ETFs, Anomalies and Market Efficiency

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Abstract

We investigate the effect of ETF ownership on stock market anomalies and market efficiency. We find that low ETF ownership stocks exhibit higher returns, greater Sharpe ratios, and highly significant alphas compared to high ETF ownership stocks. We show that high ETF ownership stocks demonstrate more pronounced information flows than low ETF ownership stocks, reducing their mispricing as they are more informationally efficient. We find similar results when we match the two groups based on size, volume, book-to-market, and momentum. Our results are robust to different matching methods and a wide array of controls in Fama-MacBeth regressions. Using Russell index reconstitution, we find causal evidence that ETF ownership attenuates anomaly returns.

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1. Introduction

ETFs were first introduced in the 1990s, and they have demonstrated significant growth over the years, with assets under management exceeding $2.5 trillion in the United States, where the majority of ETF trading occurs. The trading volume of ETFs accounts for more than 35% of the volume of the U.S. market, covering almost 90% of the publicly traded equities. This asset class is prevalent among retail and institutional investors because – in contrast to conventional index funds – it offers intra-day liquidity and allows for tax management. In addition, ETFs compete with mutual funds and futures contracts due to lower management fees, making them a popular low-cost vehicle for domestic and foreign investments (e.g., Ben-David, Franzoni, and Moussawi (2018) and Filippou, Gozluklu, and Rozental (2022)).

However, it is still unclear whether the ease of ETF trading affects the mispricing of the underlying securities. ETFs are highly liquid, attracting demand from high-frequency traders and other institutional investors. This demand can impact the stocks of the ETF basket via ETF arbitrage. For example, a deviation of the price of the ETF from its net asset value (NAV) due to a demand shock could cause arbitrageurs to trade the underlying stocks in the same direction as the shock in the ETF market. To this end, we might observe the propagation of demand shocks from the ETF market to the underlying stocks. But whether or not the propagation affects the mispricing of the stocks is unknown. Ben-David, Franzoni, and Moussawi (2018) and Agarwal et al. (2018) show that these shocks can increase the volatility and the commonality in liquidity of ETF-underlying securities, but the impact on mispricing is largely unknown.

Intuitively, one could argue that stocks with high ETF ownership exhibit more enhanced information flow, making the underlying securities more informationally efficient. This effect could mitigate the mispricing of the underlying stocks and reduce anomaly profits. Consistent with this argument, Huang, O'Hara, and Zhong (2021) shows that industry ETF reduces PEAD and improves market efficiency for stocks with high industry risk exposure. In contrast to their studies, in this paper, we examine market efficiency in a broader setting. We study the attenuation effect of ETF trading on a comprehensive set of market anomalies in the US equity market compiled by Chen and Zimmermann (2020).

First, we investigate the effect of ETF ownership on anomalies one at a time. For each anomaly, we partition stocks in their long and short legs into three groups based on ETF ownership and compare the difference in performance between the anomaly consisting of only the top 1/3 and the bottom 1/3 stocks, respectively. If there were no effect of the ETF ownership, the difference should be zero theoretically and should be empirically indistinguishable. We find that of all the anomalies considered, the bottom ETF anomalies always perform better than the top ETF anomalies, indicating that ETF ownership has a significant impact on all the anomalies and high ETF ownership weakens the returns.

Second, we move on to aggregate all the information from the 205 anomaly variables by constructing a Net measure following Engelberg, McLean, and Pontiff (2018). The measure counts the number of times a stock occurs in the long leg of the anomalies relative to that of the short leg. Through the lens of Net portfolio analysis, we find that the market anomalies almost entirely 'reside' in the low ETF ownership group, which has a much higher average return, Sharpe ratio, and highly significant alphas across all leading factor models. The results hold after we match stocks on size, volume, and propensity score trained on stock characteristics.

Third, we show the attenuation effect of ETF ownership on anomaly mispricing through Fama and MacBeth (1973) cross-sectional regression. We run the regression of the future return on ETF ownership, Net, and the interactions between Net and ETF ownership with common control variables. We find that the interaction term is highly negative and significant across all of our regression settings, implying that for higher ETF ownership stocks, the typical anomaly variables no longer have conditional predictive power for future stock returns. The effect is not subsumed by the typical size and volume amplification effect as in Han et al. (2022) and Hou, Xue, and Zhang (2020).

Fourth, we explore the potential mechanism through which ETF attenuates stock mispricing. We find that high ETF ownership group stocks have significantly lower price delay by Hou and Moskowitz (2005), yielding quicker response of stock returns to market-wide news. This suggests that the ETFs propagate macro information flow more easily to individual stocks so that the impacted stock prices better reflect the macro information. As a result, mispricing declines.

Fifth, we further zoom in on the high-frequency news release and earnings announcement days, to see whether ETFs affect stock return predictability during the public information announcement. Engelberg, McLean, and Pontiff (2018) find that stock returns are more predictable based on anomalies during these news days and earnings announcement days, a fact that is consistent with investors correcting biased expectations upon the arrival of new information. Using their setting, we test whether ETFs attenuate ex-ante biased expectations or encourage more information-gathering ex-ante for underlying securities. We find that, at the news release time, ETFs reduce the predictability of stock returns from anomaly characteristics. As ETF ownership increases from 25% percentile to 75% percentile, the anomaly return on news release days decreases by 82.1%. This evidence suggests ETFs encourage the acquisition of systematic information ex-ante, which reduces anomaly returns at the time of public information release.

Last but not least, using the quasi-natural experiment of Russell index reconstitution, we demonstrate a causal effect of ETF ownership on anomaly profitability. The Russell 1000 and 2000 index reconstitutes their constituents every June following mechanical rules. They ranked the top 3000 stocks based on their market cap in May and split them around the 1000th stock's market cap to form the two indexes. Therefore, stocks around the cutoff can be seen as randomly entering into one index versus the other. Harnessing this random experiment, we select stocks around the 1000 cutoff and use Russell index constituents as an instrument for ETF ownership. In so doing, we find a significant attenuation effect of ETF ownership on anomaly returns, suggesting a causal relationship between ETF ownership and systematic mispricing.

Overall, our results appear to suggest that the ETF, arguably the most important disruptive innovation in the asset management industry over the last 30 years, has great potential for eliminating mispricing both at the aggregate level and for individual stocks.

The rest of the paper is organized as follows: Section 2 describes the channels and mechanisms through which ETF can influence systematic mispricing. Section 3 summarises our data, including ETF, stock return, construction of the Net portfolio, news announcement, and Russell index constituents. Section 4 presents our main empirical results based on portfolio sorts, matching, and Fama-MacBeth cross-sectional regression. Section 5 zooms in on the high-frequency evidence from the news release and earnings announcement. Section 6 summarizes the Russell index reconstitution natural experiment results. Section 7 concludes.

2. Mechanism and Channels

In this section, we explore the potential channels ETFs can influence the returns of stock market anomalies. Anomalies represent the systematic predictability of stock returns relative to benchmark models based on ex-ante observable characteristics. ETFs can influence the systematic component of stock returns because they can attract new groups of investors to the underlying securities or enable new trading strategies that are not easy to implement before, which can potentially change the market equilibrium and the price discovery process.

