 to 3)*
Model $FRET_{BETW} = \alpha + \beta_1 * FRET_{ANNC} + \beta_2 * SEC + \beta_3 * FRET_{ANNC} * SEC + \varepsilon$ *(for column 4)*

	1 All ETFs	2 sector ETFs	3 Non-Sector	4 All ETFs
Intercept	0.000	0.000	0.000	0.000
	(0.37)	(0.43)	(0.18)	(0.18)
$FRET_{ANNC}$	**-0.071*****	**-0.037*****	**-0.109*****	**-0.109*****
	(-3.89)	**(-1.89)**	**(-3.54)**	**(-3.54)**
SEC				0.000
				(0.18)
$FRET_{ANNC}$*SEC				**0.071****
				(1.99)
# of obs	31,992	16,281	15,711	31,992
Adj R square	0.32%	0.08%	0.55%	1.34%

Panel B: Adjustment by Investors between leader's and followers' earnings announcement during pre-ETF period

Model $FRET_{BETW} = \alpha + \beta_1 * FRET_{ANNC} + \varepsilon$ *(for columns 1 to 3)*
Model $FRET_{BETW} = \alpha + \beta_1 * FRET_{ANNC} + \beta_2 * SEC + \beta_3 * FRET_{ANNC} * SEC + \varepsilon$ *(for column 4)*

	1 All ETFs	2 sector ETFs	3 Non-Sector	4 All ETFs
Intercept	0.001***	0.001***	0.001**	0.001**
	(4.30)	(3.80)	(2.40)	(2.40)
$FRET_{ANNC}$	**-0.085*****	**-0.100*****	**-0.072*****	**-0.072*****
	(-8.53)	**(-7.21)**	**(-5.26)**	**(-5.26)**
SEC				0.001
				(1.57)
$FRET_{ANNC}$*SEC				**-0.027**
				(-1.42)
# of obs	68,752	29,888	38,864	68,752
Adj R square	0.30%	0.46%	0.20%	0.31%

Panel C: Adjustment by Investors between leader's and followers' earnings announcement partitioned by ETF Volumes

Model: $FRET_{BETW} = \alpha + \beta_1 * FRET_{ANNC} + \beta_2 * SEC + \beta_3 * FRET_{ANNC} * SEC + \varepsilon$ *(for columns 1 to 3)*

Model: $FRET_{BETW} = \alpha + \beta_1 * FRET_{ANNC} + \beta_2 * SEC + \beta_3 * FRET_{ANNC} * SEC + \beta_4 * HIGH + \beta_5 * FRET_{ANNC} * HIGH + \beta_6 * HIGH * SEC + + \beta_7 * FRET_{ANNC} * HIGH * SEC + \varepsilon$ *(for column 4)*

	1 All pairs	2 High Volume pairs	3 Low Volume pairs	4 All pairs with interaction
Intercept	0.000	0.000	0.000	0.000
	(0.18)	(0.52)	(0.22)	(0.22)
$FRET_{ANNC}$	**-0.109*****	**-0.147*****	**-0.073****	**-0.073****
	(-3.54)	**(-2.86)**	**(-2.34)**	**(-2.34)**
SEC	0.000	0.000	0.000	0.000
	(0.18)	(0.19)	(0.03)	(0.03)
$FRET_{ANNC}$*SEC	**0.071****	**0.104***	**0.045**	**0.045**
	(1.99)	**(1.83)**	**(0.99)**	**(0.99)**
HIGH				-0.000
				(-0.54)
SEC*HIGH				-0.000
				(-0.16)
$FRET_{ANNC}$*HIGH				-0.074
				(-1.25)
$FRET_{ANNC}$*SEC*HIGH				**0.059**
				(0.81)
# of obs	31,992	16,301	15,691	31,992
Adj R square	0.32%	0.55%	0.15%	0.35%

TABLE 5
Sector ETFs and Investor Overestimation of Intra-Industry Information Transfers

This table replicates the analyses from Thomas and Zhang (2008) using a sample of firms in the pre-ETF time period from 1985 to 1998 and post ETF period from 2002 to 2015. Firm-quarters are classified into sector and non-sector based on whether the sector ETF ownership is greater than 0 or not in 2002 to 2015. t-values are reported below each coefficient. All regressions are clustered at firm and year level. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests.

