ETF Activities and Analysts' Forecasts*

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Abstract

We document an improvement in analysts' forecast accuracy following increased sector ETF ownership. We identify a possible channel for this result, i.e., because ETFs are more informative with respect to industry-level information, analysts learn directly and efficiently from ETFs about this type of information component in individual firms' earnings. As a result, analysts have an opportunity to re-optimize their attention to firm-specific information and improve forecast accuracy. Consistent with such a channel, analysts of follower firms revise their earnings forecasts more efficiently (i.e., exhibit greater sensitivity) to an announcer firm's earnings announcement in the same sector ETF. Furthermore, this revision is stronger when ETFs are more actively traded, when analysts are less experienced with individual firms, and when analysts follow more firms and cover more industries.

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1 Introduction

Exchange-traded-funds (ETF) have become an increasingly important investment vehicle since their introduction in the early 1990s. Assets under management in the ETFs eclipsed traditional index-tracking mutual funds for the first time in 2020.[1] ETFs are more liquid and lower in expenses than non-traded mutual funds, which is particularly appealing to many retail and liquidity traders (Ben-David et al., 2018). However, market participants and regulators are concerned about the potential negative impact of ETFs on the informational efficiency of the underlying securities. The concern is that ETFs might attract speculative herding and passive trading, which can undermine market efficiency in individual securities (Bhattacharya and O'Hara, 2017; Cong and Xu, 2016).[2] Evidence about the informational efficiency externality of ETFs is not yet conclusive.[3] In this paper, we examine ETFs' effect on the accuracy of analysts' earnings forecasts as a means of inferring whether ETFs foster informational efficiency.

Recent studies suggest that ETFs are more efficient in incorporating aggregate information than firm-specific information (Bhattacharya and O'Hara, 2017; Cong and Xu, 2016).[4] In particular, broad-based ETFs consist of heterogeneous economy-wide constituents, and thus are more likely to be informative about macroeconomic information than firm-specific information. Similarly, sector-based ETFs consist of firms in the same industry or sector and thus are more likely to be informative about industry information than firm-specific information (Bhojraj et al., 2020).[5]

We hypothesize that because macro- and sectoral ETFs are informative about

[1] Robin Wigglesworth (MAY 10, 2021). Global passive assets hit $15tn as ETF boom heats up. Financial Times. https://www.ft.com/content/7d5c2468-619c-4c4b-b3e7-b0da015e939d

[2] Criticisms of ETFs typically argue that more passive participation and liquidity trading may lead to less efficient market prices in a typical rational expectations framework (Grossman & Stiglitz, 1980). For instance, Gorton and Pennacchi (1993) showed that index securities reduce uninformed losses to informed traders—and correspondingly reduce the incentives for informed traders to become informed.

[3] Glosten et al. (2021) find that ETFs improve short-run informational efficiency by the timely incorporation of the systematic earnings information, while Israeli et al. (2017) find that the ETFs ownership reduces the long-run informational efficiency of underlying securities.

[4] Bhattacharya and O'Hara (2017) and Cong and Xu (2016) show that introducing ETFs may improve the overall pricing efficiency if the firm-specific information asymmetry is small relative to the systematic informational asymmetry.

[5] Specifically, Bhojraj et al. (2020) document that broad-based ETFs are associated with a lower response to idiosyncratic information, while sector ETFs are associated with a stronger response to industry information.

macroeconomic and industry, analysts have a greater opportunity to focus on firm-specific information. This would enhance the accuracy of analysts' earnings forecasts. Individual firms' earnings consist of macro-, industry- and firm-specific components. To forecast each individual firm's earnings, analysts gather information and spend time and efforts in analyzing all different components of information, including disclosure and prices of the firms and their industry peers (Clement et al., 2011; Kumar et al., 2021). Because analysts can glean macroeconomic and industry information through ETF prices and trading activity, it enables analysts to focus on acquiring firm-specific information. This is predicted to improve analysts' forecast accuracy.

We further hypothesize that sector EFT ownership plays a stronger role on analysts' forecast accuracy. The actively-managed sector ETFs are more likely to incorporate sector-specific information into the ETF prices through higher stock turnover, whereas the passively-managed broad-ETFs are less likely to incorporate information into stock price due to lower stock trading.[6] Consistent with this expectation, Bhojraj et al. (2020) find that information transfers occur among basket of sector ETF stocks when an ETF member stock announces earnings news, while such effect is not witnessed for broad ETFs. To test the conjecture, we exploit the Russell 1000/2000 annual reconstitution, a well-established identification strategy to exploit exogenous variation in ETF ownership (Coles et al., 2022; Heath et al., 2021; Ben-David et al., 2018; etc).[7] The tests use a DID analysis, which helps us establish causality.

Effects of ownership changes on forecast accuracy. The Russell 1000/2000 annual reconstitution imparts significant exogenous variation in ETF ownership. Firms switching from the Russell 2000 index to the Russell 1000 index experience a 9.4% decrease in the broad ETF ownership, but a 41.6% increase in the sector ETF ownership. The converse is true of firms switching from the Russell 1000 index to the Russell 2000 index. This differential change in

[6] Easley et al. (2021) document that active-in-function ETFs, such as sector ETFs, tend to have higher turnover in the secondary market, as they are designed to provide exposure to specific segments of the market and can be easily and cheaply traded.
[7] Russell implements a new banding rule starting from June 2007, which created two new discontinuities at the lower band (the Russell 1000 to the Russell 2000 switchers) and upper band (the Russell 2000 to the Russell 1000 switchers). This allows us to perform the DID analysis, which helps establish a causality, in these two distinct sets of treated and control groups.

the broad and sector ETF ownership enables us to pinpoint the impact of the broad vs. sector ETF ownership on analysts' forecasts. We find that analysts' forecast accuracy significantly improves by 7.8% after firms switch from the Russell 2000 to the Russell 1000 index. Conversely, switching from the Russell 1000 to the Russell 2000 lowers forecast accuracy by 8.6%.

To ascertain which type of the ETF ownership change contributes to the results, we sort the sample based on the change magnitude in each type of ETF ownership and then perform the DID test again. We document that it is primarily the change in the sector-ETF ownership, instead of the broad-ETF ownership, that drives the results. Our findings suggest that the industry-level aggregate information incorporated by the sector-ETF activities is more important for financial analysts than the macro-level aggregate information incorporated in the broad-sector ETF.

Next, we test whether ETF trading activity that is hypothesized to enrich prices with industry information affects analyst forecast accuracy. The set of tests use trading activity to discern whether analysts indeed learn new information from the sector-ETF trading activities.[8] Previous research shows that an earnings announcement conveys information to analysts not only about the firm itself, but also about its industry peers. To test the learning channel, we perform an announcer-follower analysis by identifying an announcer with the largest ETF holdings and then examine the impact of the announcer's earnings announcement on analysts' forecasts of peer firms' earnings. Consistent with a learning effect, analysts' forecast revisions are significantly and positively associated with the announcer's earnings surprise within the same sector ETF. One standard deviation increase in the announcer's earnings surprise leads to a 5.9% increase in the analyst revision of the follower firm within the sector ETF subsample. However, there is no such correlation if the pair belongs to the same broad ETF or if the pair is only an industry match without the common sector-ETF ownership.

Additional cross-sectional tests demonstrate that the above effect is stronger when

[8] We focus on learning instead of information acquisition. This is because it is empirically challenging to direct test information acquisition activities of analysts. But it is also plausible that increasing ETF ownership also shifts analysts' effort to acquire more industry-level information, which may have an incremental effect on analysts' forecast accuracy above the learning channel.

ETFs are more actively traded (thus more efficient in aggregating industry information) and when analysts are more likely to have attention constraints. First, we find that analysts' revision response to the announcer's news is significant only when the sector-ETF is actively traded ETFs as measured by the secondary-market ETF turnover ratio. Second, we measure analysts' attention constraints using analysts' experience with an individual firm, as well as the number of firms and industries covered by analysts. We find that analysts' revision response to announcer's earnings surprise is stronger for analysts with less experience and for analysts with more firms and more complex industry composition in their portfolio. Both provide supporting evidence to our mechanism that ETF trading activity indeed improves analysts' forecasts by enhancing information efficiency with respect to aggregate industry information and reducing the information acquisition cost for analysts with more attention constraints.

Contribution to the literature. First, our findings complement the growing literature on the real effects of ETFs. Prior studies show that ETF activities lead to increased volatility, excess return co-movement and lower liquidity (e.g., Ben-David et al., 2018; Bhattacharya and O'Hara, 2017; Da and Shive, 2018). A few studies examine the informational efficiency in terms of market reaction or information transmission within an ETF, but do not find conclusive evidence (e.g., Bhojraj et al., 2020; Glosten et al., 2021; Israeli et al., 2017). Antoniou et al. (2022) document the real effect of ETFs in improving investment efficiency. A closely related study (Coles et al., 2022) shows that index investing reduces information production by investors using Google searches, EDGAR views and analyst reports as three different measures of information production. However, Coles et al. (2022) do not differentiate the broad ETF from the sector ETF. We focus directly on analysts' forecasts, which are an important source of earnings and cash flow information (Denis et al., 1994; Kothari, 2001).

Our findings echo Bhojraj et al. (2020) who find greater reaction around an ETF-leader's earnings announcement within the sector-based ETFs. They suggest that sector-based ETFs, which generally focus on stocks with common sector-based factors, are more efficient in transmitting sector-level information to their constituents. We extend their setting by showing that even professional analysts benefit from such information aggregation and transmission through sector-based ETF activities. Our findings highlight the importance to differentiate among types of ETFs when examining their impact on financial markets and suggest that the sector-ETF ownership improves the quality of information produced by financial analysts and thus increases informational efficiency.

Second, our study extends the literature that examines whether and how analysts learn from different sources of information. For example, Clement et al. (2011) find that analysts use stock returns and other analysts' forecast revisions in revising their own forecasts after an earnings announcement. Kumar et al. (2021) show that analysts learn from "peer" analysts associated with other firms in their respective portfolios. Hilary and Hsu (2013) find that experienced analysts respond quickly and efficiently to management forecasts. Our findings show that trading activity in a sector ETF provides opportunities for analysts to learn about the aggregate-level information when they revise earnings forecasts in response to peer firms' earnings announcements.

Third, our results also add to our understanding of analysts' expertise and information production. Prior studies show that analysts' information advantage over managers in earnings forecasting resides at the macroeconomic level, instead of the industry level (Hutton et al., 2012). Bloomfield (2009) suggests that interpreting other analysts' forecast requires expertise and effort and that mutual observation of each other's forecast facilitates information aggregation and improves forecast accuracy. Similarly, Clement et al. (2011) suggest that analysts have expertise in extracting valuable information from public signals. We show that trading activity in an ETF facilitates such information aggregation process and makes the public signal (the ETF price reaction) more informative about an industry or a sector.