Cong and Xu (2016) show that after the ETF creation, systematic, informed traders would trade in the ETF market instead of individual stocks because ETFs have better liquidity and provide better exposure to the systematic factor the traders have information for. Before the introduction of ETFs, factor-informed traders could only trade in individual liquid stocks, leaving illiquid stocks unsynchronized to the systematic news. As a result, because of the participation of factor-informed traders, the creation of ETFs would impound more systematic information into the underlying stocks. The major friction in the model is the incompleteness of the market. Systematic traders have been constrained to only trade a small fraction of stocks but not a basket of all the stocks. Because ETF can alleviate this market incompleteness friction, it enables smooth, systematic information flow from the informed traders to the stock price. As a result of the increased information flow, the stock market becomes less predictable based on ex-ante stock characteristics. On the other hand, Ben-David, Franzoni, and Moussawi (2018) argue that ETFs would attract an additional layer of noise trader demand because it offers instant liquidity to the market. The noise trader combined with limits to arbitrage can cause the underlying security price to deviate further from its fundamental value. The ETF trading will transmit the behavioral bias of noise traders to the underlying securities, which can cause further systematic deviation of the underlying stock price to the rational benchmark. As a result, stock returns can be more predictable based on ex-ante characteristics.

Therefore, studying the effect of ETF on anomaly returns can resolve this tension: whether this financial innovation mitigates frictions, facilitates arbitrage trading, and enhances price discovery, or it increases the systematic risk, attracts speculations, and limits arbitrage. It can also shed light on the new group of investors attracted to the product and characterize the new equilibrium from the interaction between arbitrageurs and noise traders.

In addition, from the perspective of incorporating information into the stock price, we can further decompose the effect of ETF on market efficiency into two channels: (1) an ex-ante view of the efficiency; (2) an ex-post view of the efficiency. The first view highlights whether ETFs create incentives for ex-ante information gathering before the announcement of public information. The second view emphasizes whether ETFs facilitate the immediate reflection of the information in stock prices by reducing the drifting trend in stock prices after the resolution of uncertainty. Glosten, Nallareddy, and Zou (2021) and Huang, O'Hara, and Zhong (2021) provide convincing evidence on the ex-post informational efficiency by showing the reduction in PEAD tendency after high ETF activities. We try to provide some ex-ante evidence by showing that ETFs reduce the predictability of stock returns on public information release, which suggests more information has been incorporated into stock price ex-ante. The ex-ante view is related to the jump ratio test proposed by Weller (2018). If ETFs serve as good trading vehicles for systematic investors to profit from their information, they have a better incentive to acquire information ex-ante. Therefore, more acquirable systematic information will be embedded in stock price, and the price response at news releases will be smaller. So the price jump at the announcement divided by the cumulative return before the announcement will be lower.

In summary, by attracting a new group of investors and enabling new trading strategies, ETFs can change the market equilibrium and the systematic component of the stock price. We aim to empirically test whether this financial innovation enhances price discovery, facilitates arbitrage trading, or introduces an additional layer of noise trader risks to the underlying securities.

3. Data and Portfolio Construction

This section provides a summary of the data we used. We first introduce the ETF and stock data we used. Next, we describe our equity market anomaly dataset from Chen and Zimmermann (2020) and the construction of the net strategy following Engelberg, McLean, and Pontiff (2018), which aggregates information from all anomalies. Lastly, we summarize the news, earnings announcement data, and the Russell index constituents data, which we use to demonstrate the mechanism and causal impact of ETF ownership on anomaly returns and market efficiency.

3.1. ETF and Stock Data

ETF Metadata. We first construct metadata of ETFs with the identifiers, birth and death time. Since ETFs are traded securities, they appear in the CRSP database with a historical share code of 73. We directly use the birth and death time from the msenames table from CRSP as the existing time period for each ETF. Next, we merge the ETFs identified with the CRSP mutual fund database, which contains the details of the names of each ETF. Following Ben-David et al. (2021), we focus on ETFs that hold U.S. stocks in their baskets, so we exclude non-equity, foreign equity, leveraged and inverse-leveraged, and active ETFs. Our sample includes 1,509 unique U.S. equity ETFs with the inception and ending dates for each ETF over the period between January 2000 and December 2020.

ETF Holdings Data. We then use the ETF metadata to fetch ETF holdings from the Thomson-Reuters Mutual Fund Ownership (TFN) and the CRSP Mutual Fund Holdings databases (CRSP) within the inception and ending dates for each ETF. We use the MFLINKS developed by Russ Wermers and Wharton Research Data Service (WRDS) to merge the two databases together. We start collecting data from the databases with the earliest available date closer to the inception date in the CRSP database. Consistent with Ben-David, Franzoni, and Moussawi (2018), we find that before 2010 the TFN data were more reliable, while after 2010, the CRSP data became more timely and reliable. Thus, we follow Ben-David, Franzoni, and Moussawi (2018) and merge the pre-2010 TFN data with the post-2010 CRSP data to generate our ETF holding data between January 2000 and December 2020. Mirroring Agarwal et al. (2018) and Ben-David, Franzoni, and Moussawi (2018), for each stock at every month, we calculate its ETF ownership as:

$$ETFOWN_{i,t} = \frac{\sum_{j=1}^{N_t} MKTCAP_{i,t}^{j}}{MKTCAP_{i,t}} \tag{1}$$

where N_t is the total number of ETFs in month t, $MKTCAP_{i,t}^{j}$ is the total market cap of stock i held by ETF j in month t and $MKTCAP_{i,t}$ is the total market cap of stock i in month t.

Stock Market Trading and Characteristics Data. We collect the monthly trading data (return, market cap, trading volume) for common stocks with share codes 10 and 11 from CRSP. We obtain book-to-market, 12-month momentum, Amihud illiquidity, short interest, and the price delay directly from Chen and Zimmermann (2020). In constructing these variables, Chen and Zimmermann (2020) follows the principle to replicate the original study proposing these cross-sectional return predictive characteristics as much as possible. They demonstrate significant replication performance compared to original studies. To avoid non-standard errors as in Menkveld et al. (2021), we directly use the readily available data from Chen and Zimmermann (2020). We consider these variables because they are shown in the literature to have significant attenuation or amplification effects on anomaly profitability.

3.2. Anomalies and CZ Net Measure

Our goal is to examine the impact of ETF trading on the mispricing of the underlying securities. To this end, we build a net strategy that identifies the most overvalued and undervalued stocks based on many anomalies. In particular, we focus on the 205 anomalies compiled by Chen and Zimmermann (2020). We consider those anomalies both individually and together by constructing a Net strategy following Engelberg, McLean, and Pontiff (2018).

Anomalies. The anomaly dataset we rely on comes from Chen and Zimmermann (2020)[1]. The authors compiled a comprehensive dataset of anomalies and provided an open-source version of anomaly construction code. Therefore, we have detailed data on each anomaly's underlying stock characteristics and the portfolio constituents for different anomalies. Be-

[1]https://www.openassetpricing.com/. We used the 2021-04-22 vintage of the dataset with 205 anomalies in total

cause the authors open-sourced all the codes, we can construct different versions of the anomalies. For example, in our main analysis, we build two versions of anomalies: stocks with high ETF ownership and stocks with low ETF ownership. We then compare the return performance of these two versions of anomalies.

CZ Net Score. Following Engelberg, McLean, and Pontiff (2018), we define a mispricing score for every stock based on all the 205 anomalies in Chen and Zimmermann (2020) and call it CZ Net score or CZ score for brevity. Specifically, every month, we allocate stocks into decile portfolios based on each of the 205 signals and create 205 spread portfolios. Then, we compute the number of times a specific stock appears on the long side and short sides of the anomaly portfolios and calculate the difference between the long and short values. For example, if a stock belongs to 10 long portfolios and five short portfolios in a specific month, the CZ score will take the value of $10 - 5 = 5$ that month. In other words, stocks with more long positions will have a positive Net value, and stocks with more short positions will have a negative Net value.

