ETFs and Information Transfer Across Firms

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Abstract: This paper examines the role that exchange-traded funds (ETFs) play in the transfer of information across firms around earnings announcements. Our analysis focuses on the differences in information transfer between broad-based and sector ETFs. We find that firms with sector ETF ownership are associated with reduced over-extrapolation of intra-industry information, increased earnings response coefficients (ERCs), greater responsiveness to the industry and idiosyncratic components of earnings surprise, and reduced post-earnings announcement drift. Conversely, broad-based ETFs are associated with decreased ERCs and lower responsiveness to industry and idiosyncratic information. Follower firms in sector ETFs show stronger reactions and weaker reversals when leader firms in the same ETFs release earnings, while follower firms in broad-based ETFs show weaker reactions and greater reversals. Overall, sector ETFs have improved informational efficiency by facilitating information transfer, while broad ETFs might have worsened informational efficiency in the context of earnings announcements.

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

JEL Classification: G12, G14, M41, D53

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1. Introduction

The last decade has seen a significant shift in the asset management landscape with the growth of exchange-traded funds (ETFs). As of the end of 2018, the ETF industry had assets under management (AUM) of roughly $3.4 trillion in the US (ICI Factbook 2019). In the 10 years ending 2018, ETFs have seen inflows of nearly $2.3 trillion. ETFs play a significant role in financial markets, particularly equity markets, constituting roughly 30 percent (23 percent) of US market trading by value (by volume).[1] Given the size of the AUM and the proportion of trading volume they represent, understanding the relation between ETFs and their constituents is important to gain insight into the benefits and costs of these instruments. This paper examines the role that ETFs play in the transfer and dissemination of information between constituent firms.

Ex-ante, the impact of ETFs on information transfer between its constituents is unclear. 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 can allow commonality in information (like industry information or market level information) to quickly percolate through to all the constituents of the ETF. Trading using ETFs can be a more efficient mechanism to capture industry-level information or market level information incorporated in any information source. ETFs can also be used to hedge out systematic risk and trade on idiosyncratic information. This would suggest that ETFs would make stock prices of its constituents more efficient. On the other hand, ETFs could be limited in their ability to transfer information effectively across firms if they are simply used as passive investment vehicles rather than as a means to efficiently trade on the information. Further, even if they are used as vehicles for trading on factor information, they are limited in that they are baskets created based on fixed rules (e.g., market capitalization-weighted). ETF trading thus could

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

cause information to be impounded in the proportion determined by the rules rather than based on the value of the information to each constituent. In addition, ETF trading driven by earnings news that is primarily idiosyncratic and has no relevance to constituents other than the announcing firm can cause mispricing in the other firms, which can persist, unless another group of investors (active managers or arbitrageurs) trade in the individual constituents to correct any mispricing.

Prior research examining the impact of ETFs on the processing of information has found mixed evidence. Many papers paint a negative picture of ETFs by showing that ETF ownership and trading leads to increased return co-movement (Leippold, Su and Zeigler 2016, Da and Shive 2018), increased volatility and bid-ask spreads (Ben-David, Franzoni and Moussawi 2017) and reduced earnings response coefficients and analyst following (Israeli, Lee and Sridharan 2017). Conversely, Glosten, Nallareddy and Zou (2017) find that ETFs improve the contemporaneous price-earnings relationship, especially among firms in poor information environments.

In this paper, we investigate the role of ETFs in facilitating the dissemination of relevant information contained in the earnings of a firm to other constituent firms. We also examine if the type of ETF (sector and broad-based ETFs) influences the role that ETFs play in facilitating earnings related information flow. Our research design focuses on the stock returns to firms around earnings announcements – both their own, as well as that of peer firms. We use multiple approaches to examine our research question. Firstly, at the firm-level, we look at a broad sample of earnings announcements conditioned on the presence of and nature of ETF ownership. Secondly, at the ETF level, we identify the constituents of each ETF and examine the returns behaviour around earnings announcements.

Our firm-level analysis initially follows Thomas and Zhang (2008) who examine the intra-industry transfer of information around earnings announcements. They find that markets overestimate the industry-level information in early announcers' earnings for late announcers' earnings and correct this overestimation when late announcers disclose their earnings. We examine whether the introduction of ETFs (particularly sector ETFs) has affected this overreaction by either exacerbating it or mitigating it. We begin by corroborating their finding using the universe of firms with available data in the 1985 to 2015 period. When we partition the sample by time, we find a significant weakening of the intra-industry overestimation in the latter period when ETF trading became more prominent (2002-2015), driven primarily by sector ETFs. To mitigate the potential confounding impact of other events during the post-ETF period (e.g., Sarbanes-Oxley), we carry a narrow window analysis in the four quarters before and after a firm first becomes part of an ETF. The staggered initiation dates provide a natural quasi-experiment for us to study the impact of ETF ownership, with each firm acting as its own control. We find that the initiation of sector ETF ownership by sector ETFs moderate the overestimation of intra-industry information, while there is no discernible effect for broad-based ETFs.

Having documented that ETFs, specifically sector ETFs, reduce the overestimation of industry information released prior to earnings announcements, we next examine whether ETFs affect how markets react to earnings news. Specifically, we consider the relationship between the earnings surprise and the stock market reaction, i.e. the earnings response coefficient (ERC). We find that sector ETFs are associated with increased ERCs, while broad ETFs are associated with lower ERCs.

Information is comprised of varying degrees of macroeconomic, industry-level and firm-specific idiosyncratic components. To understand the relation between the type of ETF and the type of information, we partition the earnings surprise into macroeconomic, industry and idiosyncratic components. We find that the earnings surprise is primarily driven by the industry and idiosyncratic components with the macroeconomic component playing an insignificant role, consistent with Jackson, Rountree and Plumlee (2018). We further find that broad-based ETFs are associated with a lower response to idiosyncratic information, while sector ETFs are associated with a stronger response to both industry and idiosyncratic information.

We next examine whether information transfer can account for the reduction in ERCs among high ETF ownership firms documented in the prior literature (Israeli, Lee and Sridharan 2017). We examine whether the decline in ERCs is a function of the ordering of earnings announcements and whether the decline varies between the two subgroups. We find that ERCs for follower firms decline as the fiscal quarter progresses. Further, this pattern of declining ERCs is only observed when the firms are ETF constituents. This suggests that the previously documented lower ERCs are partly attributable to information transfers facilitated by ETFs.

Our final firm-level test examines 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. We find that ETF ownership mitigates the drift – i.e. information is impounded into prices earlier for firms with greater ETF ownership. Crucially, this effect is driven entirely by sector ETF ownership. For broad-based ETF ownership, we see a limited impact of ETF ownership on the drift. This supports our interpretation that ETF ownership, especially sector ETF ownership, facilitates information transfer across firms.

In our ETF level analysis, we examine the relationship between returns around earnings announcements of the firms that are owned by a given ETF. We identify the five largest holdings within each ETF for a large sample of ETFs from 2002-2015 and examine the stock returns of the first firm to announce earnings (the leader) and the four following firms (followers). We carry out this analysis separately for firms in sector ETFs and broad-based ETFs. We also examine another sample consisting of pairings of the leader firms with followers in the same sector but which are not members of the sector ETF. This allows us to provide a benchmark to control for the simple intra-industry information transfer that could be driving the sector ETF results. We find that, on average, follower returns are positively associated with leader returns around the leader's earnings announcement. This effect is significantly stronger than for firms in the same sector but with no sector ETF exposure. This is consistent with sector ETFs trading influencing the returns of other constituents around the earnings announcement of one of its members. To lend further credence to our ETF argument, we partition out the sample based on ETF volume and find that the sector ETF effect of leader announcement on follower firms is stronger when the level of ETF trading is high. We also find that firms in broad-based ETFs have the least response which is consistent with their having a lower degree of information commonality.

While sector ETFs seem to generate a greater association between leader and follower returns it is not clear if this increased association is the result of more informational efficiency or greater overreaction. We examine this by focusing on the returns in between the leader's earnings announcement and the follower's own earnings announcement. We find that followers in sector ETFs experience a more muted reversal as compared with follower firms that are in the same sector but not in sector ETFs. This suggests that the response observed during the leader's announcement is more efficient in the case of sector ETFs. The reversal for broad ETF constituents is more pronounced suggesting that the initially observed returns were an overreaction. It is possible that the reversals themselves could be a short-term phenomenon and the firms could exhibit longer-term drift. However, the firm-level results examining PEAD suggest that this is not the case.

Our results bridge the seemingly inconsistent results in the prior academic literature on ETFs and market efficiency. By separating ETFs into sector ETFs and broad-based ETFs, we can compare ETFs better designed to impound industry-level information in earnings to other kinds of ETFs. Broad-based ETFs can cause ETF constituents to react to information that may not be relevant (around earnings announcements in particular), causing anomalous return co-movement and future reversals, which in turn leads 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.

Our paper also contributes to the literature on intra-industry information transfer (Freeman and Tse 1992, Thomas and Zhang 2008). Our results suggest that the anomalous over-extrapolation of intra-industry information is reduced among firms with ETF ownership, and in fact becomes insignificant for firms with sector ETF ownership.

Our paper is also related to the work on institutional ownership. As registered investment companies (open-ended funds), ETFs represent a form of institutional ownership. Prior research shows that institutional ownership improves price efficiency in markets because their trading reflects their information (e.g., Jiambalvo et al., 2002; Piotroski and Roulstone, 2004). However, ETFs are different from the standard institutional ownership because they are instruments that can be freely traded in the secondary market by any of the market participants including retail and other institutions. ETFs can be shorted and reduce the cost of trading. Given these significant differences, the results from institutional ownership cannot be simply extended to understand the impact of ETFs. In fact, our results suggest that researchers should treat ETF ownership differently when calculating institutional ownership as well as when partitioning ownership into active and passive. This is because even though ETF ownership might seem passive they can be used actively to trade on information thereby behaving differently from other forms of institutional ownership.

The rest of the paper is organized as follows. Section 2 provides institutional details regarding ETFs and discusses prior research that motivates our research questions. Section 3 describes the research design. Section 4 discusses the results from the firm-level analysis, and Section 5 discusses the results from ETF level analysis. Section 6 concludes the paper.