The remainder of the paper proceeds as follows. Section 2 describes the institutional background of our research setting and the DID identification. Section 3 presents our main tests and findings. Section 4 explores the mechanism of analysts' learning from ETFs and presents the cross-sectional analyses. Section 5 concludes.

2 Institutional background and DID identification

2.1 Institutional background: Sector vs broad ETFs

Exchange-Traded-Funds (ETFs), first introduced in early 1990s, trade a basket of stocks like an individual security trades on the exchange. ETFs today are a cheap means of achieving diversification with low average management fees and high liquidity. Naturally, ETFs have exploded in popularity. Initially ETFs replicated broad-based stock indices. Progressively, they have expanded to replicate indices around various sectors or certain valuation factors.

Broad-based and sector-based ETFs are different in several key aspects. First, broad-based ETFs passively track and replicate an index with as many as thousands of constituents, whereas sector-based ETFs invest in a relatively small number of stocks that belong to a particular industry or sector. Examples of broad-based ETFs based on stock indices include SPDRs, QQQQs, DIAMONDS or iShares Russell 2000 that replicate the S&P 500, the Nasdaq 100, the DJIA and the Russell 2000 indices, respectively. Examples of sector-based ETFs are the SPDR S&P Biotech ETF (XBI) which tracks the biotechnology segment of the S&P Total Market Index and the Fidelity MSCI Consumer Staples (FSTA) ETF which specifically tracks the consumer discretionary sector.

Second, broad-ETFs are typically market-capitalization weighted, but sector ETFs mostly focus on large- and mid-capitalization companies. For example, the 10 U.S. sector ETFs debuted as early as 2000 from iShares are straightforward large-cap sector funds that track the investment results of the Russell 1000 ICB (Industrial Classification Benchmark) Capped Index. Vanguard has 11 sector ETFs that track specific sectors within the MSCI USA Index, i.e., the large- and mid-cap segments of the US market.

Third, sector-based ETFs generally have much higher turnover ratios than broad-based ETFs in both primary and secondary markets. Broad-based ETFs typically have a lower turnover ratio than actively managed or more concentrated ETFs (Easley et al., 2021).[9] Sector

[9] For comparison, Vanguard Total Stock Market (VTI) ETF, a broad-based ETF that tracks the CRSP US Total Market Index, has a turnover of 3% while the median turnover ratio of U.S. equity ETFs is around 25%.

ETFs, by design are more concentrated. They have higher turnover and they are more actively managed than broad-based ETFs (Easley et al., 2021; Huang et al., 2021).

Finally, from the information perspective, investors demand and trade ETFs based on the aggregate information relevant to the basket of securities. Thus actively-managed sector ETFs are more likely to incorporate sector-specific information into the ETF prices, whereas broad-ETFs are more likely to incorporate macroeconomic information. Glosten et al. (2020) find that ETF activity results in prices that reflect systematic information in a timely manner rather than idiosyncratic earnings information. Bhojraj et al. (2020) show that sector ETFs help information transfer among stocks when one ETF member stock makes an earnings announcement, while broad ETFs do not exhibit a similar effect. Following this strand of literature, we explore the difference between sector and broad ETFs and examine whether analysts can learn information from the different types of ETFs.

2.2 The DID identification

To identify an exogenous change in the ETF ownership, we follow prior studies which exploit the Russell index reconstitution as an exogenous shock to the ETF or passive fund holdings. In particular, the new assignment regime ("banding") starting from June 2007 created two discontinuities at the upper and lower bands: whether a stock switches or stays in the index within a sufficiently narrow window around each band can be treated as randomly assigned (Heath et al., 2021). The market capitalization of stocks around each band are comparable to each other, but a stock who has switched its index may experience a significant change in the passive fund holdings or ETF ownership as shown in prior studies (Glosten et al. 2021, Ben-David et al. 2018; Appel et al. 2016, 2018, 2020). To the extent that analysts forecast may be endogenously correlated with the stock market value change, we rely on the Russell index switching around each band as an exogenous shock to the ETF ownership that is not driven by the market capitalization.

Furthermore, in this paper, we are interested in differentiating the effects of broad- and sector-ETF ownership changes. We propose that Russell index switching can be used as a setting to differentiate exogenous changes in different types of ETF ownership. Prior studies typically suggest that when the lowest-market-capitalization stocks switches from the Russell 1000 index to the Russell 2000 index, the total ETF ownership of that stock increases significantly due to the value-weighting in index.[10] Conversely, the switch from the Russell 2000 to the Russell 1000 index tends to increase the broad-based ETF ownership. We argue that this change applies primarily to ETFs that passively track indexes, i.e., the broad-based ETFs.

Sector ETFs, by contrast, mostly track industrial indices (e.g., Russell Industrial Indices) which tend to include large- and mid-capitalization companies. For example, the U.S. Industrials ETF from iShares (managed by Blackrock), which is the largest issuer of ETFs in the US and globally, tracks the investment results of the Russell 1000 Industrials 40 Act 15/22.5 Daily Capped Index, which is a subset of the Russell 1000 Index. As a result, firms switched from the Russell 2000 index to the Russell 1000 index are more likely to be included in sector ETFs and experience an increase in the sector ETF ownership after switching, opposite to the effect on the broad ETF ownership. Conversely, the switch from the Russell 1000 to the Russell 2000 index may lead to a decrease in the sector ETF ownership.

Later in our empirical tests we will confirm the opposite effects of Russell reconstitutes on the broad and sector ETF ownership.

3 Data and sample construction

3.1 Data and variable definitions

To perform the DID tests, we obtain data for four quarters before and after Russell index assignment for both treatment and control firms in the lower and upper band samples in Table 1. The ETF holdings data come from CRSP Mutual Fund database. We rely on Lipper Fund Classifications from CRSP Mutual Fund Databases to identify the broad- and sector-

[10] Chang et al. (2015) find that stocks at the top of the Russell 2000 are about 10 times larger in their portfolio weight than stocks at the bottom of the Russell 1000 due to the value weighting, although the assets under management of passive funds benchmarked to the Russell 1000 are about 2 to 3.5 times bigger than those tracking the Russell 2000.

based ETFs. Specifically, following Ben-David et al. (2018), we select broad-based ETFs with Lipper Objective Codes of CA, EI, G, GI, MC, MR, SG, and SP, and sector-based ETFs with Lipper Objective Codes of BM, CG, CS, FS, H, ID, NR, RE, TK, TL, S, and UT.

ETF ownership for each stock *i* and quarter *t*, ETF_OWN_{it}, is measured as the proportion of a stock's total number of shares outstanding owned by all the ETFs (see Glosten et al. 2021):

$$ETF\_OWN_{it} = \frac{\sum_{j=1}^{J} Shares_{jt}}{Total\_Shares\_Outstanding_{it}} \tag{1}$$

where *J* is the set of ETFs holding stock *i*, $Shares_{jt}$ is the number of stock *i*'s shares held by ETF_j at the end of quarter *t*, and $Total\_Shares\_Outstanding_{it}$ is the total shares outstanding for stock *i* at the end of quarter *t*. We follow the same method to calculate the proportion of shares held by broad-based ETFs and sector-based ETFs for each stock and quarter, $SECTOR\_OWN_{it}$ and $BROAD\_OWN_{it}$, respectively.

We define analysts' forecast accuracy $ACCU_{it}$ as the stock *i*'s absolute forecast error of consensus forecasts for the quarter *t*, deflated by absolute actual earnings and multiplied by -1.

$$ACCU_{it} = -\frac{\|Median\_Consensus\_Forecast_{it} - Actual\_Earnings_{it}\|}{\|Actual\_Earnings_{it}\|} \tag{2}$$

The use of absolute actual earnings instead of stock price as a deflator in measuring analysts' forecast accuracy follows Horton et al. (2013) and Cotter et al. (2012) who argue against using share price as the deflator because of the potential confounding effects of significant stock price fluctuations during the sample period. In our setting, a similar concern arises as firms switching between Russell indexes experience significant market price movements. For example, when a firm switches from the Russell 1000 to the Russell 2000 after a significant price drop, analyst forecast errors deflated by the stock price will increase in absence of any change in analysts' forecast behavior. Our construction of *ACCU* avoids this confounding effect.[11]

Other variables used in the analysis are: *ANALYST_NO*, the number of analysts

[11] In untabulated results, we use the stock price as an alternative deflator and find stronger results.

following the firm during the quarter; *INST_PERC*, the percentage of shares held by institutional investors at the end of the quarter; and Δ*INST*, the quarterly change in institutional ownership for the firm during the quarter. We obtain analysts' earnings forecast and the number of analysts following data from I/B/E/S and the institutional ownership data from Thomson Reuters 13f Institutional Holdings Database.

3.2 DID sample construction

Following Coles et al. (2022) and Heath et al. (2021), we obtain the Russell index membership data to construct a cohort containing two sets of treated and control stocks. Using the lagged index membership, we select stocks whose index memberships were potentially switched between the upper and lower bands within a window of +/-100 rank.[12] We begin with a sample size of 8,120 firm-quarters. After eliminating observations with missing variables, our final DID sample covers 6,960 unique firm-quarters over the period from 2010 to 2020 with non-missing variables. Our DID sample size is comparable to the sample size in the studies of Coles et al. (2022) and Heath et al. (2021).

Table 1 presents the annual number of firm-quarters for the treated group of firms and the control group in both upper and lower bands from 2011 to 2019. The total number of treated observations moving from the Russell 2000 to the Russell 1000 is 1,957, compared to 2,349 control observations, while the total number of treated observations moving from the Russell 1000 to the Russell 2000 is 1,745, compared to 909 control observations. The number of observations in the treatment and control groups around two Russell banding discontinuities are relatively balanced.

[12] We illustrate this process by an example following the construction and methodology guidelines provided by Russell FTSE. Suppose during this year, the cumulative market capitalization of the largest 1,000 securities is $164 billion, which accounts for around 89.99% total market capitalization of the Russell 3000E Index. The upper band breakpoint is therefore 87.49% (by subtracting 2.5% from 89.99%), which is the cumulative market capitalization percentile of the largest 850 stocks. Similarly, the lower band percentile is 92.49%, which is the cumulative market capitalization percentile of the largest 1200 stocks. Assume stock A and stock B were both members of the Russell 1000 before the Russell index reconstitution. The ranking of stock A's market capitalization drops from 980th to 1,190th, while the ranking of stock B's market capitalization drops from 990th to 1,210th. The new banding policy implies that stock A remains in the Russell 1000 index (and serves as a control observation), whereas stock B is switched to the Russell 2000 index (and serves as a treated observation).