CZ Net portfolios. Every month, we allocate stocks into deciles based on the previous month's CZ Net score. High CZ Net portfolios comprise undervalued stocks, while low CZ Net portfolios include overvalued stocks. We construct a zero-cost portfolio that buys high CZ Net stocks and sells low CZ Net stocks and labels it as CZ Net.

3.3. Earnings Announcement and News

We also obtain the earnings announcement and news release date data to shed light on the mechanism through which ETFs affect market efficiency. These salient information events arrive with a resolution of uncertainty. So anomaly returns on these event days would capture the ex-ante mispricing of stocks. Ex-ante means before the announcement of public information. On the other hand, ex-post mispricing would represent PEAD type of mispricing: whether there is a delayed reaction of stock price to public information.

Engelberg, McLean, and Pontiff (2018) document higher anomaly returns on corporate news days and earnings announcement days. Their results are consistent with anomaly returns arising from biased expectations, which are at least partially corrected upon new arrival. We are interested in examining how ETF ownership affects news-day anomaly returns to shed light on its effect on biased expectations.

Our corporate news data are from the RavenPack news database, which provides a comprehensive sample of firm-specific news stories from the Dow Jones News Wire[2] To ensure a news story is specifically about a given firm, we rely on the "relevance score" variable provided by RavenPack. The score ranges from 0 to 100, where a score of 0 (100) means that the entity is passively (predominantly) mentioned. Our sample only uses news stories with a relevance score of 100. To keep only fresh news about a company, we exclude repeated news by requiring the "event novelty score" from RavenPack to be 100. Following Jiang, Li, and Wang (2021a) and Jiang, Li, and Yuan (2021), we classify 12 out of 29 newsgroups as fundamental news, including acquisitions-mergers, analyst-ratings, assets, bankruptcy, credit, credit-ratings, dividends, earnings, equity-actions, labour-issues, product-services, and revenues. The remaining 17 newsgroups are classified as non-fundamental news.[3] If the news is announced after the market closes on the day t, we match the news with the close-to-close stock return on the day $t + 1$.

We obtain the earnings announcement dates from Compustat. Since Compustat does not report the time of the earnings announcement, we follow Engelberg, McLean, and Pontiff (2018) to examine the trading volume of the stock scaled by the market trading volume before, on, and after the reported earnings announcement and set the day with the highest scaled trading volume as the trading day for the earnings announcement. Throughout our news analysis, we exclude the 3-day earnings announcement date window from the corpo-

[2]Recent studies using this data set include Kelley and Tetlock (2017), Jiang, Li, and Wang (2021a), and Jiang, Li, and Yuan (2021).

[3]Note that applying these filters does not introduce look-ahead bias because RavenPack processes all news articles within milliseconds of receipt, and the resulting data are immediately sent to subscribers. Thus, the information is available in real-time.

rate news release days to gauge the effect of corporate news and earnings announcements separately.

3.4. Russell Index Constituents

Last but not least, to address the endogeneity concern, we use the Russell index reconstitution quasi-natural experiment to measure the causal effect of changes in ETF ownership on underlying stocks informational efficiency.

Our procedures follow Chang, Hong, and Liskovich (2015) and Appel, Gormley, and Keim (2016). We obtain the Russell constituents' data from Russell investments. The data include the Russell 1000 and 2000 index constituents each month and the market cap Russell used to calculate the portfolio weights and determine portfolio reconstitution. Following Appel, Gormley, and Keim (2016), we limit our sample to be between January 2000 and May 2007 because starting from May 2007, Russell changed its mechanical market cap-based ranking rule to a more flexible one which makes the market cap, not the sole determinant of getting into one index versus the other.

Since our identification comes from the regression discontinuity setting around the market cap, we need to specify a bandwidth and keep only the stocks within the bandwidth. Following Appel, Gormley, and Keim (2016), we examine bandwidth of 200, 300, and 400, i.e., we keep Russell 2000 stocks whose end-of-May market cap is within the rank $1000 \pm bandwidth$.

4. Empirical Results

In this section, we present our main empirical analysis of the effect of ETFs on market efficiency through the lens of stock market anomalies. Section 4.1 presents our sample's summary statistics of the stocks and ETFs. Section 4.2 shows our portfolio analysis for 205 individual anomalies. Section 4.3 presents the portfolio analysis based on aggregated information from all anomalies into a Net variable. Section 4.4 and 4.5 present the controlled portfolio analysis and Fama-MacBeth regression results. We control for the usual suspects that have attenuation or amplification effects on stock mispricing and show the significant effect of ETF ownership on anomaly profitability. Last but not least, section 4.6 examine the price delays for stocks with different level of ETF ownership, and section 4.7 classifies the ETF into active and passive ones and examine their influence on anomaly returns separately. These two sections inspect the potential mechanism through which ETFs can affect market efficiency.

4.1. Summary Statistics

Stock Characteristics. We present descriptive statistics of stocks with low and high ETF ownership. Specifically, we define the high ETF ownership stocks as the top $\frac{1}{3}$ stocks and the low ETF ownership stocks as the bottom $\frac{1}{3}$ stocks and calculate the average return, the average ETF ownership, the log market capitalization, the dollar volume, the log book-to-market ratio, the past 2-to-12-month cumulative return, and the price delay measure from Hou and Moskowitz (2005).

Table 1 shows the results for low ETF ownership (Panel A) and high ETF ownership (Panel B) stocks. We find that low ETF ownership stocks exhibit higher returns, lower market capitalization, lower dollar volume, lower cumulative returns, and higher price delay. On average, low ETF ownership stocks are more volatile as evidenced by the higher return standard deviation. On the other hand, high ETF ownership stocks tend to be larger in size and have higher dollar trading volumes.

ETF Characteristics. We report the number of US equity ETFs over time. Graph (a) of Figure 1 shows the number of ETFs in our sample from January 2000 until December 2020. We find that there is significant growth in ETFs. Specifically, at the beginning of our sample, we have a limited number of ETFs, while in 2020, we observed more than 800 ETFs. Graph (b) of Figure 1 shows the proportion of the equities market that ETFs own.

We observe that the proportion steadily increases over time and reaches more than 7% in December 2020. Graph (c) of Figure 1 displays the proportion of stocks that are held by ETFs over time. We find that ETFs cover almost all available stocks by the end of our sample period. Specifically, we observe a sharp increase in ETF coverage between 2000 and 2004; afterward, ETFs cover more than 80% of the U.S. equities. We also find in Graph (c) of Figure 1 that the total Net Asset Value (NAV) of ETFs in our sample increases over time, reaching around $3 trillion in December 2020. The results jointly indicate the growing importance of ETF as an investment vehicle.

4.2. Anomalies and ETF Ownership

In this section, we examine individually which anomalies are more impacted by ETF ownership. Specifically, conditional on the long or short leg of a given anomaly, we further equally partition each portfolio into three groups by ETF ownership. We define the high ETF ownership group as the top $\frac{1}{3}$ stocks and the low ETF ownership group as the bottom $\frac{1}{3}$ stocks. We form 205 long-short portfolios using low and high ETF ownership stocks, respectively, and we calculate the return difference between high and low ETF ownership anomalies. We find that the overall anomalies are much stronger for the low ETF ownership group. None of the 205 anomalies has significantly higher mean returns in the high ETF ownership group than in the low ETF ownership group at 5% level, while 26 of them have significantly lower mean for the high ETF ownership group than the low ETF ownership group.