2. Institutional background and prior research on ETFs

2.1 The Emergence of 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. Assets in ETFs had grown from 33 billion dollars to 1 trillion dollars in the 2000s and the size has subsequently tripled to 3.5 trillion dollars by 2018. As of the end of 2015, there were 1,500 ETFs. ETFs historically have tracked indices but more recently (starting in 2008), ETFs also include actively managed vehicles.[2]

An ETF is created by a sponsor who chooses the investment objective, benchmark and weighting mechanisms. This could be a market capitalization 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.

ETFs are unique investment vehicles that share some similarities and differences with open-ended mutual funds. They are similar to other open-ended funds because ETFs own the underlying assets (e.g., stocks, bonds, commodities, futures, foreign currency, etc.) and divide ownership of those assets into shares. However, there are several advantages of ETFs over mutual funds. First, while an open-ended fund is priced daily and its NAV is known at the end of the

[2] 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).

trading day, an ETF is a derivative instrument that is traded and priced throughout the day and its NAV is available at any time during the trading day. In addition, ETFs are more transparent in their holdings. Unlike mutual funds that provide quarterly disclosure on holdings, ETFs provide holdings information daily in disclosures referred to as creation baskets. Finally, investors can purchase ETF shares on margin, short sell shares, or hold for the long term. The ease of trading and low cost of diversification has contributed to the surge in ETF popularity and allowed investors to trade more often. ETFs on average represent roughly 30 percent of daily market volume. In 2016, the top twelve most traded securities were all ETFs, beating the most traded individual security (AAPL).

2.2 Primary and Secondary ETF Trading

ETFs are subject to two types of trading: primary market trading and secondary market trading. Trading in the primary market involves the process of creation and redemption of ETFs. The sponsor manages the process of creating and redeeming ETFs 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). It is worth noting that on average, about 10 percent of the daily ETF volume occurs in the primary market.

Trading in the secondary market is the dominant form of trading in ETFs accounting for about 90 percent of ETF volume. Secondary ETF trading occurs without the creation of new ETF shares or the redemption of existing ETF shares. Secondary ETF trading can affect the price of the ETF and by extension the price of the underlying securities. For example, if buyers exceed sellers, it puts upward price pressure on the ETF and causes a spread between the price of the ETF and the

NAV based on the underlying stocks. APs and other market participants ensure that the spread is quickly corrected by buying the underlying the basket while simultaneously selling (or short-selling) the ETF. Trading in both the primary and the secondary market will have an impact on the pricing of the underlying constituents. To create more ETF shares or redeem existing shares, the APs have to buy or sell the underlying constituents causing the price of the underlying constituents to rise or fall. Similarly, to arbitrage price differences in the secondary market, arbitrageurs will have to buy (sell/short-sell) or sell/short-sell (buy) the ETF (underlying constituents), again moving the price of the underlying constituents.

2.3 How ETF Trading can influence the efficient pricing of the underlying securities

One of the biggest benefits of ETFs is that they allow for trading a large number of stocks in a cost-efficient manner. Subrahmanyam (1991) and Cong and Xu (2017) argue that ETFs are particularly useful to factor-informed traders as they can easily trade on their information advantage.[3] For example, prior to the introduction of market-wide ETFs (e.g., SPY), investors who possessed information that could affect the overall market had a high barrier to trade on their information as they would have to trade hundreds of individual stocks to profit from their private information. ETFs make this process easier by reducing transaction costs and speeding up trade executions. Given that most of the ETF trading occurs in the secondary market, ETFs can reduce the constraints that arise due to limited liquidity in some of the underlying constituents. ETFs also make it easier to trade on negative information because it significantly eases the locate process (one locate instead of several)[4] and reduces the cost of shorting. They also allow firms to isolate

[3] Examples of factor information could include industry-level, economy-wide, or market-level information.

[4] Locate refers to the process through which institutional investors obtain the shares for short selling.

and trade on firm-specific information by hedging the industry or macro component (Huang, O'Hara and Zhong, 2018).

By lowering the bar for trading by factor-informed investors, ETFs allow commonality in information (i.e., industry or market-level information) to quickly percolate to all the constituents of the ETF. Especially, ETFs trading can provide an efficient pricing mechanism by incorporating industry-level information or market-level information from a wide source of information. Consistent with this, Glosten, Nallareddy and Zou (2017) find that ETFs lead to timelier impounding of systematic information, especially for firms in weak information environments.

Alternatively, ETFs could also contribute negatively to efficient pricing. As ETFs are baskets created based on fixed rules (e.g., market capitalization weighted), they could be limited in their ability to transfer information effectively across firms. When factor-informed investors use ETFs, they force information to be impounded based on the proportion set by the rules rather than based on the relevance of the information to each of the constituents. Further, ETF trading can cause anomalous movement in the stock price of underlying securities, when ETFs are traded based on the information that is irrelevant to a given constituent. This can result in mispricing of the constituent, unless active managers or arbitrageurs quickly eliminate such mispricing. Cong and Xu (2017) analyze that increased ETF ownership may disincentivize traders from acquiring information of individual stocks, leading to fewer firm-specific informed traders and greater pricing inefficiency. Corroborating this argument, Israeli, Lee and Sridharan (2017) find that greater ETF ownership results in lower analyst following.

2.4 Broad-based ETFs vs Sector ETFs

While prior studies have viewed ETFs as a homogenous group, in reality ETFs can be broadly partitioned into at least two distinctly different groups. The first group is broad market level ETFs such as SPY (S&P 500 SPDR ETF) and VOO (Vanguard S&P 500 ETF). The second group is sector or industry-level ETFs such as XLK (Technology Select Sector SPDR ETF) and XLY (Consumer Discretionary Select Sector SPDR ETF). 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. At the end of 2016, sector ETFs were the top five highest turnover ETFs and accounted for eight of the top 10. These securities could result in greater efficiency compared to market-weighted ETFs, as they are better designed to capture industry information.

Sector ETFs are more likely to contribute to efficient information transfers, as their composite firms come from a more homogenous group. Thus, when one firm releases news, the news is probably relevant for other firms in the ETF is higher. Conversely, broad-based ETFs consist of more heterogeneous constituents, which makes it more likely that the information released by one firm is irrelevant for other firms. In our analysis, we will consider the important conditioning role of the nature of the ETF to attempt to reconcile the seemingly contradictory findings in prior research.

A recent working paper by Huang et al. (2018) examines how investors short sector ETFs to hedge industry risk and isolate idiosyncratic risk. They show that high ETF short interest predicts positive ETF returns, rather than negative returns if the short interest was based on information. Our paper is focused on a different channel - the role of ETFs in disseminating systematic information to its constituents. We examine the flow of information (as reflected in stock returns) from one constituent to another. While our paper examines a different aspect of ETFs using a different research design, some of our results corroborate Huang et al. (2018). For instance, our finding that the idiosyncratic component of information is better priced for sector ETFs is consistent with investors using ETFs to isolate the idiosyncratic component of information. Untabulated results show that our results continue to hold for both high and low ETF short interest firms, the latter being the primary mode through which the Huang et al., (2018) mechanism works.

3. Research Design

3.1 Analysis of Returns around Earnings Announcement

We examine the role that ETFs play in information transfer by focusing on earnings announcements as a source of information. Different constituent firms within an ETF release earnings at different points of time in a given quarter. This provides us with an opportunity to study whether other ETF constituents react when a firm within an ETF releases earnings. This also allows us to examine whether the initial reaction was efficient or not, by examining subsequent returns.

We carry out our analysis at two levels – the firm-level and the ETF level. At the firm-level, we look at a broad sample of firm-level earnings announcements. We start by examining the effect of ETFs on a well-established result in the information transfer literature: the anomalous over-extrapolation of industry information as documented by Thomas and Zhang (2008). We test whether ETF ownership and the nature of ETF ownership (sector vs. broad) are associated with the pattern of over-extrapolation. Other firm-level analyses include examining ERCs and ETFs, parsing the information in earnings surprise into macroeconomic, industry and idiosyncratic components and finally the influence of ETFs on post earnings announcement returns. At the ETF level, we examine information transfer among constituent firms within an ETF, by the returns of the first firm to announce earnings (the leader) and the other four firms (followers). We also investigate whether this reaction varies with the nature of the ETF and whether it is efficient or anomalous.

3.2 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. 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,[5] similar to the number from Israeli, Lee and Sridharan (2017) and Glosten, Nallareddy and Zou (2017). We identify sector ETFs by analyzing the title of the ETF, as sector ETFs typically specific sectors and industries. NYSE, NASDAQ and several popular ETF websites (i.e.,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 broad-based ETFs. For comparison, Huang, O'Hara and Zhong (2018), using an automated methodology, identify 217 industry ETFs before narrowing their sample down based on additional screens.

Panel B displays the sample distribution across time. The sample has fewer observations in the early years, with 106 distinct ETFs in 2002. This has increased sharply to 473 by 2008, declining slightly after that. Overall, there is little evidence of time clustering in our sample. Panel C presents the distribution of the industries of the sector ETFs in our sample. The 214 sector ETFs can be classified into 32 distinct sectors or subsectors. While many sectors have only a handful of

[5] We start our ETF level 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 quarterly, rather than semi-annually in 2002.

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).

4. Firm-level Analyses

4.1 Do ETFs affect the overestimation of intra-industry information?

Thomas and Zhang (2008) document that investors overestimate the intra-industry implications of early announcers' earnings for late announcers' earnings and that this overestimation is corrected when late announcers disclose their earnings. If ETFs have led to more efficient information transfer, we should observe an attenuation of the overestimation, especially for sector ETFs. Thomas and Zhang (2008) define peer firms (early announcers) for any particular firm as the firms in the same industry that report earnings at least 5 days preceding that firm's earnings announcement date. *ARET* represents the size-adjusted excess return for the 3-day window around the announcer's earnings announcement. *RESP* is the average excess return of the firm around its peer firms' earnings announcement dates.