[Insert Table 1 about here]

Panel A in Table 2 presents descriptive statistics of key variables. We winsorize all continuous variables at the levels of 1% and 99%. The mean (median) percentage ETF ownership is 9.85% (9.73%). The mean sector ownership and broad ownership are 0.87% and 8.96%, respectively.[13] In our sample, the total institutional ownership has a mean (median) of 80.44% (90.56%), much higher than the ETF ownership level. In addition, we observe a relatively small quarterly change in the institutional ownership, averaged at 0.13%. The statistical distributions of both ETF and institutional ownerships in our sample are consistent with prior studies.[14] The mean (median) analyst coverage for each firm is around 12 (11), which is larger than the average analyst coverage in Israel et al. (2017) because our sample focuses on the relatively large firms.

[Insert Table 2 about here]

Table 2 Panel B provides means of the ETF ownership and other variables before and after switching in our treatment group and control group. For the treated firms in the lower band, the mean broad-ETF ownership increases significantly from 7.64% to 9.63%, which represents a 26% increase in the broad-ETF ownership after switching; whereas the mean sector-ETF ownership declines slightly from 0.99% to 0.88%, which represents an 11.1% decrease in the sector-ETF ownership. By contrast, for the treated firms in the upper band, the mean sector-ETF ownership is 0.77% before treatment and increases significantly to 1.09% after switching from the Russell 2000 to the Russell 1000, while the mean broad-ETF ownership drops slightly from 9.07% to 8.22%. Percentage wise, the sector-ETF ownership increases by 41.6% while the broad-ETF ownership decreases by 9.4% in the upper band. The mean difference before and after the upper band Russell index switches of the treatment group is significant at 1% level for the sector ETF ownership, and significant at 5% level for the broad

[13] In comparison to broad ETFs, which typically have 579 underlying firms, sector ETFs on average have 101 member firms. The distinction in constituent numbers could explain the discrepancy between the levels of sector and broad ETF ownership.

[14] Glosten et al. (2021) document a mean (median) institutional ownership of 64.8% (70.4%) between 2004 and 2013, and a mean (median) quarterly change in institutional ownership of -1.4% (0.1%). Antoniou et al. (2022) report a mean ETF ownership of 8% as of year 2016.

ETF ownership. For the control group in both lower and upper bands, we observe a consistent increasing but insignificant trend in the total ETF ownership, broad ETF ownership as well as the sector ETF ownership during the sample period.

The comparison of summary statistics of *INST_PERC* before and after switching shows that the total institutional ownership of treated firms does not change much, consistent with prior studies that Russell index assignment does not affect firms' total institutional ownership (Appel et al., 2020; Wei and Young, 2021).

Figure 1a and 1b plot the two types of ETF ownerships of the treated and control firms around the Russel yearly reconstitution (i.e., from quarter $t-3$ to quarter $t+4$) Figure 1a shows that the sector-ETF ownership of treated firms decreases sharply from quarter t to quarter $t+1$ in the lower band (switchers from the Russell 1000 to the Russell 2000), whereas the treated firms' sector ownership increases from quarter t to quarter $t+1$ in the upper band (switchers from the Russell 2000 to the Russell 1000). Figure 1b displays an opposite trend in the broad-ETF ownership following Russell index annual reassignment. These figures also confirm the parallel trend of sector- and broad-ETF ownerships in treated and control firms before the event, i.e., from quarter $t-3$ to quarter t.

[Insert Figure 1 about here]

4 DID estimation results

4.1 The DID estimation of ETF ownerships

We first validate the different types of ETF ownership changes through DID regression estimates. Following Coles et al. (2022) and Heath et al. (2021), we estimate difference-in-differences specifications of the ETF ownerships, with fixed effects for each stock in each cohort that absorbs both unobserved firm characteristics and time-varying aggregate shocks. Our estimation uses quarterly observations one year before and one year after the assignment. For the lower-band treatment effect, we estimate the following specification,

$$ETF\_OWN_{it} = \beta_1 I_{R1000 \to 2000_i} \cdot PostAssignment_t + \phi_i + \lambda_t + \epsilon_{it}, \quad (3)$$

where ϕ_i and λ_t are firm and year-quarter fixed effects respectively, *PostAssignment* is an indicator variable that equals one after the index assignment, $I_{R1000\rightarrow2000i}$ equals one if a firm switched from the Russell 1000 to the Russell 2000.

For the upper-band treatment effect, the specification is

$$ETF\_OWN_{it} = \beta_2 I_{R2000\rightarrow1000_i} \cdot PostAssignment_t + \phi_i + \lambda_t + \epsilon_{it}, \tag{4}$$

where $I_{R2000\rightarrow1000i}$ equals one if a firm switched from the Russell 2000 to the Russell 1000.

Panel A and Panel B of Table 3 show the DID estimation results in the lower and upper bands respectively. Column (1) from both panels presents the index switching's effects on the total ETF ownership. The regression estimation shows that for firms in the lower band treatment, the total ETF ownership increases are economically significant. The total-based ETF ownership in the treated group increases by 11% more than the control group after switching to the Russell 2000 index. In contrast, for firms experiencing the upper band treatment effect, the total ETF ownership decreases by 6.2% more than the control group after switching to the Russell 1000 index. The results are consistent with previous studies which also use the Russell reconstitution as a shock to the level of ETF ownership (e.g., Agarwal et al., 2019; Appel et al., 2018; Ben-David et al., 2018).

Column (2) and (3) report the effects of the Russell index switching on the sector-ETF and broad-ETF ownership, respectively. The estimates from the lower band (Panel A) and upper band (Panel B) both suggest that the change in the broad-based ETF ownership is in the same direction as that in the total ETF-ownership. The broad-based ETF ownership in the treated group increases by 13.2% more than the control group in the lower band, while decreases significantly by 9.1% more than the control group in the upper band. This is consistent with the fact that most ETFs are broad-based and that the reconstitution indeed drives the predicted changes in these index-based ETFs. However, the changes in the sector-ETF ownership around the reconstitution are in the opposite direction. The sector-based ETF ownership in the treated group decreases by 4.7% more than the control group in the lower band, while increases significantly by 12% more than the control group in the upper band. This supports our argument that the sector ETF is more likely to follow the Russell 1000 stocks with large market capitalization and the reconstitution's effect on these sector ETFs is opposite to that on broad ETFs. In the last column of Table 3, we investigate the effect on the total institutional ownership. Consistent with prior studies (e.g., Appel et al., 2016, 2018; Wei and Young, 2019), we find no significant impact of index reassignment on the total institutional ownership.

[Insert Table 3 about here]

4.2 DID estimation of analysts' forecast accuracy

We now test whether analysts' forecast accuracy changes after the Russell index reassignment. The estimate follows the difference-in-differences specifications in (3) and (4) for the lower-band and upper-band treatment effects, respectively, with $ACCU_{it}$ as the dependent variable.

$$ACCU_{it} = \beta_1 I_{R1000 \to 2000_i} \cdot PostAssignment_t + Controls + \phi_i + \lambda_t + \epsilon_{it} \qquad (5)$$
$$ACCU_{it} = \beta_2 I_{R2000 \to 1000_i} \cdot PostAssignment_t + Controls + \phi_i + \lambda_t + \epsilon_{it} \qquad (6)$$

Table 4 presents the DID estimation of analysts' forecast accuracy. The results suggest that analysts' forecast accuracy significantly increases after the firm switches from the Russell 2000 to the Russell 1000 index but decreases when the switch is in the other direction. Columns (1) and (3) report the lower band and upper band treatment results without control variables. Specifically, column (1) shows that switching from the Russell 1000 to the Russell 2000 leads to an 8.60% decrease in analyst forecast accuracy. In contrast, column (3) shows that switching from the Russell 2000 to the Russell 1000 leads to a significant increase of 7.82% in forecast accuracy. The increase in the upper band treatment sample is much more significant than the decrease in the lower-band treatment sample.

Column (2) and (4) report the estimates after controlling for variables that may have also contributed to the change in analysts' forecast accuracy around the treatment. Prior studies find that institutional ownership increases analysts' forecast accuracy (e.g., Kumar, 2010), we control for the change of institutional holdings not explained by the ETF activity (*INST_RESIDUAL*), following Glosten et al. (2021). Israeli et al. (2017) show that increasing the ETF ownership may decrease the number of analysts following, which may in turn affect analysts' forecast accuracy. We therefore also control for the number of analysts following (*ANALYST_NO*) in our test.

As shown in Columns (2) and (4), the coefficient of *INST_RESIDUAL* is insignificant, which suggests it is ETF ownership, not institutional ownership, that affects analyst forecast accuracy. The number of analysts following is insignificant in the lower band test but is significantly positive in the upper band. The positive impact of analyst coverage on analysts' forecast accuracy is in line with prior studies' finding that greater analyst coverage enhances forecast accuracy (e.g., Lys and Soo, 1995; Tan et al., 2011). After controlling for the number of analysts following a firm and change in institutional ownership, the decrease in forecast accuracy in the lower band test (column 2) remains significant, and the increase in forecast accuracy also remains significantly positive at the 5% level (column 4).

[Insert Table 4 about here]

4.3 Broad- versus sector-ETF effects

As we discussed in Section 3.2, the Russell index annual reconstitution is a quasi-experiment setting which captures opposite directions of changes in sector- and broad- ETF ownership. The results in Table 4 thus need to be further examined to differentiate and pin down the exact cause (broad-based vs. sector-based ETF ownership change) of the change in analysts' forecast accuracy. We therefore control for the confounding effect from the simultaneous changes in the other type of ETF ownership. Specifically, we estimate the triple difference by identifying the change in one type of the ETF ownership after controlling for the variation in the other type of ETF ownership.

For each cohort (the lower or the upper band sample), we first sort the entire sample based on the absolute change of one type of ETF ownership, and then perform the triple difference test to examine the effects of broad and sector ETF ownership change on analyst forecast accuracy. Columns (1) and (2) in Table 5 report the results when sorting by the magnitude of the broad-ETF ownership change; columns (3) and (4) report the results when sorting by the change in the sector-ETF ownership. *Large* in each column is an indicator that equals one for the firm-quarter with an above-median change in the broad-ETF or sector-ETF ownership, and zero otherwise when firms are reclassified by the Russell constituents. The three-way interaction essentially captures the impact of only one type ETF ownership change.