Table 2 presents the anomalies with significant return differences at 5% level between high and low ETF ownership groups under the Benjamini and Hochberg (1995) multiple testing adjustment. There are 26 anomalies in total. They all have higher returns in the low ETF ownership group compared to the high ETF ownership group. We further present the category each anomaly belongs to. We find ETF ownership has a strong effect on anomalies belonging to the following categories: earnings event, earnings growth, earnings forecast, external financing, and momentum, all of which reflect ETFs' role in incorporating fundamental information faster into the stock price and reducing the medium-term momentum of stock price movement.

4.3. CZ Net Strategy

To examine the relation between ETF ownership and anomalies, we aggregate the information of all anomalies together into a Net measure as discussed in Section 3.2, and present summary statistics of the CZ Net strategy for low and high ETF ownership portfolios.

CZ Net Score. Table 3 provides the summary statistics of the long and short counts and the CZ Net score defined as *Long* - *Short* for the whole sample in Panel A, the high ETF ownership group in Panel B, and the low ETF ownership group in Panel C. The average CZ Net score is 1.93 for all stocks, 5.56 for low ETF ownership stocks, and -0.37 for high ETF ownership stocks, indicating that low ETF ownership stocks are more likely to be on the long leg of the anomaly portfolios on average.

CZ Net Performance. Table 4 further summarizes the mean, standard deviation, and Sharpe ratio of CZ-Net-score-sorted portfolios. P1 denotes stocks in the lowest decile (e.g., overvalued stocks), and P10 denotes stocks in the top decile (e.g., undervalued portfolios). We also report results for a strategy that buys P10 and sells P1 and label it as CZ Net in the last column. Panels A, B, and C respectively present results for all stocks, low ETF ownership stocks, and high ETF ownership stocks, respectively.

For the long-short portfolio formed by different stock samples, high ETF ownership group stocks produce a mean return spread of 1.04% per month with an annualized Sharpe ratio of 0.77, much lower than the mean of 2.81% and Sharpe ratio of 2.22 produced by low ETF ownership stocks. This sharp contrast echoes our previous finding that anomalies are attenuated among stocks with high ETF ownership.

Alphas. We further run time-series regressions of the CZ Net portfolio returns against several leading factor models, including CAPM, Fama and French (2015) with momentum (FF6), Hou, Xue, and Zhang (2015) (HXZ), Stambaugh and Yuan (2017) (SY), and Daniel, Hirshleifer, and Sun (2020) (DHS). We find that the anomalies almost completely 'reside" among the low ETF ownership group. Across different factor model specifications, the low ETF ownership group exhibits highly significant alphas with t-statistics above ten while for the high ETF ownership group, the alphas are much weaker in both magnitude and economic significance. Based on the new threshold set by Harvey, Liu, and Zhu (2016), three new factor models (HXZ, SY, and DHS) can successfully digest the mispricing among the high ETF ownership group.

Another corroborating evidence comes from the time-series plot of the log cumulative return on the long-short CZ Net portfolio. Figure 2 illustrates the performance of the CZ Net portfolio for all stocks, stocks with high ETF ownership, and those with low ETF ownership. Strikingly, the low ETF ownership portfolio continues to rise throughout the entire sample without major drawdowns, whereas the high ETF ownership portfolio exhibits an elbow breakpoint around 2003 and remains relatively flat afterward. The latter evidence is also documented by Green, Hand, and Zhang (2017). Note that 2003 is the time period with the fastest rise in ETF coverage, as shown in Figure 1. Yet the elbow breakpoint does not appear among low ETF ownership stocks, suggesting that high ETF ownership can potentially explain the attenuation of anomalies.

4.4. Matched Sample of Low and High ETF Ownership Stocks

Despite the aggregate pattern, many factors, such as size and volume, can contribute to attenuating anomaly profitability among high ETF ownership stocks. To isolate ETF's role in stock mispricing, we report results based on high and low ETF ownership stocks with similar characteristics. Specifically, we perform three stock matching procedures: matching by size, matching by size and volume, and a propensity score matching that simultaneously considers many characteristics. We mainly focus on the results based on matching with size and our findings are robust to different matching methods.

Matching procedure. We perform a nearest neighbour without a replacement matching algorithm to balance the number of matched stocks. Our matching runs in iterations. For each iteration, we try to match each stock in the treatment group (high ETF ownership) with one stock from the control group (low ETF ownership) with the closest matching variable. If multiple treated stocks are mapped to the same stock from the control group, we keep the pair with the smallest distance. Note that the distributions of the characteristic to be matched can be very different in the treated and the control group. The observations lie in the common support of the distributions should be matched. observations outside the common support will be too far away from each other. As our matching algorithm iterates, we are exhausting the observations whose matching characteristics lie in the common support. If there is no observations sharing similar characteristics, nearly all the observations in the treated group will be matched to the same observation in the control group. There will be only one pair of matches. We don't want to go to this extreme as the matched pair will have very different characteristics. Therefore, we stop the loop when the marginal increase in the number of pairs matched is less than 100, which suggests the overlapping support for the distribution of treated and control groups is close to measuring 0. In our empirical setting, we find typically; the algorithm finishes in less than ten iterations.

Table 6 presents the number of stocks matched and the characteristics before and after the match. As can be seen, the successfully matched pair ranges from 20.7% to 24.2% across different matching methods. The characteristics before and after the matching are very close, confirming that our research design effectively controls for leading confounding variables such as size and volume.

Matching results. Table 7 presents the CZ Net decile portfolios for low and high ETF ownership groups. As can be seen, the long-short portfolio average return is 2.26% per month (with an annual Sharpe ratio of 1.41) for the low ETF ownership group compared to 1.33% per month (with an annual Sharpe ratio of 0.56) for the high ETF ownership group. We perform a statistical test for Sharpe ratio based on Ledoit and Wolf (2008) and show the results in Table 6. The difference in Sharpe ratio is significant at 5% level with a p-value of 0.016.

Furthermore, we provide evidence on portfolio α in Table 8. As can be seen, all LS portfolios in the low ETF ownership group have significant α concerning all factor models. On the other hand, the high ETF ownership group's LS return can be fully digested by almost all the models. From the results, ETF ownership provides additional attenuation to trading profits of anomalies after controlling for size.

Robustness Check. In addition to matching based on size, we also perform matching based on size and volume as well as propensity score matching. For size and volume matching, the distance between two stocks is determined by the Euclidean distance between standardized size and volume tuples. The matching procedure is the same as the one for size alone. For propensity score matching, we first fit a logit model of an ETF ownership dummy variable on size, volume, book-to-market, and 12-month momentum, where the high ETF ownership is labeled as 1 while low ETF ownership is 0. We then match stocks based on the fitted propensity score from the logit model.

Across all the different specifications, we find that our findings' portfolio return results and α results are robust. Table 9 presents the portfolio results for size and volume matching and propensity score matching. In both cases, we find that low ETF ownership stocks offer higher stock returns and Sharpe ratios.

4.5. Cross-sectional Regressions

In addition to the portfolio analysis, we provide additional support to our hypothesis using Fama and MacBeth (1973) cross-sectional regression of future stock returns on the CZ

Net, ETF ownership, the interaction between the CZ Net and ETF ownership, and a number of controls. Based on our hypothesis, ETF ownership would have an attenuation effect on the mispricing from the anomalies. Therefore, it would predict a significant negative regression coefficient for interaction between the CZ Net and the ETF ownership.