Thomas and Zhang (2008) document a significant negative relationship between *ARET* and *RESP* confirming that investors overestimate the intra-industry implications of early announcers' earnings for late announcers' earnings. They show that a trading strategy that goes long in the firms in the lowest decile of *RESP* and short in firms in the highest decile of *RESP* earns significant hedge returns of 1.16% around the announcement period.

We begin with a replication of their approach with one modification – we use the Fama and French (1997) industry classification instead of four-digit SIC code, as it potentially better reflects the composition of firms within sector ETFs (e.g. Technology ETF, Telecommunications

ETF, Biotech ETF).[6] Firms' quarterly earnings announcement dates are from quarterly Compustat files. Both *ARET* and *RESP* measure excess returns accumulated over 3 trading days around the earnings announcement date, computed as raw returns minus the returns from the same NYSE/AMEX/NASDAQ size decile firms over the same event window. In our replication, we find that the returns to the hedge strategy decline from 1.16% in the pre-ETF period (1985-2001) where ETF ownership of stocks was virtually nonexistent, to 0.77% in the ETF period (2002-2015), with the difference of 0.39% being highly significant (t-stat 3.63).

Thomas and Zhang (2018) confirm their findings in a multivariate analysis controlling for other determinants of announcement period returns by estimating the following specification.[7] We replicate their regression and present the results in Panel A of Table 2.

$$ARET = \alpha + \beta_1 {*}RESP + \beta_2 {*}ACC + \beta_3 {*}RET6 + \beta_4 {*}ERLYPRARET + \beta_5 {*}ARET1 + \beta_6 {*}ARET4 + \beta_7 {*}INST + \beta_8 {*}SIZE + \beta_9 {*}LOGBM + \varepsilon \qquad (1)$$

The first column presents the results for the entire sample (1985-2015). Consistent with Thomas and Zhang (2008), we find a significant negative relationship between *ARET* and *RESP*, with *RESP* having a coefficient of -0.1950 (t-statistic -10.78). We next partition our sample into a pre-ETF period (1985-2001) and the ETF period (2002-2015). We find that the reversal in returns is stronger in the pre-ETF period (-0.2348, t-stat -10.01) than the ETF period (-0.1488, t-statistic -11.78). The final regression shows that the difference between these coefficients is highly significant (0.0807, t-stat 3.10). This provides prima-facie evidence that the overreaction to industry information has weakened during the period when ETFs become prevalent. However, this period was also associated with numerous other changes in various aspects of the capital

[6] Results are similar if we use 4-digit SIC codes to identify peer firms.

[7] The control variables are accruals (*ACC*), buy-and-hold returns for the six months prior to announcement (*RET6*), average of early peer's three day earnings announcement excess returns (*ERLYPRARET*),one quarter and four quarter lagged announcement returns (*ARET1*, *ARET4*), institutional ownership percentage (*INST*), log of market capitalization (*SIZE*) and log of the B/M ratio (*LOGBM*).

markets such as market microstructure (decimalization), regulation (Sarbanes-Oxley), availability of peer information (EDGAR, XBRL) and functioning of analysts (global settlement).

To better link the change in intra-industry information transfer to ETF ownership, we consider the impact of ETF ownership at the firm-level. For each firm, we identify the first instance of ownership by ETFs and study the narrow window around the initiation of ETF ownership – the four quarters before and after ETF ownership. For each firm, the initiation of ETF ownership is not a fixed date but varies by firm. The staggered initiation dates provide a natural quasi-experiment for us to study the impact of ETF ownership. Each firm acts as its own control, and we can have greater confidence in ascribing any effects we identify as being associated with ETF ownership. The short window increases the confidence that any differential effect we find is more likely to be associated with ETF ownership rather than other confounding events.

For each firm, we create the following three indicator variables. *ETF* is an indicator variable that equals 1 if ETFs own stock of the given firm in the given quarter and 0 otherwise. By construction, each firm will appear eight times in the regression, four times with *ETF*=0 and four times with *ETF*=1. *BROAD* is an indicator variable that equals 1 if broad-based ETFs own stock in the given firm and 0 otherwise. *SECTOR* is an indicator variable that equals 1 if sector ETFs own stock of the given firm in the given quarter and 0 otherwise. In our regressions, we interact *RESP* first with *ETF*, and then with *BROAD* and *SECTOR*.

The results are presented in Panel B of Table 2. Column 1 presents the regression using the interaction of *RESP* with *ETF*. The main effect on *RESP* represents the reversal in the immediately pre-ETF period, while the coefficient on *RESP*ETF* represents the change in the reversal in the immediately post-ETF period. *RESP* has a significant negative coefficient (-0.2434, t-stat -9.13) confirming the baseline Thomas and Zhang (2008) result. The interaction of *RESP*ETF* has an insignificant positive coefficient (0.0491, t-stat 0.82) suggesting that ETF ownership does not significantly mitigate intra-industry overestimation. Column 2 presents the regression using the interaction of *RESP* with *BROAD* and *SECTOR*, respectively. Consistent with our expectations, we find greater mitigation when sector ETFs own a constituent firm. The interaction of *RESP*SECTOR* has a significant positive coefficient (0.1321, t-stat 2.71), while the interaction of *RESP*BROAD* is insignificant (-0.0576, t-stat -0.98). Hence, we find a significant weakening of the intra-industry over-extrapolation when sector ETFs own shares in firms, but fail to find an effect for overall ETFs. These results consistent with sector ETFs being a more effective mechanism to transfer information between its constituents.

4.2 ETFs and Earnings Response Coefficients

To better understand how ETFs play a role in the processing of earnings information, we next examine the impact of ETF ownership on how markets react to earnings news. Specifically, we consider the relationship between the earnings surprise and the stock market reaction to the earnings surprise, i.e. the earnings response coefficient or ERC. If ETFs have helped in the efficient processing of earnings information, we should see an increase in ERCs. On the other hand, if ETFs have hindered the efficient processing of information, we should see a decrease in ERCs.

Our dependent variable is *ARET*, the size-adjusted three day buy-and-hold returns in the 3-day window (-1,+1) around earnings announcements. The main variable is *SURP*, the earnings surprise defined as the difference between actual earnings per share and the last consensus EPS forecast prior to fiscal quarter end, scaled by the stock price. See the Appendix for detailed definitions. In addition, we control for the well-known determinants of announcement-period stock returns, similar to our Thomas and Zhang (2008) replication.

Beaver, McNichols and Wang (2017) show that ERCs have increased over the past two decades. To ensure that we are not merely picking up intertemporal increases in ERCs and attributing them to ETFs, we carry out our analysis in the sample period after the emergence of ETFs. We run the following regression in the ETF period of our sample (2002-2015).

$$ARET = \alpha_0 + \alpha_1 * ETF + \alpha_2 * BROAD + \alpha_3 * SECTOR + \beta_1 * SURP + \beta_2 * SURP * ETF + \beta_3 * SURP * BROAD + \beta_4 * SURP * SECTOR + controls + \varepsilon \quad (2)$$

The results are presented in Panel A of Table 3. The first baseline regression establishes that the average ERC is 0.5366. In the next regression, we interact *SURP* with the indicator variable *ETF*. We find an insignificant reduction in ERCs, as the coefficient on *SURP*ETF* is -0.0600 (t-stat -1.49). In the next regression, we replace *ETF* with two separate indicator variables for broad-based *ETF*s (BROAD) and sector *ETF*s (SECTOR). The coefficient on *SURP*BROAD* is significantly negative (-0.1709, t-stat -3.93), while the coefficient on *SURP*SECTOR* is significantly positive (0.3172, t-stat 7.08). Thus, the presence of broad-based ETFs is associated with reduced ERCs, while sector ETFs are associated with increased ERCs. This finding is broadly consistent with our prior analysis, both at the sector level analysis as well as the firm-level, that sector ETFs may have improved the efficient processing of earnings information, while broad-based ETFs may have adversely affected the processing of earnings information.

4.3 **ETFs and components of information**

As discussed earlier, information can be viewed as consisting of three components – macroeconomic information, industry information and firm-specific idiosyncratic information. To better understand why broad-based ETF ownership is associated with lower ERCs while sector ETF ownership is associated with higher ERCs, we attempt to isolate the macroeconomic, industry and idiosyncratic components of earnings surprise. We calculate the average surprise for all firms in the economy over the past 30 days to calculate the macroeconomic component of earnings surprise (*MACRO*). Similarly, we calculate the average surprise for all firms in the same industry to isolate the industry component of earnings surprise (*IND*), and further isolate the pure industry component (*PUREIND*) by removing the macroeconomic component that affects all industries. Finally, we extract the purely firm-specific idiosyncratic component of surprise (*IDIO*). Appendix II highlights the methodology we use to calculate the three components of SURP.

We replace *SURP* with the three components and rerun the ERC regressions. The results are presented in Panel B of Table 3. The first baseline regression considers the three components and control variables. *MACRO* has an insignificant positive coefficient, while both *PUREIND* and *IDIO* have significant positive coefficients. This is consistent with Jackson, Rountree and Plumlee (2018), who highlight the importance of firm-specific and industry-specific information. The next regression interacts the components of information with the ETF indicator variable. None of the interactions are significant, suggesting that ETF ownership by itself does not affect ERCs.

In our final regression, we replace *ETF* with separate indicators *BROAD* and *SECTOR*. We find that broad-based ETF ownership is associated with a decline in the response to idiosyncratic information, as the coefficient on *IDIO*BROAD* is -0.1692 (t-stat -3.89).[8] On the other hand, we find that sector-based ETF is associated with an increase in the response to both industry-information (coefficient on *PUREIND*SECTOR* is 0.6200, t-stat 2.69) as well as idiosyncratic information (coefficient on *IDIO*SECTOR* is 0.3186, t-stat 7.10). The increased response to industry-information is consistent with our results thus far that sector ETFs help the processing of industry information. The increased response to idiosyncratic information is consistent with Huang, et al., (2018)'s finding that investors trade sector ETFs to get more focussed exposure to firms that release earnings.

[8] While it appears that broad based ETFs are associated with lower efficiency in the context of earnings announcements, it is possible that they play a more constructive role around macroeconomic events like GDP announcements and interest rate changes, which we do not examine in this paper.