[Insert Table 5 about here]

Coefficients on the triple interaction term *Treat*Post*Large* in Columns (1) and (2) are not significant, which suggest that the change in the broad-ETF ownership does not explain the change in analysts' forecast accuracy after reconstitutes for both the lower and upper band samples. By contrast, in columns (3) and (4), the sector-ETF ownership change is significantly correlated with the change in analysts forecast accuracy after reconstitutes. When firms switch from the Russell 1000 to the Russell 2000, where the sector-ownership decreases on average, the triple interaction estimate is significantly negative. For the group with a larger decrease in the sector ownership, analysts forecast accuracy deteriorates by 19.66% more than that for the group with a small change. For the upper band, the triple interaction estimate is significantly positive, suggesting that the group with larger increase in the sector-ETF ownership experiences an 11.81% a greater improvement in analysts' forecast accuracy than the benchmark group.

Combining all the results together, we infer that it is the increase (decrease) in the sector-ETF ownership, instead of the decrease (increase) in the broad -ETF ownership, that drives the increase (decrease) of analysts' forecast accuracy after firms switch from the Russell 2000 (1000) to the Russell 1000 (2000). The estimation results are significantly negative in the lower band samples and significantly positive in the upper band samples after sorting by sector ETF ownership, which is consistent with our conjecture that the sector-ETF ownership, rather than the broad-based ETF, plays a dominant role in influencing analysts' forecast accuracy.

5 Mechanism: Learning from sector ETFs

In this section, we directly investigate the channel through which the sector ETF activities affect analysts' forecast accuracy. Analysts actively acquire and produce valuable information using their expertise and knowledge and provide forecasts and research reports to investors. Prior studies show that analysts also learn and extract information from different sources of public information. Firms in the same industry are affected by common factors and thus their earnings exhibit co-movement. Prior studies show that analysts learn from earnings announcements of the target firm's industry peers (Lim et al., 2001). The availability of ETF products and trading further facilitate such learning process because sector-based ETFs facilitate efficient aggregation and transfer of common-factor information contained in the earnings announcement by constituent firms. Bhojraj et al. (2020) recently documented that ETFs, especially sector-based ETFs, facilitate information transfer across firms within the same ETF around earnings announcements. Whether professional analysts benefit from such information transfer is an empirical question examined below.

5.1 ETF sample construction

To test our story of analysts learning from peer firms' earnings announcements through sector-ETFs, we construct an ETF sample using all U.S. equity ETFs. First, we use CRSP daily stock file to obtain ETFs traded on major US exchanges (CRSP share code of 73). ETFs are required to update their portfolio holdings on a quarterly basis on SEC forms N-CSR and N-Q. This gives us 1,095 equity ETFs with constituent holding information during the period from 2010 to 2020. As mentioned in Section 3.1, we rely on Lipper Fund Classifications from CRSP Mutual Fund Databases to identify the broad- and sector-based ETFs. Specifically, we obtain 447 distinct sector-based ETFs and 648 broad-based ETFs in our sample.

Table 6 Panel A shows the sample distribution and the average ETF ownership in each year. The ETF observations increase steadily from 319 in 2010 to 828 in 2020. The number of sector-based ETFs also experiences a significant increase over time. The average sector-ETF ownership increases from 0.21% in 2010 to 1.09% in 2020 and the broad-ETF ownership increases from 3.58% in 2010 to 11.11% in 2020. The number of ETFs and the magnitude of ETF ownership in our sample are comparable to those in Antoniou et al. (2022) and Glosten et al. (2021).

Table 6 Panel B displays the industry distribution of the sector ETFs in our sample. We follow Lipper Fund Classifications to classify sector ETFs into 11 distinct sectors. Science & Technology has a relatively larger number of competing ETFs, representing around 17% of the total ETFs, while Telecommunication sector represents only 4% of all ETFs. Overall, the sector-based ETF distribution across industries in our sample looks like that in Bhojraj et al. (2020).

[Insert Table 6 about here]

In each ETF, the firm with the largest holdings is identified as the "announcer", and for each announcer we identify four "followers" who meet the following requirements. First, we require the announcer and follower pairs' quarterly earnings announcements (EA) are at least two days apart. Second, the follower has an immediate forecast revision for the next quarter's earnings within the 10-day window after the announcer's EA, but before the follower's own EA for the current quarter. Third, the four non-announcing followers we select have larger holdings in each ETF than other non-announcing member firms. When an earnings release and/or analyst forecast revision takes place after the market close, the announcement date is set to be the next trading day. We remove ETFs with less than five member firms in our sample. We also remove duplicate pairs when two firms in a pair appear in multiple ETFs. We apply two-step screening to delete repeated leader-follower pairs in any given quarter. For repeated pairs, we keep the pair that is from a sector ETF and/or the pair that has more holdings in the ETF. The final sample contains 7,034 announcer-follower pairs from distinct sector-ETF-quarters and 19,763 pairs from distinct broad-ETF-quarters from 2010 to 2020.

We create a control sample to distinguish the learning effects driven by industry peers and by sector-ETF peers. For each follower firm of the sector-ETF pairs, we identify a comparable firm in the same Fama and French (1997) industry, but not a constituent of the same sector ETF, using propensity score matching, following Bhojraj et al. (2020). We use the one-nearest-neighbor matching without replacement based on size, return on assets, the number of analysts and institutional ownership. We again require firms in the control group to have both quarterly EA at least two days apart from the announcer's EA, and an immediate forecast revision for the next quarter within the 10-day window after the announcer's EA, but before the followers' own EA for the current quarter. The final control sample contains 6,120 quarterly common-sector pairs that do not belong to the same sector ETF.

5.2 Analysts' revisions within sector ETF

To better understand the ETF's role in transmitting information contained in announcer's earnings news across firms within the same ETF, following Lim et al. (2001), we first examine the relationship between the top-holdings announcer's earnings surprise and the non-announcing follower firms' first forecast revision for the next forecast quarter issued within the 10-day window after announcer's EA. If sector ETFs are indeed more efficient in aggregating common-information relevant for the peer firms, we expect analysts of followers within the same sector-ETF to be more likely to revise their forecasts and respond more to new information contained in the announcer's earnings news.

Our revision test slightly differs from Lim et al. (2001) in that we focus on analysts' revisions of next quarter's earnings forecasts while Lim et al. (2001) use soon-to-be-released current quarter earnings. There are two main reasons for this. First, latest forecasts for the current quarter are more likely to be biased and analysts tend to omit information from the latest forecasts, as prior studies find that managers guide analysts' earnings forecasts downward due to incentives for meeting or beating earnings expectations (e.g., Bartov et al., 2002; Berger et al., 2019; Matsumoto, 2002). By focusing on analysts' revisions of forecasts a quarter further into the future instead of soon-to-be-released current quarter earnings, we capture analysts' response to new information without the manager's influence. Second, we require the non-announcing followers to immediately revise their forecasts within the 10-day window after the announcer's EA. Similar to Clement et al. (2011), we find that, on average, analysts revise earnings forecasts for 80% of non-announcer firms for the quarter $t + 1$ within 10 days of the announcer's EA for the quarter t. Focusing on analysts' forecast revisions of followers issued within the 10-day window after announcer's EA date reduces the influence of confounding factors.

We employ the following regression to examine the relation between the announcer's earnings surprise (*SUE_A*) and the follower firms' immediate analyst earnings forecast revision (*REV_F*) after the announcer's earnings announcement.

$$\begin{aligned} REV\_F = & \alpha + \beta_1 * SECTOR + \beta_2 * SUE\_A + \beta_3 * SECTOR * SUE\_A + \\ & Controls + Announcer\_FE + Year - Qtr\_FE + \epsilon, \end{aligned} \tag{7}$$

where *REV_F* is defined as the followers' first forecast revision for the next quarter $t + 1$, issued within the 10-day window after the announcer's quarter t earnings release, scaled by the stock price at the beginning of quarter t. *SUE_A* represents the announcer's earnings surprise for quarter t, which is defined as the actual EPS in quarter t minus the latest median analyst forecast before EA, scaled by the stock price at the beginning of quarter t. *SECTOR* is an indicator variable which equals one if the announcer-follower pair belongs to the same sector ETF and zero otherwise.

We add several other control variables in the model. Following Clement et al. (2011), we control for *LAG_SUE_F*, which is the follower's lagged earnings surprise for the quarter $t - 1$, to rule out the confounding effect of the follower's own earnings news from the previous quarter. We also include the level of ETF ownership at the end of last quarter, *ETFOWN*, to control for the ETF ownership's effect on the information efficiency as documented by prior studies (Glosten et al. 2021). We also control for other characteristics that might be related to the announcer's earnings news and shown to affect the followers' analyst forecast revisions: namely, the follower firm's size measured by the logarithm of market capitalization (*SIZE*), lagged institutional ownership (*INST_PERC*), the number of analysts following (*ANALYST_NO*), the book-to-market ratio (*BTM*), an indicator variable for loss (*LOSS*), return on assets (*ROA*), the ratio of sector-based ETF ownership to total ETF ownership (*PERC_SEC*), and the stock return during the previous three quarters ($RET_{t-4,t-1}$). Our regressions include announcer and year-quarter fixed effects to account for time-series as well as cross-sectional correlations between firm-specific measures, and the t-statistic controls for clustering at the announcing firm level because the same announcer is paired with multiple followers.

[Insert Table 7 about here]

Table 7 presents the regression results. In column (1), the coefficient of SUE_A is positive and significant (0.077 with t-value 2.89) for followers in the same sector ETFs as the announcer, but in column (2) the coefficient is negative and insignificant (-0.021 with t-value -1.19) in the broad-based ETFs sample. The positive and significant estimate on *REV_F* in column (1) suggests that analysts revise their forecasts of follower firms' future earnings in the direction consistent with the announcer's earnings surprise, immediately after a peer in the same sector ETFs announces its earnings. The opposite and not statistically significant estimate on *SUE_A* in column (2) indicates that, on average, follower firms in the same broad ETF do not seem to respond to the announcer's analyst earnings news. Column (3) presents the results using the combined sample of sector and broad ETFs, and the interaction term *SECTOR* $*$ *SUE_A* captures the difference between the sector-ETF and broad-ETFs. The coefficient of *SECTOR* $*$ *SUE_A* is significant and positive. Furthermore, we can infer that one standard deviation increase in the announcer's earnings surprise leads to a 5.9% increase in the analyst revision of the follower firm within the sector ETF subsample, whereas it results in a 1.7% decrease in the analyst revision of the follower firm within the broad ETF subsample.

Next in Column (4) we examine analyst forecast revisions for the follower firms in the same industry but not in the same sector ETFs. The coefficient of SUE_A is insignificant in this subsample of control firms, and one standard deviation increase in the analyst revision magnitude of the follower firm results in a mere 0.7% change in the analyst revision. We also combine the samples of the same sector-ETF pairs and same industry pairs in Column (5) and perform the regression with the interaction term *SECTOR* $*$ *SUE_A*, where SECTOR is an indicator if the pair belongs to the same sector ETF. The coefficient on the interaction is significantly positive. This suggests that the information learning is stronger through the sector ETFs than the pure intra-industry information transmission.