The basic regression we run takes the following form:

$$\begin{aligned} Ret_{i,t+1} =& \alpha_t + \beta_{1,t}\text{ETF Ownership}_{i,t} + \beta_{2,t}\text{CZ Net}_{i,t} + \delta_{1,t}\text{ETF Ownership}_{i,t} \times \text{CZ Net}_{i,t} \\ &+ \eta_t\text{Controls} + \epsilon_{i,t+1} \end{aligned} \tag{2}$$

where control variables include size, volume as well as their interactions with CZ Net because they are known to have an amplification effect for anomaly mispricing (Hou, Xue, and Zhang (2020), Han et al. (2022)). We also include typical predictors related to stock returns, including BM and 12-month momentum.

Table 10 reports all the regressions we run. As can be seen, the interaction between ETF ownership and CZ net is highly significant and large in magnitude across different regression specifications suggesting ETF ownership has an incremental attenuation effect on anomaly profits beyond the control variables.

4.6. ETFs Induce Information Flows

To inspect the mechanism through which ETFs attenuate the trading profit of anomalies, we provide the initial evidence of informational efficiency based on the price delay measure proposed in Hou and Moskowitz (2005). This measure captures whether there is a delay in response of stock returns to market-wide news. In the June of each year, Hou and Moskowitz (2005) regress each stock's returns on contemporaneous market returns and lagged market returns from the past 4 weeks using the past 1 year observations:

$$R_{it} = \alpha_i + \beta_i R_{mkt,t} + \sum_{j=1}^{4} \delta_i^{(-j)} R_{mkt,t-j} + \epsilon_{it} \tag{3}$$

The price delay is defined as:

$$PD = 1 - \frac{R^2_{\delta_i^{-j}=0, \forall j \in [1,4]}}{R^2} \tag{4}$$

It measures the decline in R^2 if we set the regression coefficient on lagged market returns to 0. If the stock price incorporates systematic market information instantaneously, the regression equation 3 would have 0 loading on past market returns. So the price delay would be 0. On the other hand, if there is a delayed response of stock return to systematic information, the PD measure will be large.

We want to use this measure to test whether ETFs enhance systematic information flow to the underlying securities. Figure 3 presents the evolution of price delay (PD) over time for the high ETF ownership and low ETF ownership groups. We can clearly see that the low ETF ownership group has a much higher price delay compared to the high group, which sees a significant decline in PD during the initial rollout period of ETF from 2000 to 2004. We also present the two groups' summary statistics of price delay in table 1.

The results suggest ETF trading links stocks closer to market fundamentals and embeds market-wide systematic information faster into stock prices.

4.7. Active vs Passive ETFs

Easley et al. (2021) document an increasing trend in the activeness of ETFs. We further break down our ETF sample into active and passive ones and examine their different effects on market efficiency.

Following Easley et al. (2021), we calculate an activeness index for each ETF j:

$$ActivenessIndex_{j,t} = \sum_{i=1}^{N} w_{j,i,t} - w_{market,i,t} \tag{5}$$

where $w_{j,i,t}$ is the weight of stock i in ETF j and $w_{market,i,t}$ is the weight of stock i in the market portfolio. By design, this activeness index will lie between 0 and 1. We define active ETFs as those with an activeness index above 0.5. This definition would encompass two kinds of ETFs in the active category: (1) ETFs that passively track a non-market index; (2) ETFs that are truly active in the sense of having full discretion over the portfolio choice. Although type (1) ETFs follow fixed rules, they usually serve as building blocks for active trading strategies. Huang, O'Hara, and Zhong (2021) documents the hedge funds' longing for the stock and shorting the industry ETF arbitrage behaviours. Therefore, the definition of active ETFs captures their contribution to active trading strategies.

We then separately perform the same portfolio analysis based on active ETF ownership and passive ETF ownership. Table 11 reports the controlled LS portfolio return statistics. We find that active ETFs have stronger impacts on anomaly returns compared to passive ETFs. Based on the active ETF ownership, the spread between average return and SR for low and high ETF ownership groups is larger than that for the passive ETF ownership. This highlights the important role active ETFs play in enhancing market efficiency.

5. News and Earnings announcement

Our analysis so far focuses on low-frequency monthly observations and highlights the significant attenuation effects ETFs have on the profitability of anomaly returns. In this section, we further analyze the high-frequency resolution of uncertainty during earnings announcements and news release days for companies using daily stock returns data. When there is more ex-ante mispricing for stocks, anomaly returns would be stronger on these news announcement days. Therefore, the news announcement and corresponding anomaly returns offer a natural setting to examine the effect of ETF on the ex-ante mispricing of the underlying securities.

Engelberg, McLean, and Pontiff (2018) found anomaly returns are 50% higher on news release days and six times higher on earnings announcement days. They provide evidence that such high returns come from biased expectations, which were partly correct at the time of the news arrival. If ETFs make stock prices more efficient ex-ante, we would expect anomaly variables to have less predictive power for stocks with high ETF ownership on news announcement days.

We run the following regression to test whether ETF alleviates ex-ante biased expectation by impounding more systematic information into the stock price.

$$\begin{aligned} Ret_{it} =& \alpha + \beta_1 Net_{i,t-1} + \beta_2 Eday_{it} + \beta_3 Nday_{it} + \beta_4 ETF_{i,t-1} + \beta_5 Net_{i,t-1} \times Eday_{it} \\ &+ \beta_6 Net_{i,t-1} \times NDay_{it} + \beta_7 Net_{i,t-1} \times ETF_{i,t-1} \times Eday_{it} \\ &+ \beta_8 Net_{i,t-1} \times ETF_{i,t-1} \times Nday_{it} + Controls_{i,t-1} + \delta_t + \epsilon_{it} \end{aligned} \tag{6}$$

where $Eday$ and $Nday$ are indicator variables that take a value of 1 on earnings announcement days and news release days, respectively. ETF is our ETF ownership measure, and Net is the CZ Net variable we constructed in our previous settings. Our controls include market cap, past 12-month momentum, book-to-market ratio, Amihud illiquidity, and short interest. The variables of interest are β_7 and β_8. Based on the results from Engelberg, McLean, and Pontiff (2018), we expect to see a positive sign for $Eday \times Net$ and $Nday \times Net$. If our hypothesis that ETF improves ex-ante market efficiency is true, we expect to see significant negative values for β_7 and β_8.

Table 12 reports the regression results for equation 6. We find that ETF ownership significantly lowers the anomaly returns on earnings announcement days and news release days. As ETF ownership increases from 25% percentile to 75% percentile, the anomaly returns on news release days would decrease by 82.1%, and their returns on earnings announcement days would decrease by 30.5%.

Furthermore, we decompose our news data into fundamental news and non-fundamental news. We run regression in equation 6 separately for these two groups. The results are reported in panel B and panel C of table 12. We find ETFs mainly affect anomaly returns by incorporating fundamental news faster into the price. The regression coefficient β_8 is significant for the regression with fundamental news, while it is insignificant in the non-fundamental news regression.

6. Russell Reconstitution Quasi-Natural Experiment

Last but not least, to address the endogeneity concern, we use the Russell reconstitution quasi-natural experiment to establish the causal effect of changes in ETF ownership on the underlying securities' informational efficiency.

The Russell 1000 and 2000 index follows mechanical annual reconstitution rules. On the last Friday of June, FTSE Russell determines which stocks will go into Russell 1000 index versus Russell 2000 index by looking into their market caps on the last trading day of May. The Russell 1000 index comprises the largest 1000 stocks, while the Russell 2000 index consists of the next 2000 stocks.