Model ARET= $\alpha + \beta_1$**RESP +* ε *(for columns to 1 to 2)*

Model ARET= $\alpha + \beta_1$**RESP+* β_2**POST +*β_3**RESP*POST +* ε *(for column 3)*

	1	2	2
	pre-ETF Period	ETF Period	ALL Periods
Intercept	0.004***	0.001***	0.004***
	(15.54)	(5.28)	(15.54)
RESP	**-0.094*****	**-0.007**	**-0.094*****
	(-7.34)	**(-0.44)**	**(-7.34)**
POST			-0.003***
			(-7.25)
RESP*POST			**0.087*****
			(4.38)
# of obs	66,079	97,043	163,122
Adj R square	0.15%	0.00%	0.17%

TABLE 6
Path Analysis

This table reports the path analysis of how leader affects followers in underlying ETFs. This table consists 31,992 leader-follower pairs. See Appendix for variable definition. The results are illustrated in Figure 1. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests.

	All ETFs	Sector ETFs	Non-Sector ETFs
Total effect			
ρ[LRET, $FRET_{ANNC}$]	0.097^{***}	0.149^{***}	0.050^{***}
	(17.43)	(19.42)	(6.25)
Direct path			
ρ [LRET, $FRET_{ANNC}$]	0.055^{***}	0.058^{***}	0.038^{***}
	(10.04)	(7.72)	(5.23)
Percentage	**57%**	**39%**	**84%**
Mediated path			
ρ [LRET, ETFRET]	0.170^{***}	0.251^{***}	0.091^{***}
	(31.31)	(11.43)	(11.48)
ρ [ETFRET, $FRET_{ANNC}$]	0.245^{***}	0.364^{***}	0.089^{***}
	(46.02)	(11.20)	(11.24)
Mediated effect	0.042^{***}	0.091^{***}	0.008^{***}
	(25.68)	(28.06)	(8.02)
Percentage	**43%**	**61%**	**16%**

TABLE 7

Impact of ETF Ownership on Post-Earnings Announcement Drift: Portfolio Analysis

This table reports post earnings announcement drift (PEAD) by standardized unexpected earnings portfolios. Panel A outlines how the PEAD sample was generated. Panel B reports summary statistics for key firm characteristics. Panel C reports the returns in the 60 day period after earnings announcement (POST60) for deciles based on the earnings surprise (SUE). The first column presents the returns for the entire sample, the next two columns present the results for the subsample with ETF ownership below and above median respectively. Variables are defined in Appendix A. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests.

Panel A; Drift Sample

Sample Selection Criterion	*Firm quarters*	*Distinct Firms*
All Compustat firms traded on NYSE NASDAQ and AMEX merged with Thomson-Reuters Mutual Fund Holding (S12) database to identify shares owned by all funds and ETF funds	230,238	7,855
Less: firm quarters with missing IBES earnings announcement date and timestamps and earnings forecasts from analysts	(89,350)	(2,155)
Firm quarters with earnings announcement dates and IBES information	140,888	5,700
Less: firm quarters with missing control variables	(4,380)	(134)
Final drift sample	136,508	5,566

Panel B: Summary Statistics (N=136,508)

Variable	*Mean*	*Median*	*P25*	*P75*	*std*
ETF%	0.044	0.037	0.015	0.066	0.034
SECT%	0.005	0.001	0.000	0.004	0.011
REST%	0.039	0.034	0.014	0.058	0.029
Post60	0.005	-0.003	-0.096	0.095	0.179
Market Capitalization ($m)	6,447	1,225	424	3,866	22,065
Assets ($m)	13,245	1,526	431	5,219	84,387