In terms of control variables, the coefficients on *LAG_SUE_F* in both types of ETF samples are positive, indicating that analysts' forecast revisions also incorporate firms' own earnings news, consistent with findings in previous research (e.g., Abarbanell and Bernard, 1992). The regression coefficients on other control variables in Table 7 are largely consistent with prior literature. The coefficients on *SIZE* and $RET_{t-4,t-1}$ are positive and the coefficient of *BTM* is negative, consistent with the literature on the size effect, the learning effect and the growth effect (Clement et al., 2011). Analysts' forecast revision is smaller when reported earnings are negative (*LOSS*), consistent with Kross & Suk (2012). The ETF ownership has significant and positive effect on revisions, but the institutional ownership's effect is insignificant, consistent with Glosten et al. (2021). The negative coefficient of analyst coverage suggests that earnings surprise conveys less new information for firms with good information environment as proxied for by analysts' coverage.

Our main DID test shows that analysts' forecast accuracy improves when the sector-based ETF ownership increases. The results of the ETF-level tests provide supporting evidence that sector ETFs facilitate the efficient information transfer about the announcer's earning news so that analysts of follower firms react more to earnings surprise.

5.3 Additional cross-sectional evidence

To provide further insight into the learning mechanism of current findings, we conduct cross-sectional analyses to identify the conditions that foster analysts' learning from sector ETF activities. We explore four different factors: 1) ETF turnover, 2) analyst experience with the firm, 3) the number of firms followed by the analyst, and (4) the number of industries followed by the analyst.

ETF-turnover. We first investigate whether the ETFs with higher turnovers have greater impact on analyst forecast accuracy. Analysts are more likely to learn from prices about the securities in an actively traded sector portfolio because trading leads to greater incorporation of information. Easley et al. (2021) document that sector ETFs are more actively managed and more actively traded than broad ETFs. They suggest that higher ETF secondary market turnover contributes to price discovery in individual stocks because active trading of these ETFs leads to more trading in the underlying stocks via the ETF creation/redemption process and ETF arbitrage. Cong and Xu (2016) and Bhattacharya and O'Hara (2017) both suggest ETFs increase informational efficiency with respect to aggregate information, but not necessarily firm-specific information. We expect that ETFs with high turnovers better aggregate the industry level information more efficiently, and as a result, analysts respond more to the information contained in the announcer's earnings surprise through sector ETFs.

We partition the sample into high- and low-turnover groups based on the average trading volume of the ETF and perform the regression in each subsample. The subsample estimation results are shown in Column (1) and (2) Table 8. In the high-turnover group, the coefficient of *SUE_A* $*$ *SECTOR* is positive and statistically significant (0.132 with t-value 4.06), but in the low turnover group, the coefficient of the interaction term is negative and statistically insignificant. In terms of the economic significance, one-unit increase in the announcing firm's earnings surprise is associated with an average increase of 6.5% in followers' analyst revisions, for firm pairs belonging to sector ETFs with above-median turnovers.

Analysts' attention constraint. We next conduct analyses to test whether the learning effect is stronger when analysts face more constraints in their resources and attention to focus on individual firms. Prior studies show that analysts who follow the firm longer gain firm-specific advantage and can process firm's information disclosure better (Clement and Tse, 2005; Hilary and Hsu, 2013) and that larger portfolios constrain the analyst's attention to each individual firm (Clement, 1999; Fang and Yasuda, 2009; Franco and Zhou, 2009). We identify three factors that may proxy for an analyst's limited attention: analyst's experience, number of firms followed, and number of industries covered in the portfolio. In all these tests, we include analyst fixed effects in addition to the two-way fixed effects to rule out the impact of analyst individual characteristics such as analyst ability.

First, we partition the ETF pair sample based on the analyst experience indicator, which equals one if the analyst has been following the firm for a longer period than the sample median and zero otherwise. Columns (3) and (4) of Table 8 show the subsample estimation results.

Consistent with our expectation, the effect is more pronounced for the analysts with less experience. For analysts who have followed the firms for a longer period, the learning effect is not significant.

Second, we partition the sample into two groups based on the number of firms followed and industries covered by an analyst. If the number of companies and industries followed by the follower's analyst is larger, we anticipate a stronger analyst learning effect. The regression results are reported in the last four columns of Table 8. Consistent with our expectation, analysts who follow more firms and cover more industries revise their forecasts more significantly in response to an announcer firm's earnings announcement within the same sector ETF.

[Insert Table 8 about here]

6 Conclusions

Analysts are critical information intermediaries who improve efficiency of securities markets. Using Russell 1000/2000 reconstitution as an exogenous shock, we provide causal evidence that sector ETF ownership facilitates analyst learning and improves their earnings forecast accuracy. To corroborate our main findings, we also analyze the dynamics of analyst learning process within an ETF. The ETF-level analysis suggests that analysts of the follower firms in the same sector ETFs respond to the announcer firm's earnings news, but not in the same broad ETFs or among industry peers. These two findings together support our prediction that analysts are cognizant of the information incorporated in the sector ETFs. The results of additional cross-sectional tests suggest that the learning effect is more pronounced when the sector-ETFs are more actively traded and when follower analysts are less experienced, follow more firms and cover more industries in their portfolio.

Our results reconcile the seemingly contradictory results in the prior literature on ETFs and market efficiency. By partitioning ETFs into sector ETFs and broad ETFs, we directly investigate the effect of changes in ETF ownership and analyst forecast accuracy. Exploiting analysts as preeminent market information intermediaries, we substantiate Huang et al. (2021) and Bhojraj et al. (2020)'s findings on industry ETFs and show that sector-based ETFs also provide information learning for professional analysts.

References

Abarbanell, J. S., & Bernard, V. L. (1992). Tests of Analysts' Overreaction/Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior. The Journal of Finance, 47 (3), 1181–1207.

Agarwal, V., Hanouna, P., Moussawi, R., & Stahel, C. W. (2019). Do ETFs Increase the Commonality in Liquidity of Underlying Stocks? 28th Annual Conference on Financial Economics and Accounting, Fifth Annual Conference on Financial Market Regulation.

Antoniou, C., Weikai Li, F., Liu, X., Subrahmanyam, A., & Sun, C. (2022). Exchange- Traded Funds and Real Investment. The Review of Financial Studies, hhac043.

Appel, I. R., Gormley, T. A., & Keim, D. B. (2016). Passive investors, not passive owners. Journal of Financial Economics, 121 (1), 111–141.

Appel, I. R., Gormley, T. A., & Keim, D. B. (2018). Standing on the Shoulders of Giants: The Effect of Passive Investors on Activism. The Review of Financial Studies, 32 (7), 2720–2774.

Appel, I. R., Gormley, T. A., & Keim, D. B. (2020). Identification Using Russell 1000/2000 Index Assignments: A Discussion of Methodologies. Working paper, Boston College.

Bartov, E., Givoly, D., & Hayn, C. (2002). The rewards to meeting or beating earnings expectations. Journal of Accounting and Economics, 173–204.

Ben-David, I., Franzoni, F., & Moussawi, R. (2018). Do ETFs Increase Volatility? The Journal of Finance, 73 (6), 2471–2535.

Berger, P. G., Ham, C. G., & Kaplan, Z. R. (2019). Do Analysts Say Anything About Earnings Without Revising Their Earnings Forecasts? The Accounting Review, 94 (2), 29–52.

Bhattacharya, A., & O'Hara, M. (2017). Can ETFs Increase Market Fragility? Effect of Information Linkages in ETF Markets. Working paper, Baruch College.

Bhojraj, S., Mohanram, P., & Zhang, S. (2020). ETFs and information transfer across firms. Journal of Accounting and Economics, 70 (2-3), 1–20.

Bloomfield, R. (2009). An Experimental Investigation of the Positive and Negative Effects of Mutual Observation. The Accounting Review, 84 (2), 331–354.

Chang, Y.-C., Hong, H., & Liskovich, I. (2015). Regression Discontinuity and the Price Effects of Stock Market Indexing. Review of Financial Studies, 28 (1), 212–246.

Clement, M. B. (1999). Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter? Journal of Accounting and Economics, 27(3), 285–303.

Clement, M. B., & Tse, S. Y. (2005). Financial Analyst Characteristics and Herding Behavior in Forecasting. The Journal of Finance, 60(1), 307–341.

Clement, M. B., Hales, J., & Xue, Y. (2011). Understanding analysts' use of stock returns and other analysts' revisions when forecasting earnings. Journal of Accounting and Economics, 51 (3), 279–299.

Coles, J. L., Heath, D., & Ringgenberg, M. C. (2022). On index investing. Journal of Financial Economics, 145 (3), 665–683.

Cong, L. W., & Xu, D. X. (2016). Asset Prices, Informational Efficiency, and Security Design. 29th Australasian Finance and Banking Conference.

Cotter, J., Tarca, A., & Wee, M. (2012). IFRS adoption and analysts' earnings forecasts: Australian evidence: Accounting and Finance. Accounting & Finance, 52 (2), 395–419.

Da, Z., & Shive, S. (2018). Exchange traded funds and asset return correlations. European Financial Management, 24 (1), 136–168.

Denis, D. J., Denis, D. K., & Sarin, A. (1994). The Information Content of Dividend Changes: Cash Flow Signaling, Overinvestment, and Dividend Clienteles. The Journal of Financial and Quantitative Analysis, 29 (4), 567–587.

Easley, D., Michayluk, D., & O'Hara, M. (2021). The Active World of Passive Investing. Review of Finance, 25 (5), 1433–1471.

Fang, L., & Yasuda, A. (2009). The Effectiveness of Reputation as a Disciplinary Mechanism in Sell-Side Research. The Review of Financial Studies, 22(9), 3735–3777.

Franco, G. D., & Zhou, Y. (2009). The Performance of Analysts with a CFA Designation: The Role of Human-Capital and Signaling Theories. The Accounting Review, 84(2), 383–404.

Glosten, L., Nallareddy, S., & Zou, Y. (2021). ETF Activity and Informational Efficiency of Underlying Securities. Management Science, 67 (1), 22–47.

Gorton, G., & Pennacchi, G. (1993). Money market funds and finance companies: Are they the banks of the future? Structural change in banking, 173–214.

Grossman, S. J., & Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. The American Economic Review, 70 (3), 393–408.