Therefore, stocks whose market cap is around the cutoff on the last Friday of June can be seen as randomly assigned into Russell 1000 vs Russell 2000. Since the two indexes are all value-weighted, stocks that end up entering the Russell 2000 will have a much larger portfolio weight than the Russell 1000 because the stock would be among the largest ones in Russell 2000 portfolio. Since there are many ETFs either passively tracking the two indexes or actively using the two indexes as a benchmark, the randomized assignment of stock would result in substantially different flow and ownership from ETFs.

Chang, Hong, and Liskovich (2015) used this natural experiment to gauge the elasticity of the stock market. Appel, Gormley, and Keim (2016) exploited this random variation to study the effect passive investors have on firms' corporate governance. In the ETF literature, Ben-David, Franzoni, and Moussawi (2018) and Glosten, Nallareddy, and Zou (2021) both apply this technique to demonstrate the causal effect of ETFs on stock volatility and PEAD behaviours.

Our empirical procedure mainly follows Appel, Gormley, and Keim (2016). In the first stage, we regress ETF ownership on an indicator variable for whether the stock is in Russell 2000, CZ Net, and other controlling variables with a time-fixed effect:

$$ETF\%_{it} = \eta + \lambda R2000_{it} + \gamma Net_{it} + Controls_{it} + \delta_t + u_{it} \tag{7}$$

where $ETF\%_{it}$ represents the ETF ownership of stock i at time t. $R2000_{it} = 1$ if stock i is in Russell 2000 at time t. It equals 0 if the stock is in Russell 1000. Our controls include size, illiquidity, short interest, index fund ownership, book-to-market ratio, and momentum. Table 13 presents the first-stage regression estimates. We can see that the ETF ownership is strongly related to the Russell 2000 assignment. The first-stage t-statistics across three bandwidth settings are higher than the critical value of 4.05 in Stock and Yogo (2002).

In the second stage, we run the following regression:

$$Ret_{i,t+1} = \alpha + \beta_1 \widehat{ETF\%}_{it} + \beta_2 Net_{it} + \beta_3 \widehat{ETF\%}_{it} \times Net_{it} + Controls_{it} + \delta_{t+1} + \epsilon_{i,t+1} \tag{8}$$

where $\widehat{ETF\%}_{it}$ refers to the fitted value of ETF ownership from the first stage. The key parameter of interest is β_3. We want to see whether changes in ETF ownership caused by the exogenous variation in Russell reconstitution will have an attenuation effect on anomaly returns.

Table 13 presents the results of the second-stage regression. We found that the interaction term $ETF \times Net$ is significantly negative across our three different specifications with different bandwidths. From the regression, a 1% increase in ETF ownership would attenuate 81.2% of anomaly returns based on Net. The regression has similar estimates across three different bandwidth settings. Therefore, from the Russell reconstitution experiment, we found causal evidence that ETFs have an attenuation effect on anomaly returns.

7. Conclusions

In this paper, we investigate the role of ETF ownership in the mispricing of anomaly portfolios. We document a strong attenuation effect ETF ownership has on the stock market anomalies' profitability.

We show the attenuation effect firstly by inspecting the profitability of each anomaly long-short (LS) portfolio. Under multiple testing adjustments, we find none of the anomaly LS portfolios has significantly higher returns in the high ETF ownership group than the low ETF ownership group. In comparison, 26 anomalies exhibit significantly higher returns in the low ETF ownership group. Then we aggregate all information contained in anomalies into a Net variable. Performing portfolio analysis for the high and low ETF ownership groups, we find that the profitability of the Net LS trading strategy only exists in the low ETF ownership group. The results suggest that anomalies completely "reside" in the low ETF ownership group. Moreover, there is no significant alpha for the Net LS portfolios across several leading factor models for the high ETF group. The results also hold for matched stock samples based on size, volume, and propensity scores. Furthermore, we corroborate the attenuation effect of ETF using the Fama-MacBeth regressions. We find a highly significant negative interaction effect between Net and ETF ownership, distinctive from other anomaly mispricing amplification channels such as size and volume.

On ex-ante market efficiency, we find the predictability of anomaly characteristics decreases on news announcement days for high ETF ownership stocks, suggesting the information has been incorporated into the stock prices before the announcement through the information acquisition of systematic investors trading ETFs. On ex-post market efficiency, we find the price delay measure of individual stocks is much lower for the high ETF ownership group compared to the low ETF ownership group. The result suggests stock prices immediately incorporate market-wide systematic news, reducing any ex-post drift trend.

Last but not least, we identify a causal effect of ETF ownership on anomaly returns through the Russell index reconstitution natural experiment. Using Russell 2000 membership as an instrument, we find a significant causal attenuation effect of ETF ownership on anomaly returns.

Overall, the evidence suggests that ETFs improve market efficiency by incentivizing ex-ante systematic information collection and incorporating systematic market news more quickly into individual stock prices.

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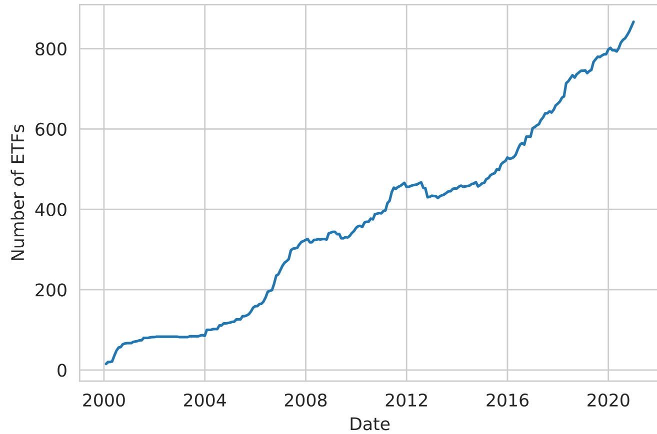
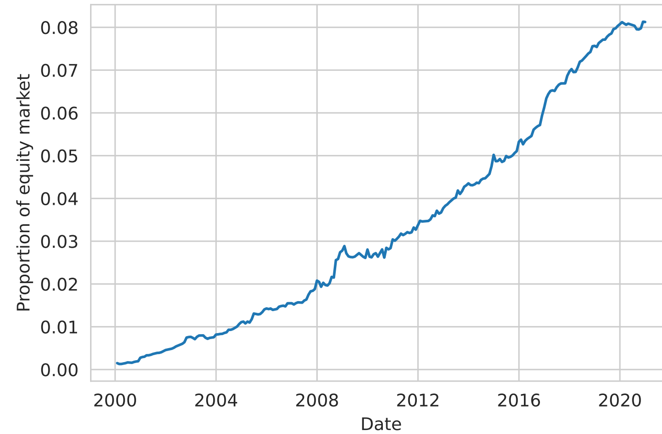
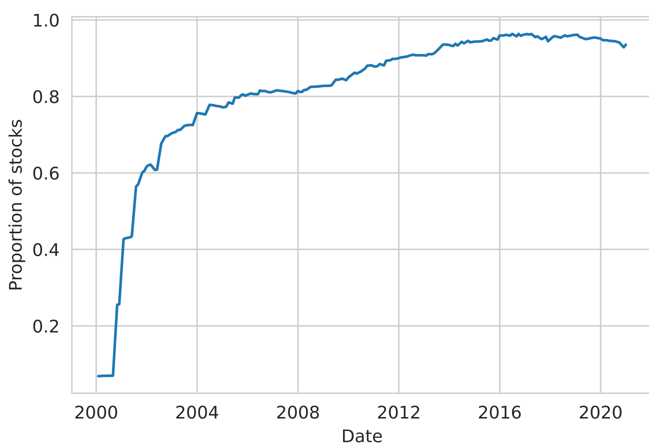