Panel C: Post-Earnings-Drift by SUE Deciles

	All Firms	*ETF% < median*	*ETF% >= median*	*Sector ETF% < median*	*Sector ETF% >= median*
SUE decile	*Post60*	*Post60*	*Post60*	*Post60*	*Post60*
1	-1.37%	-1.72%	-0.80%	-1.81%	-0.58%
2	-0.73%	-1.13%	-0.29%	-0.94%	-0.48%
3	-0.45%	-0.56%	-0.35%	-0.44%	-0.46%
4	0.05%	-0.08%	0.17%	-0.11%	0.18%
5	0.49%	0.51%	0.48%	0.68%	0.37%
6	0.95%	0.98%	0.93%	1.08%	0.86%
7	1.32%	1.35%	1.29%	1.58%	1.10%
8	1.88%	1.99%	1.77%	2.03%	1.74%
9	2.40%	3.00%	1.80%	2.98%	1.78%
10	3.81%	3.73%	3.93%	4.76%	2.35%
(10)-(1)	5.18%***	5.44%***	4.73%***	6.57%***	2.93%***
	(13.19)	(10.58)	(7.83)	(12.92)	(4.73)
		Impact of ETF ownership	-0.89%	Impact of sector ETF ownership	-3.63%***
			(-0.89)		(-4.56)

TABLE 8

Impact of ETF Ownership on Post-Earnings Announcement Drift: Multivariate Analysis

This table reports regression with the dependent variable as the returns in the 60 day period after earnings announcement (POST60). Sample consists of 136,508 firm-quarters in the 2002-2015 period. See Appendix for variable definitions. Regressions are run either pooled with t-statistics controlling for two-way clustering by ETF and year, or run annually and summarized using the Fama and MacBeth (1973) method. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, using two-tailed tests. The first two columns present regressions using the below model. In the next two columns, we replace ETF% with SECT% and REST%

$POST60 = \alpha + \beta_1{*}RSUE + \beta_2{*}ETF\% + \beta_3{*}SIZE + \beta_4{*}BETA + \beta_5{*}MTB + \beta_6{*}PRERET + \beta_7{*}RSUE{*}ETF\% + \beta_8{*}RSUE{*}SIZE + \beta_9{*}RSUE{*}BETA + \beta_{10}{*}RSUE{*}MTB + \beta_{11}{*}RSUE{*}PRERET + \varepsilon.$

	Pooled	*Fama-Macbeth*	*Pooled*	*Fama-Macbeth*
Intercept	-0.087***	-0.088***	-0.086***	-0.087***
	(-19.63)	(-9.75)	(-19.06)	(-9.39)
RSUE	0.111***	0.112***	0.108***	0.107***
	(14.66)	(14.20)	(13.87)	(14.70)
ETF%	0.061**	0.209		
	(2.56)	(1.39)		
SECT%			0.146**	0.492*
			(2.20)	(1.79)
REST%			0.043	0.174
			(1.44)	(1.11)
RSUE*ETF%	**-0.143*****	**-0.265***		
	(-3.53)	**(-1.79)**		
RSUE*SECT%			**-0.516*****	**-0.700****
			(-4.41)	**(-2.63)**
RSUE*REST%			**-0.066**	**-0.168**
			(-1.32)	**(-1.13)**
SIZE	0.008***	0.009***	0.008***	0.008***
	(14.57)	(8.38)	(14.33)	(8.14)
BETA	-0.013*	-0.018	-0.013*	-0.018
	(-1.72)	(-1.08)	(-1.72)	(-1.12)
MTB	0.003***	0.003***	0.003***	0. 003***
	(9.55)	(6.58)	(9.57)	(6.59)
PRERET	-0.017**	-0.013	-0.017**	-0.013
	(-1.97)	(-0.84)	(-1.96)	(-0.86)
*RSUE*SIZE*	-0.009***	-0.009***	-0.009***	-0.009***
	(-9.16)	(-9.80)	(-8.75)	(-10.32)
*RSUE*BETA*	0.031**	0.037**	0.031**	0.038**
	(2.53)	(2.38)	(2.53)	(2.43)
*RSUE*MTB*	-0.001	-0.000	-0.001*	-0.000
	(-1.64)	(-0.72)	(-1.67)	(-0.71)
*RSUE*PRERET*	0.027*	0.020	0.027*	0.020
	(1.88)	(1.23)	(1.84)	(1.20)
Adj. R^2	1.19%	1.77%	1.20%	1.83%
N	136,508	136,508	136,508	136,508