Heath, D., Macciocchi, D., Michaely, R., & Ringgenberg, M. C. (2021). Do Index Funds Monitor? (H. Mueller, Ed.). The Review of Financial Studies, 35 (1), 1–41.

Hilary, G., & Hsu, C. (2013). Analyst Forecast Consistency. The Journal of Finance, 68 (1), 271–297.

Horton, J., Serafeim, G., & Serafeim, I. (2013). Does Mandatory IFRS Adoption Improve the Information Environment?: Does Mandatory IFRS Adoption Improve the Information Environment? Contemporary Accounting Research, 30 (1), 388–423.

Huang, S., O'Hara, M., & Zhong, Z. (2021). Innovation and Informed Trading: Evidence from Industry ETFs. The Review of Financial Studies, 34 (3), 1280–1316.

Hutton, A. P., Lee, L. F., & Shu, S. Z. (2012). Do Managers Always Know Better? The Relative Accuracy of Management and Analyst Forecasts. Journal of Accounting Research, 50 (5), 1217–1244.

Israeli, D., Lee, C. M. C., & Sridharan, S. A. (2017). Is there a dark side to exchange traded funds? An information perspective. Review of Accounting Studies, 22 (3), 1048–1083.

Kothari, S. P. (2001). Capital markets research in accounting. Journal of Accounting and Economics, 31 (1), 105–231.

Kross, W. J., & Suk, I. (2012). Does Regulation FD work? Evidence from analysts' reliance on public disclosure. Journal of Accounting and Economics, 53 (1-2), 225–248.

Kumar, A. (2010). Self-Selection and the Forecasting Abilities of Female Equity Analysts. Journal of Accounting Research, 48 (2), 393–435.

Kumar, A., Rantala, V., & Xu, R. (2021). Social learning and analyst behavior. Journal of Financial Economics, 143 (1), 434–461.

Lim, S. C., Ro, B. T., & Pyo, Y. (2001). Analysts' earnings forecast revision around industry member firms' earnings announcement. Advances in Accounting, 18, 149–168.

Lys, T., & Soo, L. G. (1995). Analysts' Forecast Precision as a Response to Competition. Journal of Accounting, Auditing & Finance, 10 (4), 751–765.

Matsumoto, D. A. (2002). Management's Incentives to Avoid Negative Earnings Surprises. The Accounting Review, 77 (3), 483–514.

Russell, F. (2021). Russell U.S. Equity Indexes Construction and Methodology v5.2.

Tan, H., Wang, S., & Welker, M. (2011). Analyst Following and Forecast Accuracy After Mandated IFRS Adoptions: Analyst following and forecast accuracy. Journal of Accounting Research, 49 (5), 1307–1357.

Wei, W., & Young, A. (2019). Selection Bias or Treatment Effect? A Re-Examination of Russell 1000/2000 Index Reconstitution. Working paper, University of Oklahoma.

Wei, W., & Young, A. (2021). Regression Discontinuity Versus Instrumental Variables: A Response to Appel, Gormley, and Keim (2020). Working paper, University of Oklahoma.

Figure 1: ETF Ownership around Russel Yearly Reconstitution

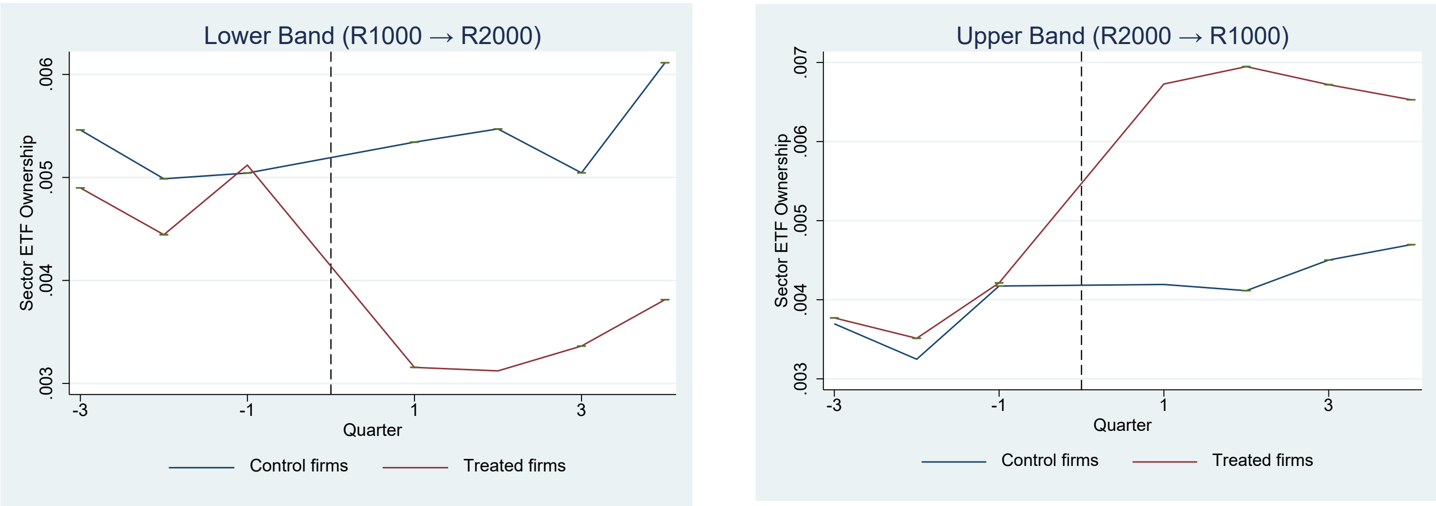

Figure 1a: Russell Index Switching and Sector ETF Ownership

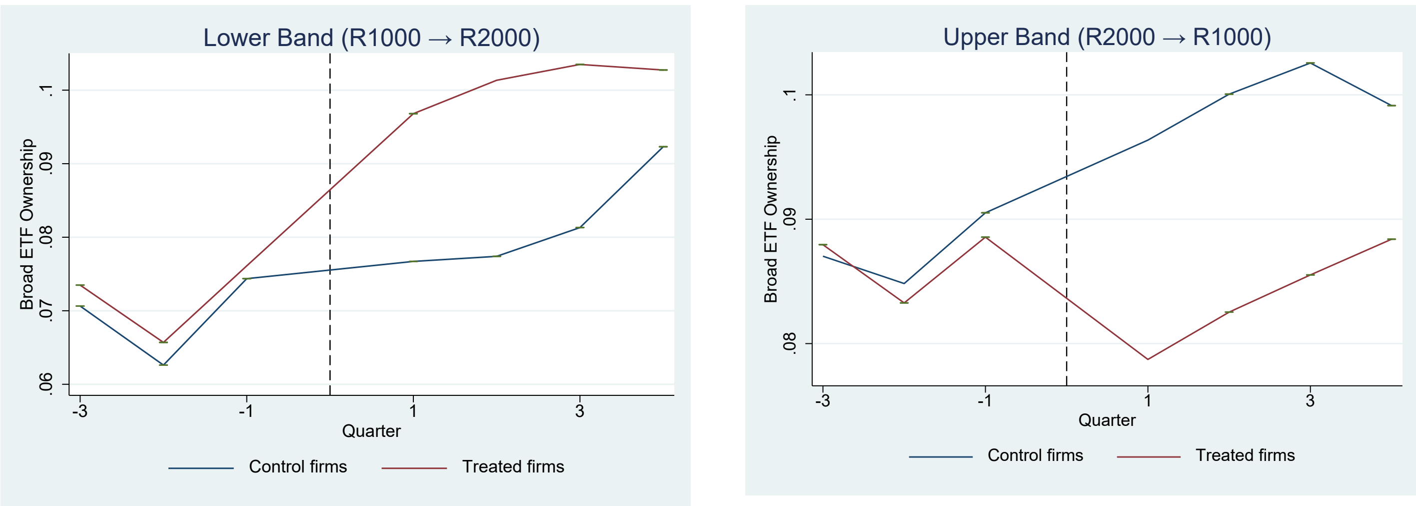

Figure 1b: Russell Index Switching and Broad ETF Ownership

Table 1: DID Sample and Distribution Across Time

Table 1 reports the number of firm-quarters in our treated and control groups in both cohorts for our DID analysis.

	Upper band (R2000→1000)		Lower band (R1000→2000)	
Cohort Year	Treatment	Control	Treatment	Control
2011	255	333	142	92
2012	201	277	175	104
2013	171	239	182	100
2014	183	161	137	94
2015	184	318	308	113
2016	172	268	271	88
2017	173	310	229	103
2018	368	239	203	96
2019	250	204	98	119
Average	217	261	194	101
Total	1,957	2,349	1,745	909

Table 2: Descriptive Statistics

Panel A presents descriptive statistics for the ownership structure and control variables for the sample used in the DID analysis. Panel B displays the pre- and post-treatment comparison of summary statistics for treated and controlled stocks in both cohorts. ETF_OWN is defined as the percentage of shares held by ETFs at the end of each quarter. SECTOR_OWN is defined as the percentage of shares held by sector-based ETFs at the end of each quarter. BROAD_OWN is defined as the percentage of shares held by broad-based ETFs at the end of each quarter. INSTOWN_PERC is defined as the percentage of shares held by institutional investors at the end of each quarter. See **Appendix A.1.** for detailed variable definitions. All variables are winsorized at 1% and 99% level.

Panel A: Summary statistics

Variable	N	Mean%	Median	Q1	Q3	Standard deviation
ETF_OWN	6,960	9.85%	0.097	0.066	0.133	0.055
SECTOR_OWN	6,960	0.87%	0.005	0.002	0.011	0.011
BROAD_OWN	6,960	8.96%	0.088	0.059	0.121	0.051
ANALYST_NO	6,960	1164.25%	11.000	7.000	15.000	5.996
ACCU	6,960	-33.63%	-0.120	-0.296	-0.046	0.697
INST_PERC	6,960	80.44%	0.906	0.749	0.993	0.262
△INST	6,960	0.13%	0.000	-0.011	0.014	0.042

Panel B: Pre- and post-treatment summary statistics

	Treatment Group				Control Group			
Variable	Pre	Post	**MeanDiff**	**Change%**	Pre	Post	**MeanDiff%**	**Change%**
Lower band (R1000→2000)								
ETF_OWN	0.087	0.106	0.019	21.52%	0.081	0.085	0.005	5.82%
SECTOR_OWN	0.010	0.009	-0.001	-11.11%	0.009	0.010	0.001	13.79%
BROAD_OWN	0.076	0.096	0.020	26.05%	0.072	0.075	0.004	5.31%
ANALYST_NO	12.670	12.135	-0.535	-4.22%	13.684	13.804	0.120	0.88%
ACCU	-0.488	-0.466	0.023	-4.63%	-0.507	-0.397	0.110	-21.74%
INST_PERC	0.766	0.778	0.012	1.54%	0.815	0.796	-0.019	-2.33%
Upper band (R2000→1000)								
ETF_OWN	0.098	0.093	-0.005	-5.28%	0.104	0.109	0.005	4.73%
SECTOR_OWN	0.008	0.011	0.003	41.56%	0.007	0.008	0.000	4.05%
BROAD_OWN	0.091	0.082	-0.009	-9.37%	0.096	0.101	0.005	4.78%
ANALYST_NO	11.450	11.908	0.459	4.01%	10.367	10.512	0.145	1.40%
ACCU	-0.374	-0.275	0.099	-26.49%	-0.205	-0.226	-0.021	10.15%
INST_PERC	0.825	0.803	-0.023	-2.73%	0.819	0.803	-0.016	-1.94%

Table 3: Effects of Index Assignment on Ownership

This table presents DID regression estimates of index reassignment on ETF and institutional ownership using the Russell index switch events. ETF_OWN is defined as the percentage of shares held by ETFs at the end of each quarter. SECTOR_OWN is defined as the percentage of shares held by sector-based ETFs at the end of each quarter. BROAD_OWN is defined as the percentage of shares held by broad-based ETFs at the end of each quarter. INSTOWN_PERC is defined as the percentage of shares held by institutional investors at the end of each quarter.