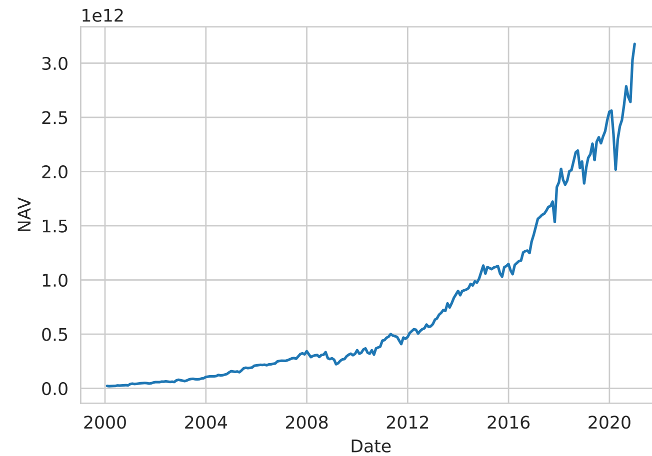
(a) Total Number of U.S. Equity ETFs



(b) Proportion of the Equity Market Owned by ETFs



(c) Proportion of Stocks held by ETFs



(d) Total Net Asset Value of U.S. equity ETFs

Figure 1: ETF Characteristics and Stock Holdings

The figure displays different summary statistics of US equity ETFs and their stock holdings. Graph (a) shows the total number of US equity ETFs over time. Graph (b) shows the proportion of the US equity market owned by ETFs, which is defined as the total ETF NAV dividing the total equity market cap. Graph (c) presents the proportion of stocks covered by ETFs. If a stock is owned by at least one ETF in our sample, we count it as being covered by the ETFs. Graph (d) shows the total net asset value (NAV) of US equity ETFs. Our sample period starts in January 2000 and ends in December 2020.

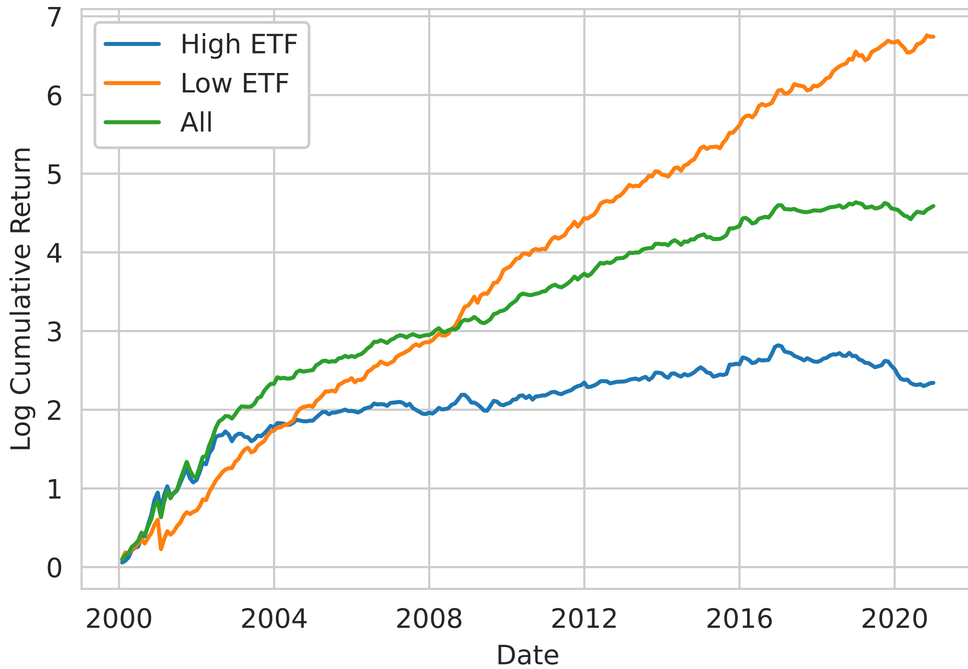


Figure 2: Log Cumulative Return of the CZ Net Portfolios

This figure plots the log cumulative portfolio value from investing in different CZ Net long-short portfolios from January 2000 to December 2020. At beginning of month t, we sort stocks based on their month $t-1$ CZ Net value into decile portfolios. We then long the top decile and short the bottom decile and hold the portfolio until the beginning of the month $t+1$. All portfolios are equal-weighted. The green line represents the strategy return using all stocks. The blue (orange) line represents the strategy return using only high (low) ETF ownership stocks. The high (low) ETF ownership stocks are defined as stocks whose ETF ownership (defined in equation 1) is in the top (bottom) tercile among all stocks.

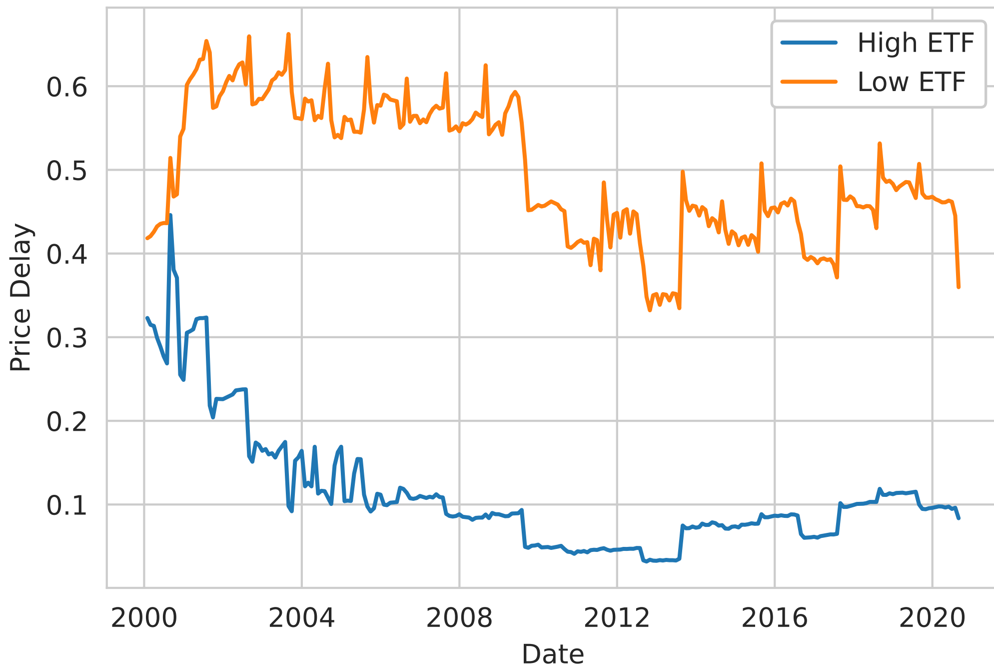


Figure 3: Average Price Delay for High and Low ETF Ownership Groups

This figure plots the cross-sectional average price delay (defined in equation 4) for high and low ETF ownership stocks from January 2000 to December 2020. The high (low) ETF ownership stocks are defined as stocks whose ETF ownership (defined in equation 1) is in the top (bottom) tercile among all stocks.

Table 1: Summary Statistics for Stocks Grouped by ETF ownership

This table reports the summary statistics for stocks grouped by ETF ownership. The high (low) ETF ownership stocks are defined as stocks whose ETF ownership (defined in equation 1) is in the top (bottom) tercile among all stocks. We report the summary statistics for returns, ETF ownership(multiplied by 100), log market cap, log dollar volume, log book-to-market ratio, 12-month momentum, and price delay (defined in equation 4) for high and low ETF ownership stocks.