4.4 ETFs and across-quarter trends in Earnings Response Coefficients

The results thus far suggest that sector ETFs allow for the effective transmission of relevant information among ETF constituents. The firm-level tests suggest that ownership by sector ETFs reduce anomalous overreaction to industry peer firms' earnings information, suggesting that the release of earnings information by a peer firm also releases correlated information, which can get impounded into stock prices through ETF trading. A corollary of this is that ERCs should decline over the quarter. For early announcers, less common information that been released, which makes the earnings release more informative. For late announcers, a portion of the information has been "pre-released" to the market which potentially makes the earnings release potentially less informative. Based on our earlier results that sector ETFs facilitate the flow of information between its constituents, we expect to find that the decline in ERCs should be stronger for firms that are constituents of these ETFs.

We test this conjecture using the following research design. We look at the universe of firm-quarters in the 1985-2015 period that have fiscal quarter ends in March, June, September and December. We consider the top five firms by market capitalization in each of the Fama and French (1997) 48 industry groupings. We rank these five firms based on their earnings release dates (RDQ) and create a rank variable called *RRDQ* that increases from zero for the first firm to four for the last firm. We run the following ERC regression, controlling for the determinants of announcement period returns. The sample consists of 24,472 firm-quarters for which complete data is available.

$$ARET = \alpha_0 + \beta_1 * SURP + \beta_2 * RRDQ + \beta_3 * SURP * RRDQ + CONTROLS \qquad (3)$$

In the above regression, the coefficient on earnings surprise (*SURP*) represents the earnings response coefficient for the first firm to release earnings information. The coefficient on the interaction (*SURP*RRDQ*) represents the trend in earnings response coefficients for later releasers.

The results are presented in Table 4. The first column presents the results for the entire sample. As expected, the coefficient on *SURP* is positive and significant (2.6634, t-stat 8.04). The coefficient on *SURP*RRDQ* is negative and significant (-0.2363, t-stat -2.32), suggesting that ERCs decline for later releasers. This potentially represents the transmission of industry specific information from early releasers to late releasers, given that we are analyzing firms within a given industry and are therefore capturing intra-industry information transfer.

To test whether the decline in ERCs is related to ETFs, we partition our sample into two subgroups. The first subgroup consists of observations where none of the five firms in the industry belong to any ETF. The second subgroup consists of observations where all five firms belong to an ETF. The next two columns present the ERC regressions for these two subgroups. For the no-ETF subsample, the coefficient on *SURP*RRDQ* is insignificantly different from zero (-0.1303, t-stat -1.29). For the all-ETF subsample, the coefficient on *SURP*RRDQ* is -0.491 (t-stat -3.80), suggesting a significant decline in ERCs as the quarter progresses.[9] The last columns consider two subgroups based on sector ETF ownership. We find an even stronger decline in ERCs when all firms have sector ETF ownership, with the coefficient on *SURP*RRDQ* (-0.7772, t-stat -3.47).

To better illustrate these results, we present them graphically in Figure 1. The coefficient on *SURP* is the ERC for the first firm. For each subsequent firm, we infer the ERC by subtracting the value of the interaction (*SURP*RRDQ*) from the ERC of the previous firm. As the graph

[9] The coefficient on *SURP* is significantly higher for the all-ETF subsample as compared to the no-ETF sample. This can largely be attributed to the trends of increasing ERCs across time as documented by Beaver, McNichols and Wang (2017). The no-ETF sample has no observations after 2003 given that we focus on the five largest firms in an industry and the ubiquity of ETF ownership in the later years of our sample. Conversely, the all-ETF sample is concentrated in the latter years of our sample.

indicates, we see a sharp decline in ERCs when all five firms in an industry are part of an ETF, and especially when they are a part of a sector ETF. This is consistent with information transfer across ETF constituents prior to the earnings release and provide an alternative to the investor inattention explanation for the lower ERCs provided by Israeli, Lee and Sridharan (2017).

4.5 Impact of ETFs on the post-earnings announcement drift

The post-earnings announcement drift (PEAD) refers to the positive correlation between the returns in the period after earnings is announced and the earnings surprise (Bernard and Thomas, 1989, 1990). This is considered an anomaly because the return drift persists for a considerable period – as long as sixty days after earnings release. The commonly accepted wisdom is that PEAD represents the delayed processing of earnings news by capital market participants.

Our results thus far suggest that ETFs, especially sector ETFs, have a significant impact on the processing of earnings information by capital markets, by facilitating the impounding of correlated information released by peer firms. If more earnings information is impounded by the time of the earnings release, we should see a weaker PEAD. Alternatively, if ETFs make markets inattentive to firm-level information we should see stronger PEAD with ETF ownership.

Earnings surprises (*SURP*) 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 end 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 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 the market closes to the next trading day, following the recent study by Beaver, McNichols 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.

We test the association between PEAD and ETF ownership in a multivariate regression setting, controlling for other known determinants of PEAD identified in prior research (Huang, Li and Wang 2015). To more easily interpret the coefficient on earnings surprise, we construct a variable *RSURP*, where the 10th decile *RSURP* equals 1 and the 1st decile *RSURP* equals 0 (2^{nd} decile RSURP=0.111, 3^{rd} decile RSURP=0.222 etc.). Thus, the coefficient for *RSURP* can be interpreted as the difference in PEAD between decile 10 and decile 1. A positive coefficient for *RSURP* suggests that the PEAD exists. In our regressions, we interact *RSURP* with the indicator variables for ETF ownership (*ETF, BROAD* and *SECTOR*). A positive coefficient indicates a worsening of the drift while a negative coefficient indicates a mitigation in the drift.

We run the regression model using two procedures – a pooled panel regression with two-way clustered t-statistics (clustered by firm and year), and quarterly regressions summarized using the Fama and MacBeth (1973) procedure. The results are presented in Table 5. The first column presents the pooled panel regression using *ETF*. Consistent with the presence of PEAD, we find that *RSURP* has a strong positive association with *POST60* with a coefficient of 0.094 (t-stat 9.51), suggesting the difference in PEAD between the firms with 10^{th} decile of earnings surprises and firms in the 1^{st} decile of earnings surprises is about 9.4 percent. Consistent with prior research, we also find that the drift is negatively associated with size, positively associated with systematic risk and momentum and negatively associated with size and market-to-book ratio. The interaction term *RSURP*ETF* has an insignificant negative coefficient (-0.007, t-stat -0.73). This suggests that overall ETF ownership does not mitigate the drift. The next column repeats the analysis using quarterly Fama and MacBeth (1973) regressions and finds similar results.

The next two columns of Table 5 repeat the analysis using the interaction of *RSURP* with *SECTOR* and *BROAD*. We find that sector ETF ownership is strongly associated with lower drift, while this effect is insignificant when ETF ownership is entirely broad-based. For instance, using the pooled specification, the coefficient on *RSURP*SECTOR* is -0.021 (t-stat -4.70), while the coefficient on *RSURP*BROAD* is 0.002 (t-stat 0.24). 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 about the efficacy of sector ETFs in the efficient processing of earnings information. Taken together, our findings suggest that sector ETF ownership leads to the impounding of relevant information in the pre-announcement period, which reduces PEAD.

5. ETF Level Analyses

To better understand the dynamics of information propagation within ETFs, we analyze the returns around earnings announcement for the firms that are owned by a given ETF. As ETFs often own a large number of stocks, including small capitalization stocks that are illiquid and thinly traded, we focus our attention on the five largest holdings in a given ETF based on dollar value weights.[10] The first firm to release quarterly information is referred to as the leader, while the other four are referred to as followers.[11]

[10]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. 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.

5.1 Sample and Variable Definitions

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, and pair the leader with four followers. We only keep firms with fiscal ending aligned with calendar ending (i.e. quarters ending in March, June, September and December) and no missing underlying ETF trading volume information. For the equally-weighted ETFs, we identify the earliest 5 firms that announce their earnings. 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 the market closes to next trading day, following the recent study by Beaver, McNichols and Wang (2017). We also delete observations where we are unable to obtain ETF trading volume. Our last data step is to remove duplicate pairs – the fact that two firms in a pair might be owned by multiple ETFs. We apply two-step screens to delete repeated leader-follower pairs in any given quarter. For repeated pairs, we keep the pair that is classified as high-volume and/or the pair that is from a sector ETF. Finally, we control for the announcement return for follower firm's prior quarter and the same quarter in the prior year, log of market capitalization, log of book-to-market ratio, follower firm's stock return over prior 6 months, and follower firm's institutional ownership. Our final sample has 30,898 leader-follower pairs from 9,830 distinct ETF-quarters. To control for intra-industry information transfer arising out of industry membership rather than sector ETF membership, we create a control sample of firms. For every leader in the treatment sample, we identify four firms that are in the same industry

[12] We start our analysis from 2002 as that is when quarterly reporting data on ETF holding starts.

but are not constituents of sector ETFs. Comparing the results of the treatment sample to this group allows us to isolate the effect of sector ETF membership.

We define *LRET* as the size-adjusted returns accumulated over 3 trading days starting from the day before the leader's announcement date. For each follower, we compute market responses over 2 windows. $FRET_{ANNC}$ measures follower's response to the leader's earnings announcement, computed as the size-adjusted returns accumulated over 3 trading days starting from the leader's announcement date. $FRET_{BETW}$ 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.

5.2 Analysis of returns around leader's earnings announcement

We begin our analysis by studying the investor response to the event window around the leader's earnings announcement. The results are presented in Table 6. 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 is paired with multiple followers.

Panel A of Table 6 examines the relationship between the leader's stock returns (*LRET*) and the follower firms' stock returns ($FRET_{ANNC}$). For followers that are in sector ETFs, the coefficient on *LRET* is 0.089 (t-stat 8.85), which decreases to 0.049 (t-stat 2.51) for followers in the same sector but not in sector ETFs and decreases to 0.024 (t-stat 4.15) for broad-based ETFs. These results show that follower firms respond to the leader's earnings announcement in all instances. However, the effect is strongest for firms that belong to sector ETFs. The effect for this group is stronger than for firms that are in the same sector but do not belong to sector ETFs. While this result suggests that sector ETFs seem to have an influence on the followers' returns, this could either be because of the greater informational efficiency at the industry- and firm-level or because of mispricing caused by ETF trading. The weakest response of broad-based ETF pairs is consistent with macroeconomic information not being a large part of earnings surprise.