Model for the lower-band treatment in Panel A:

$$Y_{it} = \beta_1 I\{R1000 \rightarrow 2000_i\} \times PostAssignment_t + \emptyset_i + \lambda_t + \epsilon_{it}.$$

Model for the upper-band treatment in Panel B:

$$Y_{it} = \beta_2 I\{R2000 \rightarrow 1000_i\} \times PostAssignment_t + \emptyset_i + \lambda_t + \epsilon_{it}.$$

t-values are reported below each coefficient. Standard errors are robust and clustered by firm and year by quarter. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests. All variables are winsorized at 1% and 99% level.

Panel A: Lower Band

	(1) ETF_OWN	(2) SECTOR_OWN	(3) BROAD_OWN	(4) INSTOWN_PERC
R1000→R2000 X PostAssignment	**0.014*** **	**-0.001***	**0.015*** **	**0.017**
	(6.17)	**(-1.86)**	**(7.38)**	**(1.54)**
Intercept	0.090***	0.010***	0.079***	0.778***
	(129.82)	(45.73)	(122.81)	(238.30)
Year X Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	2,653	2,653	2,653	2,653
Adjusted R-squared	0.931	0.804	0.940	0.905

Panel B: Upper Band

	(1) ETF_OWN	(2) SECTOR_OWN	(3) BROAD_OWN	(4) INSTOWN_PERC
R2000→R1000 X PostAssignment	**-0.008*** **	**0.003*** **	**-0.010*** **	**0.015**
	(-4.32)	**(7.18)**	**(-6.11)**	**(1.55)**
Intercept	0.103***	0.008***	0.095***	0.814***
	(277.60)	(88.55)	(263.41)	(416.08)
Year X Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	4,303	4,303	4,303	4,303
Adjusted R-squared	0.9308	0.8579	0.9311	0.8329

Table 4: Effects of Index Assignment on Analyst Forecast Quality

This table presents DID regression estimates of index reassignment on analyst forecast quality using the Russell index switch events. Column (1) and (2) report the DID results for the lower band treatment, i.e., Column (3) and (4) report the DID results for the upper band treatment. ACCU is the proxy for analyst earnings forecast accuracy, which is calculated as the absolute value of the difference between the median consensus forecast value and actual earnings of the firm for the quarter, deflated by absolute actual earnings and multiplied by -1. ANALYST_NO is defined as the number of analysts that follow the firm during the quarter. INST_RESIDUAL is constructed as orthogonalized institutional ownership following Glosten et al. (2020).
Model for the lower-band treatment in Column (1) and (2):

$$ACCU_{it} = \beta_1 I\{R1000 \rightarrow 2000_i\} \times PostAssignment_t + \text{Controls} + \emptyset_i + \lambda_t + \epsilon_{it}.$$

Model for the upper-band treatment in Column (3) and (4):

$$ACCU_{it} = \beta_2 I\{R2000 \rightarrow 1000_i\} \times PostAssignment_t + \text{Controls} + \emptyset_i + \lambda_t + \epsilon_{it}.$$

t-values are reported below each coefficient. Standard errors are robust and clustered by firm and year by quarter. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests. All variables are winsorized at 1% and 99% level.

Dep. Var: ACCU	(1) Lower Band	(2) Lower Band	(3) Upper Band	(4) Upper Band
R1000→R2000 X PostAssignment	**-0.086***	**-0.087****		
	(-1.82)	**(-2.02)**		
R2000→R1000 X PostAssignment			**0.078****	**0.062****
			(2.62)	**(2.18)**
ANALYST_NO		-0.003		0.018**
		(-0.27)		(2.48)
INST_RESIDUAL		0.090		0.334
		(0.23)		(1.22)
Intercept	-0.435***	-0.396***	-0.276***	-0.471***
	(-34.66)	(-2.93)	(-67.23)	(-6.06)
Year X Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	2,653	2,653	4,303	4,303
Adjusted R-squared	0.154	0.153	0.237	0.240

Table 5: Effects of Broad and Sector ETF Ownership Change on Analyst Forecast Quality

This table presents DID regression estimates of index reassignment on analyst properties using the Russell index switch events. For each cohort (the lower or the upper band), We sort the absolute change of one type of ETF ownership and examine the effects of broad and sector ETF ownership change magnitude on analyst forecast accuracy. In Column (1) and (2), Large is an indicator variable equal to 1 if the broad ETF ownership change magnitude is above the sample median average, and 0 otherwise. In Column (3) and (4), Large is an indicator variable equal to 1 if the sector ETF ownership change magnitude is above the sample median average, and 0 otherwise. ACCU is the proxy for analyst earnings forecast accuracy, which is calculated as the absolute difference between the median consensus forecast value and actual earnings of the firm for the quarter, deflated by absolute actual earnings and multiplied by -1. ANALYST_NO is defined as the number of analysts that follow the firm during the quarter. INST_RESIDUAL is constructed as orthogonalized institutional ownership following Glosten et al. (2020). t-values are reported below each coefficient. Standard errors are robust and clustered by firm and year by quarter. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests. All variables are winsorized at 1% and 99% level.

	(1)	(2)	(3)	(4)
Type of ETF ownership change	**Broad ETF**	**Broad ETF**	**Sector ETF**	**Sector ETF**
Dep. Var: ACCU	Lower Band	Upper Band	Lower Band	Upper Band
R1000→R2000 X PostAssignment	-0.023		0.009	
	(-0.21)		(0.14)	
R1000→2000 X PostAssignment X Large	**-0.081**		**-0.196****	
	(-0.74)		**(-2.24)**	
R2000→R1000 X PostAssignment		0.065**		-0.026
		(2.13)		(-0.68)
R2000→1000 X PostAssignment X Large		**-0.013**		**0.138*****
		(-0.35)		**(2.89)**
Large	-0.091	-0.019	0.061	-0.014
	(-1.04)	(-0.66)	(0.84)	(-0.59)
ANALYST_NO	-0.002	0.018**	-0.002	0.018**
	(-0.21)	(2.50)	(-0.21)	(2.49)
INST_RESIDUAL	0.090	0.334	0.102	0.336
	(0.23)	(1.22)	(0.26)	(1.23)
Intercept	-0.342**	-0.463***	-0.439***	-0.464***
	(-2.32)	(-6.16)	(-3.20)	(-5.95)
Year X Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
N	2,653	4,303	2,653	4,303
Adjusted R-squared	0.153	0.240	0.155	0.241

Table 6: ETF Level Distribution

Panel A presents the sample distribution across time. # Distinct ETFs, # Sector ETFs and # Broad ETFs are the number of distinct ETFs, sector-based ETFs and broad-based ETFs in each year, respectively. The ETF sample includes 1,095 distinct equity ETFs with constituent holding information in the period from 2010 to 2020, with 447 sector ETFs and 648 broad-based ETFs. Panel B presents the industry distribution of the sector ETFs for our ETF-level test sample. # Distinct sector ETFs is the number of distinct sector ETFs in each year. % of Sector ETFs means the specific sector ETF's percentage of total sector ETFs.

Panel A: Distribution across Time (ETF Level)

Year	# Distinct ETFs	# Sector ETFs	# Broad ETFs	ETF Ownership	Sector ETF Ownership	Broad ETF Ownership
2010	319	157	162	3.79%	0.21%	3.58%
2011	387	184	203	4.84%	0.33%	4.51%
2012	338	142	196	5.39%	0.38%	5.01%
2013	326	139	187	5.93%	0.47%	5.46%
2014	336	139	197	6.41%	0.55%	5.86%
2015	419	164	255	7.12%	0.62%	6.50%
2016	500	214	286	8.03%	0.60%	7.43%
2017	587	234	353	9.70%	0.75%	8.95%
2018	727	288	439	11.05%	1.01%	10.05%
2019	763	297	466	11.72%	0.93%	10.79%
2020	828	311	517	12.19%	1.09%	11.11%

Panel B: Distribution of Sector ETFs by Sector

Sector	# Distinct sector ETFs	% of Sector ETFs
Basic Materials	33	7.38%
Consumer Goods	21	4.70%
Consumer Services	35	7.83%
Financial Services	46	10.29%
Health/Biotechnology	48	10.74%
Industrials	43	9.62%
Natural Resources	34	7.61%
Real Estate	24	5.37%
Science & Technology	78	17.45%
Specialty/Miscellaneous	48	10.74%
Telecommunication	18	4.03%
Total	**447**	**100%**

Table 7: Follower First Forecast Revision after Announcer's EA

This table presents the regressions examining the correlation between the announcer's earnings surprise and followers' immediate forecast revision. The main dependent variable is REV_F, which represents the followers' first forecast revision for the next forecast quarter issued within the 10-day window after announcer's EA, scaled by the stock price at the begin of the follower's revision issuance quarter. SUE_A represents the announcer's earnings surprise, which is defined as the actual value of quarter t's EPS minus the most recent median consensus analyst forecast of that quarter's EPS, scaled by the stock price at the beginning of each quarter. SECTOR is an indicator variable that equals 1 for sector ETFs and 0 otherwise. See **Appendix A.2.** for variable definitions. t-values are reported below each coefficient. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests. All continuous variables are winsorized at 1% and 99% level.