If ETFs 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. To better link our findings with ETF trading, we partition our ETF pair sample into above and below median groups based on their trading volume over the 3 trading days around the leader's earnings announcement date [-1,1]. The results are provided in panel B of Table 6. The coefficient on *LRET* is similar for high volume and low volume ETFs suggesting that the response of broad-based followers to the leader's announcement is not determined by ETF trading volume. However, panel B of Table 6 shows that the sector ETF pair results seen in panel A of Table 6 are primarily driven by high volume ETFs. The coefficient on the interaction term *LRET*SECTOR* is large and highly significant for high volume ETFs (0.096, t-stat 5.70) and smaller for low volume ETFs (0.030, t-stat 2.05).

Overall, the results in Table 6 suggest that while firms within an ETF react significantly to the early announcing firm's earnings announcement, this effect is particularly strong for sector ETF firms, and when ETF trading volumes are higher. These results are also consistent with the increased return co-movement associated with ETFs documented in prior work (e.g., Da and Shive 2018, Israeli, Lee and Sridharan 2017), although our next analysis suggests a different explanation for this increased co-movement.

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

The results in Table 6 suggest that ETFs are associated with the extent to which follower firms react to the leader's earnings announcement. They do not, however, examine whether this reaction is price efficient. Indeed, the reaction shown in Table 6 could well be an anomalous overreaction, akin to the *RESP* variable used in our firm-level analysis. To test this, we examine the followers' returns in the period between the leader's and the followers' earnings announcements. We measure the size-adjusted returns ($FRET_{BETW}$) for follower firms in the period between the leader's earnings announcement and the follower firm's own earnings announcement. We test the correlation between $FRET_{BETW}$ and $FRET_{ANNC}$, and a negative correlation suggests a reversal of the initial reaction.

The results are presented in panel A of Table 7. The first column presents the results for the sector ETFs. We find evidence of a weakly significant reversal as the coefficient on $FRET_{ANNC}$ is -0.037 (t-stat -1.67). The reversal for both broad-based ETFs firms as well as firms in the same sector but not in sector ETFs are larger and highly significant. The difference in reversal between sector ETF firms and the other two groups is statistically significant. 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. Firms in the same sector but not in sector ETFs seem to exhibit an overreaction similar to that documented in Thomas and Zhang (2008). Broad-based ETFs seem to be associated with an overreaction in follower returns, consistent with trading in these ETFs potentially causing a mispricing of the follower stocks around earnings announcement. Again, there could be other settings wherein macroeconomic information is important and broad-based ETFs can be useful in disseminating information but their usefulness seems to be limited in the context of earnings announcements.

If ETFs do play 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 B of Table 7. For broad-based ETFs, we see a significant reversal in both high and low trading volume (coefficients for $FRET_{ANNC}$ are -0.097 and -0.111). For sector ETFs, we see weaker reversal with high trading volume than in lower trading volume ($FRET_{ANNC}$ + $FRET_{ANNC}*SEC=-0.016$ in high trading volume vs. $FRET_{ANNC}$ +

$FRET_{ANNC}*SEC=-0.062$ in low trading volume ETFs), though the difference between interaction terms is not statistically significant.

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 common information while broad-based ETFs appear to be associated with potential mispricing in the underlying securities in the context of earnings announcements.

6. Conclusion

This paper examines the role of ETFs in facilitating the flow of information between firms. Using earnings announcements as our information event, we examine the effect of ETF ownership on the flow of information between firms in two distinct ways – at the firm-level focusing on how ETF ownership affects intra-industry information transfers and earnings response coefficients, and at the ETF level focusing on how firms within the same ETF react to each other's earnings releases.

At the firm-level, we find that the presence of ETF ownership of firms reduces the incidence of anomalous over-extrapolation of intra-industry information, especially for the case of sector ETF ownership. Further, we find that earnings response coefficients (ERCs) are higher for sector ETFs and lower for broad-based ETFs. Parsing the earnings surprise into macroeconomic, industry and idiosyncratic components suggests that sector ETFs are associated with a greater reaction to industry and idiosyncratic information, while broad-based ETFs are associated with a lower response to idiosyncratic information. Our final firm-level tests document lower post-earnings announcement drift (PEAD) in the presence of ETF ownership, but only for sector ETFs.

At the ETF level, we focus on the largest constituents of ETFs and separating them in the lead announcer and the follower firms. We find that while followers experience significant reaction to the earnings news of the leader, this is followed by a reversal, consistent with followers overreacting to the leader's earnings news. However, for sector ETFs, we find a much stronger initial reaction to the leader's earnings news followed by a much weaker reversal. Cross-sectional analyses suggest that the results are stronger when ETFs have high trading volume.

The emergence of ETFs has occurred in a time period that has also seen a number of significant changes influencing the capital markets including changes in market microstructure (decimalization), regulation (Sarbanes-Oxley), availability of peer information (EDGAR, XBRL) and functioning of market intermediaries such as analysts (global settlement). Hence ascribing causality to our results can be challenging. However, some of our additional analyses lend greater confidence to the explanation that the emergence of ETFs, especially sector ETFs, has influenced the transmission of information among firms. For example, in our firm-level analysis, we find a mitigation of the anomalous over-extrapolation of industry information in the short window around the initiation of ETF ownership. Similarly, cross-sectional tests in our ETF level analysis suggest that the results are stronger when ETFs have high trading volume and when compared to firms in the same sector without ETF ownership.

These results suggest that the answer to the question of whether ETFs help or hurt the flow of information between firms is contextual. Markets seem to effectively use sector ETFs to transmit factor (industry) information impounded in earnings news but broad-based ETFs are not very useful (and potentially detrimental) for this type of information. Our results hence bridge the conflicting results documented in prior work on whether ETFs help or hinder market efficiency.

While our results seem to suggest that sector ETFs have enhanced market efficiency, we need to caveat our finding that broad-based ETFs may have hindered market efficiency. It is possible that broad market ETFs are not very effective in the context of earnings announcements, as these announcements often do not contain significant macroeconomic information. Broad-based

ETFs might be effective in other settings which we do not examine where macroeconomic information is being released and impounded by markets (e.g., GDP, interest rate or inflation data).

Our results corroborate Huang, O'Hara and Zhong (2018) who find that industry ETFs help facilitate the hedging of industry-specific risks, by allowing traders to take long positions in individual stocks and short industry ETFs. While our focus is on a different channel, in that we examine the role that ETFs (particularly sector ETFs) play in information transfer, the overall message of both papers is that sector ETFs facilitate greater market efficiency.

Finally, our findings have implications for the research on institutional ownership. Our results suggest that researchers should treat ETF ownership differently when calculating institutional ownership as well as when partitioning ownership into active and passive. This is because even though ETF ownership might seem passive they can be used actively to trade on information thereby behaving differently from other forms of institutional ownership.

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APPENDIX I

Variable Definitions

Panel A: Firm-Level Analysis

Variable	Definition
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's earnings announcement date. The peer firm is defined as the firms from the same Fama French (1997) 48 industry.
ARET	Size-adjusted returns accumulated over 3 trading days starting from the firm's earnings announcement date.
ACC	Accruals measured as change in non-working capital less depreciation scaled by average total assets.
RET6	Buy and hold stock returns for the six-month period up to one week before the firm's earnings announcement.
ERLYPRARET	Average of early peers' three-day announcement size-adjusted returns in the same quarter, where the peers' earnings announcements are at least five days prior to the firm's announcement.
ARET1	ARET lagged by one quarter
ARET4	ARET lagged by four quarters (same calendar quarter from prior year)
INST	Percentage of shares held by institutional investors
SIZE	Log of Market Capitalization at the end of prior fiscal year.
LOGBM	Log of the book-to-market ratio at the end of prior fiscal year.
ETFPERIOD	Indicator variable that equals 1 for periods 2002 and after and 0 otherwise
ETF	Indicator variable that equals 1 if cumulative holding by ETFs in a firm is greater than zero and 0 otherwise
BROAD	Indicator variable that equals 1 if cumulative holding by broad-based ETFs in a firm is greater than zero and 0 otherwise
SECTOR	Indicator variable that equals 1 if cumulative holding by sector ETFs in a firm is greater than zero and 0 otherwise
SURP	Earnings Surprise 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.
RRDQ	Rank of Earnings release date for firms within a given Fama-French (1995) classification group for a given quarter minus 1. Equals 0 for the first firm, 1 for the second firm, 2 for the third firm, 3 for the fourth firm and 4 for the fifth firm.

Panel B: ETF-Level Analysis

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
SECTOR	Indicator variable that equals 1 for sector ETFs and 0 otherwise
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 and 0 otherwise.

Panel C: Post-Earnings Announcement Drift Analysis

Variable	Definition
POST60	Size-adjusted stock returns for the 60-day period after earnings.
ETF	Indicator variable that equals 1 if cumulative holding by ETFs in a firm is greater than zero and 0 otherwise
BROAD	Indicator variable that equals 1 if cumulative holding by broad-based ETFs in a firm is greater than zero and 0 otherwise
SECTOR	Indicator variable that equals 1 if cumulative holding by sector ETFs in a firm is greater than zero and 0 otherwise
SURP	Earnings Surprise 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.
RSURP	Decile rank of SURP
SIZE	Log of market capitalization 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.

APPENDIX II

Calculating macroeconomic, industry and idiosyncratic components of earnings surprise.

We outline the methodology we use to decompose earnings surprise into a macroeconomic component, industry component and idiosyncratic component.

We first define SURP as the difference between realized earnings per share (ACTUAL) less mean consensus forecast earnings per share (MEANEST), scaled by price per share at fiscal quarter end (PRCCQ). We use the last available consensus forecast prior to fiscal quarter end.

We first compute the macroeconomic earnings surprise. For every observation in our sample, we first obtain the surprise for all firms in the market who realized earnings in the past 30 days. We then calculate a weighted average of the surprise across all firms, with the weights increasing with market capitalization and decreasing with the gap with respect to the given firm's earnings surprise. A firm with a market capitalization of $500 million will count only half as much as a firm with a market capitalization of $1000 million. Similarly, a firm whose earnings were ten days before will get one-tenth the weight of a firm whose earnings were just one day before.

To illustrate, assume Firm A announces earnings on a given day. Assume Firm B released earnings five days before and has a market capitalization of $1000 million, while Firm B released earnings ten days prior and has a market capitalization of 5000. In computing the averages, Firm A gets a weight of (1000/5), while firm B gets a weight of (5000/10). We refer to this average as MACRO.

We next use the same weighting methodology to compute the industry earnings surprise, but only focus on firms within the same industry (using the Fama French 48 industry methodology). We refer to this average as IND.

Note that IND also includes the macroeconomic component, which affects all firms. We isolate the pure industry component as below

PUREIND = IND – MACRO

Finally, we remove the macroeconomic and pure industry components of earnings to isolate the idiosyncratic component of earnings. It is easy to see that

IDIO = SURP - MACRO - PUREIND

In our analyses, we substitute SURP with the three above components to see how the markets react to the three components of earnings surprise.

We present the summary statistics for the components of information.

Variable	Mean	Q1	Median	Q3	Stdev
SURP	-0.0002	-0.0009	0.0004	0.0022	0.0149
MACRO	0.0005	0.0002	0.0005	0.0008	0.0008
IND	0.0005	0.0001	0.0005	0.0010	0.0024
PUREIND	0.0000	-0.0005	0.0000	0.0006	0.0024
IDIO	-0.0007	-0.0018	-0.0001	0.0019	0.0150
ARET	0.0044	-0.0368	0.0012	0.0410	0.0838

As SURP can take on negative and positive values, it is tough to estimate how much of the surprise belongs in each of the categories of the decomposition. To better estimate this, we present the summary statistics after partitioning our sample based on whether the surprise was positive or not.

Subset with SURP > 0

Variable	Mean	Q1	Median	Q3	Stdev
SURP	0.0050	0.0007	0.0017	0.0044	0.0110
MACRO	0.0005	0.0002	0.0006	0.0008	0.0008
IND	0.0006	0.0001	0.0005	0.0011	0.0024
PUREIND	0.0001	-0.0005	0.0000	0.0006	0.0024
IDIO	0.0044	0.0001	0.0013	0.0041	0.0113
ARET	0.0151	-0.0265	0.0084	0.0493	0.0805

Subset with SURP <=0

Variable	Mean	Q1	Median	Q3	Stdev
SURP	-0.0071	-0.0057	-0.0015	-0.0001	0.0166
MACRO	0.0004	0.0002	0.0005	0.0008	0.0009
IND	0.0004	0.0000	0.0005	0.0010	0.0024
PUREIND	0.0000	-0.0006	0.0000	0.0006	0.0024
IDIO	-0.0075	-0.0064	-0.0022	-0.0007	0.0166
ARET	-0.0098	-0.0516	-0.0091	0.0287	0.0861

When SURP > 0, the mean SURP is 0.005, which consists of MACRO 0.0005 (10%), PUREIND 0.0001 (2%) and IDIO 0.0044 (88%). When SURP < 0, the mean SURP is -0.0071. Interestingly, when mean surprise is negative, MACRO still has a positive mean, and IDIO is more negative than SURP.

We present below a correlation table between SURP, components of SURP and the size-adjusted announcement period returns, ARET

	SURP	MACRO	IND	PUREIND	IDIO	ARET
SURP		0.051	0.034	0.017	0.987	0.094
MACRO	0.050		0.201	-0.141	0.018	0.006
IND	0.062	0.218		0.941	-0.128	0.009
PUREIND	0.033	-0.327	0.774		-0.135	0.007
IDIO	0.905	-0.026	-0.242	-0.220		0.092
ARET	0.171	0.014	0.009	0.002	0.151	

Figures above/below the diagonal represent Pearson/Spearman rank-order correlations.

A quick perusal of the correlation suggests the following. As expected, SURP is positively correlated with all the components – MACRO, IND and PUREIND, but is dominated by the idiosyncratic component (IDIO). This is consistent with the fact that during earnings release, the information is largely idiosyncratic.

The returns around earnings announcements (ARET) also weak positive correlations with the macroeconomic and industry components of surprise, but clearly IDIO is the most important.

Figure 1: Trends in Earnings Response Coefficient across the Quarter

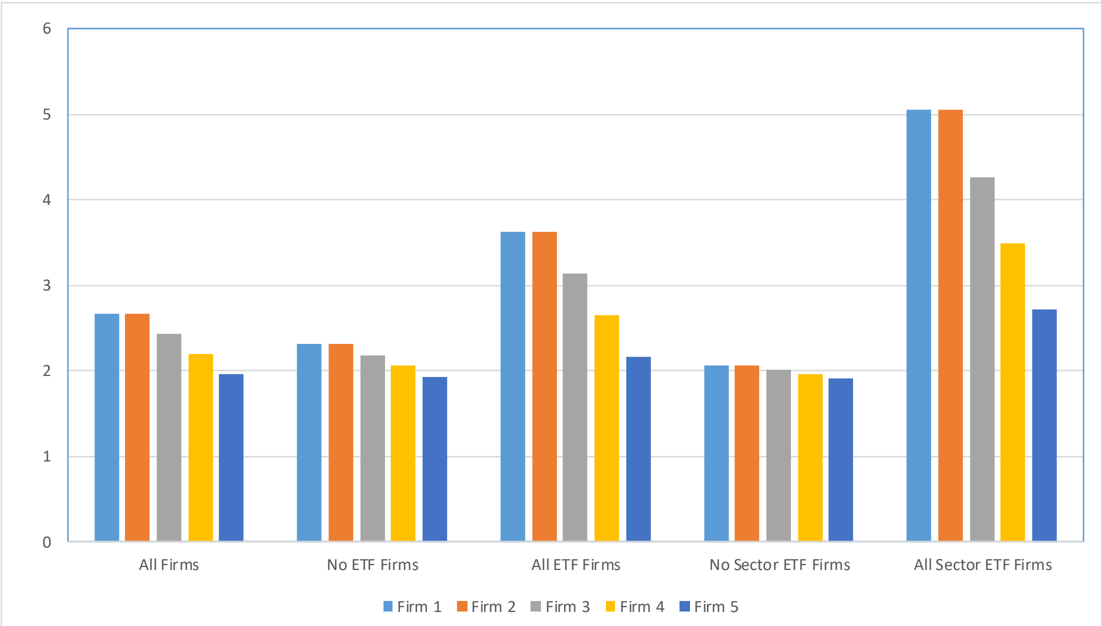

TABLE 1

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 broad-based 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
ETFs and Investor Overestimation of Intra-Industry Information Transfers

This table considers a sample of 255,015 firm-quarters from 1985 to 2015. See the appendix for variable definitions. The dependent variable is ARET, which represents the 3-day size adjusted excess returns around earnings announcement. The independent variable of interest is RESP, the average of firm's 3-day size-adjusted returns around its peers' earnings announcements. Panel A runs the regressions for entire sample. Panel B runs the regression for a matched pair-sample using only the subset of data corresponding to firm that had ETF ownership sometime in the sample period. See section 4 for details of the research design. 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.

Panel A: Intra-Industry Information Transfers in the pre-ETF and post-ETF periods

Model $ARET = \alpha_0 + \alpha_1{*}ETFPERIOD + \beta_1{*}RESP + \beta_2{*}RESP{*}ETFPERIOD + \beta_3{*}ACC + \beta_4{*}RET6 + \beta_5{*}ERLYPRARET + \beta_6{*}ARET1 + \beta_7{*}ARET4 + \beta_8{*}INST + \beta_9{*}SIZE + \beta_{10}{*}LOGBM + \varepsilon$

	Entire Sample	Pre-ETF Period	Post-ETF Period	Entire Sample
RESP	**-0.1950*****	**-0.2348*****	**-0.1488*****	**-0.2315*****
	(-10.78)	**(-10.01)**	**(-11.78)**	**(-10.00)**
RESP*ETFPERIOD				**0.0807*****
				(3.10)
ACC	0.0285***	0.0281***	0.0289***	0.0286***
	(10.06)	(7.59)	(6.26)	(10.02)
RET6	0.0066	0.018*	-0.0078	0.0066
	(0.81)	(1.89)	(-0.68)	(0.81)
ERLYPRARET	0.1078***	0.1077***	0.1067***	0.1073***
	(6.12)	(5.17)	(4.01)	(6.06)
ARET1	0.0226***	0.0313***	0.0152***	0.0227***
	(5.69)	(8.05)	(2.72)	(5.71)
ARET4	0.0015	0.0006	0.002	0.0015
	(0.60)	(0.13)	(0.62)	(0.58)
INST	0.0106***	0.0096***	0.0105***	0.0106***
	(10.75)	(5.29)	(8.12)	(10.83)
SIZE	-0.0007***	-0.0012***	-0.0002	-0.0007***
	(-3.60)	(-5.69)	(-0.63)	(-3.64)
LOGBM	0.0028***	0.0031***	0.0024***	0.0028***
	(5.26)	(3.43)	(4.30)	(5.24)
Adj. R^2	0.64%	0.87%	0.47%	0.65%
N	255,015	124,566	130,449	255,015

Panel B: Intra-Industry Information Transfers in the pre and post-ETF period for firms with ETF ownership

Model $ARET = \alpha_0 + \alpha_1{*}ETF + \alpha_2{*}BROAD + \alpha_3{*}SECTOR + \beta_1{*}RESP + \beta_2{*}RESP{*}ETF + \beta_3{*}RESP{*}BROAD + \beta_4{*}RESP{*}SECTOR + \beta_5{*}ACC + \beta_6{*}RET6 + \beta_7{*}ERLYPRARET + \beta_8{*}ARET1 + \beta_9{*}ARET4 + \beta_{10}{*}INST + \beta_{11}{*}SIZE + \beta_{12}{*}LOGBM + \varepsilon$