	(1)	(2)	(3)	(4)	(5)
Pairs From:	Sector ETFs	Broad ETFs	Both types of ETFs	Same-sector-nonETF	Sector ETFs and same-sector-nonETF controls
	REV_F	REV_F	REV_F	REV_F	REV_F
SUE_A	0.077***	-0.021	-0.017	0.014	0.006
	(2.89)	(-1.19)	(-1.03)	(0.32)	(0.15)
SECTOR			-0.000*		-0.000
			(-1.83)		(-1.46)
SECTOR*SUE_A			**0.076*** **		**0.082*** *
			(2.97)		**(2.12)**
LAG_SUE_F	0.003	0.016*	0.011*	-0.009**	-0.006
	(0.37)	(1.75)	(1.73)	(-2.20)	(-1.49)
ETFOWN	0.003	0.004***	0.003***	-0.000	0.003*
	(0.96)	(3.06)	(2.84)	(-0.17)	(1.88)
PERC_SEC	0.001	0.001**	0.001**	0.000	0.001
	(0.87)	(2.18)	(2.13)	(0.22)	(0.94)
$RET_{t-4, t-1}$	0.000	0.000**	0.000**	0.000	0.000
	(0.19)	(2.45)	(2.05)	(1.49)	(1.46)
INST_PERC	-0.000	0.000*	0.000	-0.001	-0.000
	(-0.64)	(1.80)	(1.64)	(-1.05)	(-1.06)
ANALYST_NO	-0.000*	-0.000***	-0.000***	0.000	-0.000*
	(-1.67)	(-4.58)	(-4.86)	(0.01)	(-1.69)
SIZE	0.000***	0.000***	0.000***	0.001***	0.000***
	(3.89)	(7.86)	(8.76)	(6.02)	(7.86)
BTM	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-4.06)	(-5.08)	(-6.56)	(-3.67)	(-6.08)
ROA	-0.008**	-0.001	-0.003*	-0.026***	-0.018***
	(-2.37)	(-0.48)	(-1.83)	(-5.71)	(-6.41)
LOSS	-0.001**	-0.000	-0.000**	-0.002***	-0.001***
	(-2.27)	(-0.97)	(-2.11)	(-6.71)	(-6.85)
_CONS	-0.006***	-0.007***	-0.007***	-0.012***	-0.008***
	(-3.23)	(-6.51)	(-7.40)	(-4.08)	(-5.95)
Announcer FE	Yes	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes
N	7,034	19,763	26,797	6,120	13,154
r2_a	0.115	0.101	0.094	0.147	0.110

Table 8: Cross-sectional Tests on Follower First Forecast Revision after Announcer's EA

This table presents cross-sectional test results for our ETF-level test. In column (1) and (2), we partition the ETF pair sample based on ETF turnover. We identify the announcer-follower pair ETF turnover as high if the average trading volume of the ETF for the quarter before announcer's earnings announcement date exceeds the sample median average, and low otherwise. In column (3) and (4), we partition the ETF pair sample based on analyst experience. We identify the follower's analyst as experienced if the analyst has been following the firm for a longer period than the sample median average, and inexperienced otherwise. In column (5) and (6), we partition the sample into high and low pairs based on the number of firms followed by the follower firm's analyst. In column (7) and (8), we partition the sample into high and low pairs based on number of industries (two-digit SICs) followed by the follower firm's analyst. See **Appendix A.2.** for variable definitions. t-values are reported below each coefficient. ***, **, * represent statistical significance at 0.01, 0.05 and 0.1 levels, respectively, based on two-tailed tests. All continuous variables are winsorized at 1% and 99% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ETF Turnover		Analyst Experience		Number of firms		Number of industries	
Dep. Var: REV_F	High	Low	Inexperienced	Experienced	High	Low	High	Low
SUE_A	-0.056**	0.005	-0.035	-0.019	-0.048**	0.028	-0.022	-0.003
	(-2.51)	(0.23)	(-1.52)	(-0.83)	(-2.00)	(1.38)	(-1.02)	(-0.16)
SECTOR	-0.000**	0.000	-0.000	-0.000*	-0.000**	-0.000*	-0.000***	-0.000
	(-2.17)	(0.47)	(-1.34)	(-1.96)	(-2.39)	(-1.78)	(-2.64)	(-0.71)
SECTOR*SUE_A	**0.132*** **	**-0.022**	**0.081*** **	**0.050**	**0.096*** **	**0.030**	**0.085** **	**0.017**
	(4.06)	**(-0.45)**	**(2.76)**	**(1.25)**	**(2.74)**	**(0.92)**	**(2.40)**	**(0.47)**
LAG_SUE_F	0.018**	0.005	-0.009	0.022***	0.007	0.007	0.004	0.010
	(2.03)	(0.60)	(-1.25)	(2.61)	(1.23)	(0.57)	(0.69)	(0.92)
ETFOWN	0.002	0.004***	0.003*	0.002	0.004**	0.001	0.000	0.007***
	(1.22)	(2.73)	(1.67)	(0.67)	(2.20)	(0.40)	(0.21)	(3.14)
PERC_SEC	0.001	0.001**	-0.001	-0.002*	-0.001*	0.001	-0.001	0.001
	(0.91)	(2.37)	(-1.08)	(-1.95)	(-1.83)	(0.78)	(-1.19)	(0.75)
$RET_{t-4, t-1}$	0.000	0.000*	0.000**	0.000	0.000	0.000*	0.000	0.000
	(0.58)	(1.92)	(2.37)	(1.37)	(1.33)	(1.67)	(0.95)	(1.40)
INST_PERC	0.000	0.001*	0.000	-0.000	-0.000	-0.000	-0.000	0.000
	(0.75)	(1.84)	(0.98)	(-1.25)	(-0.24)	(-0.66)	(-0.17)	(0.55)
ANALYST_NO	-0.000***	-0.000***	-0.000	-0.000	-0.000	-0.000**	-0.000	-0.000*
	(-3.75)	(-3.94)	(-0.95)	(-1.11)	(-0.55)	(-2.18)	(-0.29)	(-1.83)
SIZE	0.000***	0.000***	0.000***	0.000**	0.000***	0.000***	0.000*	0.000***
	(6.41)	(5.85)	(4.02)	(2.17)	(2.99)	(4.28)	(1.96)	(4.58)
BTM	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(-4.89)	(-4.50)	(-3.91)	(-3.22)	(-3.89)	(-2.99)	(-4.76)	(-3.33)
ROA	-0.004	-0.001	-0.007**	0.001	-0.003	-0.005*	-0.003	-0.006*
	(-1.57)	(-0.51)	(-2.54)	(0.31)	(-1.00)	(-1.72)	(-1.27)	(-1.96)
LOSS	-0.000	-0.000	-0.000**	0.000	-0.000	-0.000	-0.000	-0.000
	(-1.27)	(-1.43)	(-1.97)	(0.87)	(-1.17)	(-0.69)	(-1.52)	(-1.41)
_CONS	-0.007***	-0.008***	-0.006***	-0.003	-0.004***	-0.006***	-0.002	-0.008***
	(-5.77)	(-5.91)	(-3.98)	(-1.61)	(-2.72)	(-3.83)	(-1.45)	(-4.75)
Announcer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,198	13,063	13,156	12,226	13,531	11,971	13,572	11,977
r2_a	0.104	0.104	0.334	0.240	0.226	0.373	0.247	0.324

Appendix A: Variable Definitions

Table A.1: Firm-level DID Analysis

Variable	Description
R1000→2000	Indicator variable that equals 1 for the firm if the firm switches from the Russell 1000 to the Russell 2000 index after Russell annual reconstitution and 0 otherwise.
R2000→1000	Indicator variable that equals 1 for the firm if the firm switches from the Russell 2000 to the Russell 1000 index after Russell annual reconstitution and 0 otherwise.
PostAssignment	Indicator variable that equals 1 for firm-quarters after index reconstitution and 0 otherwise.
Large	Indicator variable equal to 1 if the broad (sector) ETF ownership change magnitude is above the sample median average, and 0 otherwise.
ETF_OWN	Percentage of shares held by ETFs at the end of each quarter.
SECTOR_OWN	Percentage of shares held by Sector-based ETFs at the end of each quarter.
BROAD_OWN	Percentage of shares held by Broad-based ETFs at the end of each quarter.
INSTOWN_PERC	Percentage of shares held by institutional investors at the end of each quarter.
△INST	The quarterly change in institutional ownership for the firm during the quarter.
INST_RESIDUAL	Orthogonalized institutional ownership. It is calculated as the residual from the cross-sectional regression in each quarter, following Glosten et al. (2021): $\Delta INST = \beta_0 + \beta_1 \Delta ETF\_OWN_{i,t} + \varepsilon_{i,t}$, where *ΔINST* and *ΔETF_OWN* are the change in percentage of shares held by institutional investors and ETFs from the end of the last quarter through the end of that quarter.
ANALYST_NO	The number of analysts that follow the firm during the quarter.
ACCU	Analyst earnings forecast accuracy calculated as the absolute value of difference between the median consensus forecast value and actual earnings of the firm for the quarter, deflated by absolute actual earnings and multiplied by -1.

Table A.2: ETF-level Analysis

Variable	Description
SECTOR	Indicator variable that equals 1 for sector ETFs and 0 otherwise.
INST_PERC	Percentage of shares held by institutional investors for the follower firm at the end of prior quarter. The data are obtained from the Thomson–Reuters s34 database.
ETFOWN	Percentage of shares held by ETFs for the follower firm at the end of prior quarter. The data are obtained from CRSP mutual funds database.
PERC_SEC	The ratio of sector-based ETF ownership to total ETF ownership for the follower firm at the end of prior quarter.
ANALYST_NO	The number of analysts that follow the follower firm during each quarter. The data are obtained from I/B/E/S.
SUE_A	The announcer's earnings surprise, which is defined as the actual value of quarter t's EPS minus the most recent median consensus analyst forecast of that quarter's EPS, scaled by the stock price at the beginning of each quarter.
REV_F	The followers' first forecast revision for the next forecast quarter issued within the 10-day window after announcer's EA, scaled by the stock price at the begin of the follower's revision issuance quarter.
LAG_SUE_F	The follower's earnings surprise for the quarter t-1.
SIZE	The logged market capitalization of the stock at the end of quarter t. The data are obtained from CRSP.
LOSS	Indicator variable that equals 1 for the follower firm if the firm makes a loss in the quarter (i.e., negative income before extraordinary items), and 0 otherwise. The data are obtained from Compustat.
ROA	Income before extraordinary items scaled by total assets for the quarter. The data are obtained from Compustat.
BTM	The book-to-market ratio of the stock at the end of quarter t. The data are obtained from Compustat.
$RET_{t-4,\, t-1}$	Compounded stock return between 12 months and 2 months prior to the current quarter t.