	Total ETF ownership	ETF ownership by ETF type
ETF	-0.0079***	
	(-3.85)	
BROAD		-0.0064***
		(-5.27)
SECTOR		0.0005
		(0.25)
RESP	**-0.2434*****	**-0.2151*****
	(-9.13)	**(-6.30)**
RESP*ETF	**0.0491**	
	(0.82)	
RESP*BROAD		**-0.0576**
		(-0.98)
RESP*SECTOR		**0.1321*****
		(2.71)
ACC	0.0253***	0.0238***
	(2.88)	(2.74)
RET6	0.0150	0.0151
	(1.17)	(1.22)
ERLYPRARET	0.1267***	0.1250***
	(3.71)	(3.71)
ARET1	0.0319***	0.0330***
	(6.66)	(6.20)
ARET4	0.0203***	0.0206***
	(2.64)	(2.71)
INST	0.0085***	0.0094***
	(6.04)	(4.95)
SIZE	-0.001	-0.0013
	(-1.23)	(-1.55)
LOGBM	0.0032	0.0030
	(1.52)	(1.52)
Adj. R^2	1.06%	1.07%
N	20,608	20,608

TABLE 3
ETFs and Market Reaction to Earnings Surprise and its Components

This table considers a sample of 95,939 firm-quarters from 2002 to 2015. See Appendix I for variable definitions. The dependent variable is ARET, which represents the 3-day size adjusted excess returns around earnings announcement. The independent variable of interest is SURP (Panel A), the earnings surprise, or its three components MACRO, PUREIND and IDIO (Panel B), using the decomposition described in Appendix II. See section 4 for details of the research design. 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.

Panel A: Impact of ETF ownership on earnings response coefficient (ERC)

Model $ARET = \alpha_0 + \alpha_1*ETF + \alpha_2*BROAD + \alpha_3*SECTOR + \beta_1*SURP + \beta_2*SURP*ETF + \beta_3*SURP*BROAD + \beta_4*SURP*SECTOR + \beta_5*ACC + \beta_6*ARET1 + \beta_7*ARET4 + \beta_8*RET6 + \beta_9*INST + \beta_{10}*SIZE + \beta_{11}*LOGBM + \varepsilon$

	Baseline	ETF	Broad vs. Sector
SURP	**0.5366***	**0.5788***	**0.5713***
	(28.99)	**(17.14)**	**(16.98)**
ETF		0.0007	
		(1.11)	
BROAD			0.0017*
			(1.87)
SECTOR			-0.0013
			(-1.47)
SURP*ETF		**-0.0600**	
		(-1.49)	
SURP*BROAD			**-0.1709***
			(-3.93)
SURP*SECTOR			**0.3172***
			(7.08)
ACC	0.0068	0.0069	0.0069
	(1.50)	(1.53)	(1.53)
ARET1	-0.0002	-0.0002	-0.0004
	(-0.07)	(-0.06)	(-0.12)
ARET4	0.0108***	0.0108***	0.0110***
	(3.27)	(3.26)	(3.30)
RET6	0.0032	0.0033	0.0035
	(0.36)	(0.37)	(0.39)
INST	-0.0074***	-0.0076***	-0.0072***
	(-5.96)	(-6.07)	(-5.54)
SIZE	-0.0005**	-0.0005**	-0.0004*
	(-2.62)	(-2.56)	(-1.83)
LOGBM	0.0006	0.0006	0.0007
	(1.51)	(1.52)	(1.59)
Adj. R^2	2.29%	2.29%	2.35%
N	95,939	95,939	95,939

Panel B: ERC regressions using components of earnings surprise

Model $ARET = \alpha_0 + \alpha_1{*}ETF + \alpha_2{*}BROAD + \alpha_3{*}SECTOR + \beta_1{*}MACRO + \beta_2{*}PUREIND + \beta_3{*}IDIO$ $\beta_4{*}MACRO{*}ETF + \beta_5{*}PUREIND{*}ETF + \beta_6{*}IDIO{*}ETF + \beta_7{*}MACRO{*}BROAD + \beta_8{*}PUREIND{*}BROAD + \beta_9{*}IDIO{*}BROAD + \beta_{10}{*}MACRO{*}SECTOR + \beta_{11}{*}PUREIND{*}SECTOR + \beta_{12}{*}IDIO{*}SECTOR + \beta_{13}{*}ACC + \beta_{14}{*}ARET1 + \beta_{15}{*}ARET4 + \beta_{16}{*}RET6 + \beta_{17}{*}INST + \beta_{18}{*}SIZE + \beta_{19}{*}LOGBM + \varepsilon$

	Baseline	ETF	Broad vs. Sector
MACRO	**0.1509**	**0.8300**	**0.7624**
	(0.38)	**(1.20)**	**(1.10)**
PUREIND	**0.5177*** **	**0.5084*** **	**0.5111*** **
	(4.01)	**(2.62)**	**(2.64)**
IDIO	**0.5373*** **	**0.5778*** **	**0.5704*** **
	(29.00)	**(17.08)**	**(16.93)**
ETF		0.0011	
		(1.50)	
BROAD			0.0019*
			(1.85)
SECTOR			-0.0010
			(-1.07)
MACRO*ETF		**-0.9004**	
		(-1.18)	
PUREIND*ETF		**0.0188**	
		(0.08)	
IDIO*ETF		**-0.0577**	
		(-1.44)	
MACRO*BROAD			**-0.4881**
			(-0.46)
PUREIND*BROAD			**-0.3437**
			(-0.92)
IDIO*BROAD			**-0.1692*** **
			(-3.89)
MACRO*SECTOR			**-0.2980**
			(-0.32)
PUREIND*SECTOR			**0.6200*** **
			(2.69)
IDIO*SECTOR			**0.3186*** **
			(7.10)
ACC	0.0068	0.0069	0.0069
	(1.49)	(1.52)	(1.52)
ARET1	-0.0002	-0.0001	-0.0004
	(-0.06)	(-0.04)	(-0.11)
ARET4	0.0109***	0.0108***	0.0109***
	(3.27)	(3.26)	(3.29)
RET6	0.0033	0.0034	0.0036
	(0.37)	(0.38)	(0.40)
INST	-0.0074***	-0.0076	-0.0072***
	(-5.94)	(-6.07)	(-5.54)
SIZE	-0.0005***	-0.0005**	-0.0004*
	(-2.60)	(-2.55)	(-1.81)
LOGBM	0.0006	0.0006	0.0007
	(1.52)	(1.53)	(1.60)
Adj. R^2	2.29%	2.29%	2.35%

TABLE 4

Impact of ETFs on Earnings Response Coefficients across Quarter

The sample consists of the five largest firms in each Fama and French (1997) industry grouping for which all data is available and comprises of 24,472 observations from 1985 to 2015. See the appendix for variable definitions. See section 4 for details of the research design. 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 $ARET = \alpha_0 + \beta_1{*}SURP + \beta_2{*}RRDQ + \beta_3{*}SURP{*}RRDQ + \beta_4{*}ACC + \beta_5{*}ARET1 + \beta_6{*}ARET4 + \beta_7{*}RET6 + \beta_8{*}INST + \beta_9{*}SIZE + \beta_{10}{*}LOGBM + \varepsilon$

	Entire Sample	No ETF Firms	All ETF Firms	No Sector ETF Firms	All Sector ETF Firms
SURP	**2.6634*****	**2.3193*****	**3.6338*****	**2.0686*****	**5.0511*****
	(8.04)	**(5.25)**	**(11.39)**	**(5.00)**	**(8.25)**
RRDQ	-0.0004	-0.0008	0.0002	-0.0006	0.0002
	(-0.91)	(-1.04)	(0.40)	(-0.83)	(0.50)
SURP*RRDQ	**-0.2363*****	**-0.1303**	**-0.491*****	**-0.0537**	**-0.7772*****
	(-2.32)	**(-1.29)**	**(-3.80)**	**(-0.55)**	**(-3.47)**
ACC	-0.0019	0.0076	0.0008	0.0062	0.0022
	(-0.22)	(0.70)	(0.06)	(0.57)	(0.12)
ARET1	0.0107	0.0444***	-0.0019	0.043***	0.0023
	(1.01)	(4.40)	(-0.11)	(4.42)	(0.16)
ARET4	0.0246***	0.0292	0.0272***	0.0319	0.0234***
	(2.66)	(1.18)	(3.27)	(1.36)	(2.48)
RET6	-0.0131	0.0212	-0.0368***	0.0156	-0.0400***
	(-0.69)	(0.58)	(-2.64)	(0.43)	(-2.79)
INST	-0.0073***	-0.0051	-0.0073***	-0.0052	0.0006
	(-3.09)	(-1.55)	(-3.04)	(-1.63)	(0.18)
SIZE	-0.0012***	-0.0012**	-0.0008*	-0.0012**	-0.0000
	(-3.88)	(-2.28)	(-1.70)	(-2.19)	(-0.01)
LOGBM	0.0000	0.0012	-0.0007	0.0012	-0.0008
	(-0.06)	(0.89)	(-0.88)	(0.85)	(-1.04)
Adj. R^2	2.28%	2.39%	3.07%	2.30%	3.46%
N	24,472	10,120	13,101	10,297	10,764

TABLE 5

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 133,971 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 firm and year, or run quarterly 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 SECTOR and BROAD.

Model $POST60 = \alpha_0 + \beta_1{*}RSURP + \beta_2{*}ETF + \beta_3{*}RSURP{*}ETF + \beta_4{*}SIZE + \beta_5{*}BETA + \beta_6{*}MTB + \beta_7{*}PRERET$
$\beta_8{*}RSURP{*}SIZE + \beta_9{*}RSURP{*}BETA + \beta_{10}{*}RSURP{*}MTB + \beta_{11}{*}RSURP{*}PRERET + \varepsilon.$

	Pooled	*Fama-Macbeth*	*Pooled*	*Fama-Macbeth*
Intercept	-0.039***	-0.043***	-0.028***	-0.031***
	(-7.13)	(-7.02)	(-4.99)	(-4.53)
RSURP	**0.094*** **	**0.094*** **	**0.077*** **	**0.075*** **
	(9.51)	**(9.49)**	**(7.59)**	**(7.24)**
ETF	0.008*	0.009		
	(1.81)	(1.57)		
SECTOR			0.014***	0.013***
			(5.26)	(3.41)
BROAD			0.003	0.004
			(0.59)	(0.64)
RSURP*ETF	**-0.006**	**-0.007**		
	(-0.73)	**(-0.89)**		
RSURP*SECTOR			**-0.021*** **	**-0.020*** **
			(-4.70)	**(-3.95)**
RSURP*BROAD			**0.002**	**0.000**
			(0.24)	**(0.01)**
SIZE	0.003***	0.003***	0.001	0.001
	(4.87)	(3.33)	(0.79)	(0.61)
BETA	-0.006	0.008	-0.008	0.007
	(-0.89)	(0.34)	(-1.07)	(0.30)
MTB	-0.000	-0.000	0.000	-0.000
	(-0.10)	(-0.29)	(0.25)	(-0.22)
PRERET	-0.029**	-0.025	-0.029	-0.025
	(-2.48)	(-1.01)	(-2.47)	(-1.01)
RSURP*SIZE	-0.008***	-0.008***	-0.004***	-0.004***
	(-8.08)	(-7.01)	(-3.69)	(-2.83)
RSURP*BETA	0.010	0.006	0.012	0.007
	(0.88)	(0.39)	(1.05)	(0.46)
RSURP*MTB	-0.001	-0.001	-0.001*	-0.001
	(-1.46)	(-1.00)	(-1.77)	(-1.03)
RSURP*PRERET	0.033*	0.018	0.032*	0.017
	(1.67)	(0.95)	(1.66)	(0.89)
Adj. R^2	0.57%	3.32%	0.60%	3.61%

TABLE 6

Investors' Reaction to Earnings News for the Leader

The sample consists of leader-follower pairs within ETFs and leader paired with followers from the same sector of economy but without Sector ETF ownership. The sample covers years from 2002-2015. 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

Model $FRET_{ANNC} = \alpha_0 + \beta_1{*}SECTOR + \beta_2{*}LRET + \beta_3{*}LRET{*}SECTOR$ +controls+ ε

	1 Leader-follower pairs from Sector ETFs	2 Leader-follower pairs from Broad-based ETFs	3 Leader paired with followers from the same sector but w/o sector ETFs ownership	4 Leader-follower pairs from All types of ETFs	5 Leader paired with followers from the same sector with and w/o ETFs sector
Intercept	-0.001	-0.007***	0.004	-0.005***	0.002
	(-0.43)	(-2.68)	(1.18)	(-2.70)	(1.34)
SECTOR				0.002***	-0.001
				(3.44)	(-0.78)
LRET	**0.089*****	**0.024*****	**0.049****	**0.023*****	**0.048****
	(8.85)	**(4.15)**	**(2.51)**	**(4.16)**	**(2.48)**
LRET*SECTOR				**0.065*****	**0.041****
				(5.77)	**(2.03)**
RET6	-0.009	-0.014	-0.029	-0.012	-0.029
	(-0.58)	(-0.91)	(-0.93)	(-1.06)	(-1.39)
ARET1	-0.003	-0.014**	0.017	-0.008*	0.008
	(-0.47)	(-2.29)	(1.12)	(-1.83)	(0.87)
ARET4	-0.003	0.004	0.007	0.000	0.003
	(-0.54)	(0.68)	(0.55)	(0.06)	(0.38)
INST	-0.000	0.002	-0.005**	0.001	-0.003**
	(-0.10)	(1.09)	(-1.99)	(0.64)	(-1.99)
SIZE	0.000	0.000**	-0.000	0.000***	0.000
	(1.24)	(2.49)	(-0.09)	(2.71)	(0.58)
LOGBM	0.001***	0.000	0.000	0.001***	0.001
	(2.73)	(0.95)	(0.01)	(2.69)	(1.15)
N	15,913	14,985	12,922	30,898	28,835
Adj. R^2	2.30%	0.40%	0.22%	1.46%	0.65%

Panel B: Investors' reaction partitioned by ETF trading volume

Model $FRET_{ANNC} = \alpha_0 + \beta_1 * SEC + \beta_2 * HIGH + \beta_3 * LRET + \beta_4 * LRET * SECTOR + \beta_5 * SECTOR * HIGH + \beta_6 * LRET * HIGH + + \beta_7 * LRET * SECTOR * HIGH + controls + \varepsilon$

	Leader-follower pairs from all types of ETFs		
	High Volume Pairs	Low Volume Pairs	All Pairs
Intercept	-0.008***	-0.002	-0.005**
	(-3.17)	(-0.88)	(-2.51)
SEC	0.002***	0.001*	0.001*
	(3.15)	(1.91)	(1.87)
HIGH			-0.001
			(-1.28)
LRET	**0.029*****	**0.020*****	**0.020*****
	(3.20)	**(2.62)**	**(2.63)**
LRET*SECTOR	**0.096*****	**0.030****	**0.030****
	(5.70)	**(2.05)**	**(2.05)**
SEC*HIGH			0.001
			(1.03)
LRET*HIGH			0.009
			(0.71)
LRET*SECTOR*HIGH			**0.066*****
			(2.96)
RET6	-0.002	-0.020	-0.012
	(-0.10)	(-1.44)	(-1.07)
ARET1	-0.009	-0.007	-0.008*
	(-1.42)	(-1.17)	(-1.81)
ARET4	0.005	-0.004	0.000
	(0.82)	(-0.77)	(0.02)
INST	0.002	-0.001	0.001
	(1.48)	(-0.60)	(0.56)
SIZE	0.001***	0.000	0.000***
	(2.92)	(1.08)	(2.77)
LOGBM	0.001***	0.000	0.001***
	(2.79)	(1.01)	(2.62)
N	15,567	15,331	30,898
Adj. R^2	2.88%	0.56%	1.68%

TABLE 7

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

The sample consists of leader-follower pairs within ETFs and leader paired with followers from the same sector of economy but without Sector ETF ownership. The sample covers years from 2002-2015. 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

Model $FRET_{BETW} = \alpha + \beta_1{*}FRET_{ANNC} + \beta_2{*}SECTOR + \beta_3{*}FRET_{ANNC}{*}SECTOR + controls + \varepsilon$

	1 Leader-follower pairs from Sector ETFs	2 Leader-follower pairs from Broad-based ETFs	3 Leader paired with followers from the same sector but w/o sector ETF ownership	4 Leader-follower pairs from All types of ETFs	5 Leader paired with followers from the same sector with and w/o sector ETF ownership
Intercept	-0.003	0.002	0.029***	-0.001	0.015***
	(-0.75)	(0.43)	(5.50)	(-0.25)	(5.22)
SECTOR				-0.000	0.005**
				(-0.47)	(2.33)
$FRET_{ANNC}$	**-0.037***	**-0.106*****	**-0.118*****	**-0.105*****	**-0.118*****
	(-1.67)	**(-3.36)**	**(-4.62)**	**(-3.32)**	**(-4.61)**
$FRET_{ANCC}$*SECTOR				**0.068***	**0.081****
				(1.80)	**(2.32)**
RET6	-0.012	-0.016	-0.063	-0.014	-0.044*
	(-0.60)	(-0.77)	(-1.54)	(-0.96)	(-1.65)
ARET1	0.019**	-0.007	0.003	0.006	0.009
	(2.09)	(-0.73)	(0.19)	(0.92)	(0.78)
ARET4	-0.007	0.008	-0.010	0.000	-0.009
	(-0.86)	(1.04)	(-0.63)	(0.07)	(-0.94)
INST	-0.001	-0.001	-0.014***	-0.001	-0.010***
	(-0.23)	(-0.38)	(-2.74)	(-0.41)	(-3.80)
SIZE	0.000	-0.000	-0.004***	0.000	-0.002***
	(0.75)	(-0.10)	(-3.99)	(0.53)	(-3.66)
LOGBM	0.000	0.002**	-0.001	0.001*	0.000
	(0.38)	(2.29)	(-0.49)	(1.84)	(0.00)
N	15,913	14,985	12,922	30,898	28,835
Adj. R^2	0.14%	0.58%	0.77%	0.31%	0.62%

Panel B: Adjustment by Investors partitioned by ETF trading volume

Model $FRET_{BETW} = \alpha_0 + \beta_1 *SECTOR + \beta_2 *HIGH + \beta_3 *FRET_{ANNC} + \beta_4 *FRET_{ANNC} *SECTOR + \beta_5 *SECTOR*HIGH + \beta_6 * FRET_{ANNC} *HIGH + \beta_7 *FRET_{ANNC} *SECTOR*HIGH + controls + \varepsilon$

	Leader-follower pairs from all types of ETFs		
	High Volume Pairs	Low Volume Pairs	All Pairs
Intercept	-0.003	0.001	-0.001
	(-0.71)	(0.26)	(-0.28)
SEC	-0.001	-0.000	-0.000
	(-0.62)	(-0.06)	(-0.02)
HIGH			0.000
			(0.04)
$FRET_{ANNC}$	**-0.097****	**-0.111****	**-0.111*****
	(-2.20)	**(-2.63)**	**(-2.62)**
$FRET_{ANNC}$*SEC	**0.081**	**0.049**	**0.048**
	(1.46)	**(0.99)**	**(0.98)**
SEC*HIGH			-0.001
			(-0.45)
$FRET_{ANNC}$*HIGH			0.013
			(0.22)
$FRET_{ANNC}$*SEC*HIGH			0.033
			(0.45)
RET6	-0.022	-0.0098	-0.014
	(-1.05)	(-0.39)	(-0.97)
ARET1	0.019**	-0.004	0.006
	(2.00)	(-0.45)	(0.92)
ARET4	-0.007	0.006	0.000
	(-0.85)	(0.83)	(0.05)
INST	0.001	-0.002	-0.001
	(0.49)	(-0.98)	(-0.42)
SIZE	0.000	0.000	0.000
	(0.64)	(0.23)	(0.56)
LOGBM	0.001	0.001	0.001*
	(1.20)	(1.47)	(1.83)
N	15,567	15,331	30,898
Adj. R^2	0.29%	0.41%	0.32%