Panel A: Low ETF ownership Stocks							
	mean	std	5%	25%	50%	75%	95%
Ret	0.013	0.235	-0.267	-0.080	-0.001	0.072	0.333
ETF ownership (%)	0.196	0.428	0.000	0.000	0.004	0.170	1.048
log(Market Cap)	17.953	1.557	15.658	16.995	17.859	18.671	20.876
log(Dollar volume)	14.694	2.320	11.308	13.143	14.471	16.030	18.876
log(BM)	-0.423	1.110	-2.360	-0.971	-0.328	0.214	1.216
Momentum	0.081	0.870	-0.735	-0.336	-0.032	0.263	1.229
Price Delay	0.552	0.317	0.055	0.266	0.565	0.853	0.993

Panel B: High ETF ownership Stocks							
	mean	std	5%	25%	50%	75%	95%
Ret	0.009	0.153	-0.211	-0.058	0.007	0.070	0.220
ETF ownership (%)	4.716	4.568	0.005	0.864	3.487	7.270	14.176
log(Market Cap)	20.992	1.515	18.645	20.027	20.945	21.931	23.525
log(Dollar volume)	19.129	1.868	15.907	18.044	19.246	20.386	21.926
log(BM)	-0.876	0.903	-2.400	-1.351	-0.806	-0.338	0.439
Momentum	0.123	0.608	-0.547	-0.156	0.068	0.296	0.889
Price Delay	0.129	0.182	0.009	0.028	0.061	0.139	0.540

Table 2: Anomalies with Significant Return Difference between High and Low ETF Ownership Groups

This table reports all anomalies with significant return differences (at 5% level) between the high ETF ownership group and the low ETF ownership group. For each anomaly, we compute two versions: one using only high ETF ownership stocks, the other using only low ETF ownership stocks. In constructing the anomalies, we use the same weighting scheme as in Chen and Zimmermann (2020). We then calculate average return differences (Diff column) and t-statistics (t-stat column) using the two versions of anomalies. The significance criterion is based on the p-value of return difference with Benjamini and Hochberg (1995) multiple testing adjustment (p_{BH} column). We also report the average anomaly returns using high (low) ETF ownership stocks (H-ETF column and L-ETF column respectively) and the average anomaly returns using all stocks (Original column). The 'Acronym' and 'Category' columns follow directly from Chen and Zimmermann (2020). There are 26 anomalies with significant return differences between the high ETF ownership group and the low ETF ownership group. All of them have higher average returns in the low ETF ownership group.

Acronym	Category	Diff	t-stat	p_{BH}	H-ETF	L-ETF	Original
AnnouncementReturn	earnings event	-1.06	-6.78	0.00	0.44	1.50	1.01
EarningsSurprise	earnings growth	-1.07	-6.14	0.00	-0.29	0.77	0.16
RevenueSurprise	sales growth	-1.15	-5.90	0.00	-0.08	1.07	0.50
NumEarnIncrease	earnings growth	-0.63	-5.51	0.00	0.02	0.65	0.30
ChangeInRecommendation	recommendation	-0.95	-4.93	0.00	-0.02	0.92	0.39
CredRatDG	other	-1.89	-4.83	0.00	-0.27	1.61	0.55
EarningsStreak	earnings growth	-0.84	-4.69	0.00	0.11	0.95	0.52
ConvDebt	external financing	-0.74	-4.43	0.00	-0.07	0.67	0.34
ShortInterest	short sale constraints	-0.94	-4.27	0.00	0.62	1.56	0.87
Mom12m	momentum	-1.89	-3.89	0.00	-0.33	1.56	0.27
DownRecomm	earnings forecast	-0.57	-3.78	0.00	0.02	0.60	0.25
DivSeason	payout indicator	-0.27	-3.77	0.00	0.16	0.43	0.26
DelFINL	external financing	-0.54	-3.74	0.00	0.01	0.56	0.33
Mom6mJunk	momentum	-1.10	-3.70	0.00	0.21	1.31	0.66
IntMom	momentum	-1.87	-3.64	0.00	0.03	1.89	0.43
ChTax	other	-0.75	-3.60	0.00	0.01	0.75	0.37
REV6	earnings forecast	-1.71	-3.55	0.01	-0.38	1.33	0.32
roaq	profitability	-1.27	-3.38	0.01	0.32	1.60	0.84
UpRecomm	earnings forecast	-0.46	-3.17	0.02	0.05	0.52	0.23
DivYieldST	valuation	-0.69	-3.01	0.03	0.04	0.73	0.45
ShareIss1Y	external financing	-0.56	-3.00	0.03	0.42	0.98	0.65
GrLTNOA	investment	-0.55	-2.96	0.03	-0.26	0.29	-0.02
NetDebtFinance	external financing	-0.57	-2.95	0.03	0.14	0.71	0.54
ResidualMomentum	momentum	-0.68	-2.89	0.04	-0.02	0.66	0.37
NetDebtPrice	leverage	-1.18	-2.87	0.04	0.39	1.57	0.77
std_turn	liquidity	-1.29	-2.81	0.04	-0.57	0.72	0.08

Table 3: Summary Statistics for the CZ Net Score

This table reports the summary statistics for the number of times a stock occurs on the long side of the anomalies (Long), the number of times it occurs on the short side of the anomalies (Short), and the difference (CZ Net Score). Panel A includes all stocks. Panel B (C) focuses on stocks in the low (high) ETF ownership group. For each statistic, we report the mean, standard deviation, min, max, and different quantile distributions.

Panel A: All Stocks									
	Mean	Std	Min	5%	25%	50%	75%	95%	Max
Long	26.36	8.84	0	10	21	26	32	41	71
Short	24.43	10.48	0	9	17	23	31	44	87
CZ Net Score	1.93	12.18	-70	-19	-5	2	10	21	61
Panel B: Low ETF Ownership									
	Mean	Std	Min	5%	25%	50%	75%	95%	Max
Long	27.18	9.85	0	8	22	28	34	42	71
Short	21.62	9.70	0	6	15	21	28	39	80
CZ Net Score	5.56	11.18	-60	-13	-1	6	13	23	61
Panel C: High ETF Ownership									
	Mean	Std	Min	5%	25%	50%	75%	95%	Max
Long	26.13	7.91	2	14	21	26	31	40	69
Short	26.50	10.39	0	12	19	25	33	46	87
CZ Net Score	-0.37	12.11	-70	-22	-8	0	8	18	54

Table 4: CZ Net Portfolio Performance

This table reports the decile portfolio performance sorted based on CZ Net for three different samples: all stocks, high ETF ownership stocks, and low ETF ownership stocks. The mean and standard deviation are calculated from monthly returns in percentage and the Sharpe ratio is annualized. All portfolios are equal-weighted. The sample period is from January 2000 to December 2020. The CZ Net column represents the decile 10 - decile 1 long-short portfolio return.

Panel A: All Stocks											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.17	0.44	0.72	0.85	0.99	1.20	1.32	1.46	1.65	2.10	1.93
Std	8.03	7.40	7.10	6.88	6.21	5.84	5.72	5.76	5.85	6.10	4.36
SR	0.07	0.20	0.35	0.43	0.55	0.71	0.80	0.88	0.98	1.19	1.53
Panel B: Low ETF Ownership											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	-0.17	0.70	0.73	1.21	1.21	1.44	1.73	1.85	2.13	2.64	2.81
Std	8.25	7.76	7.13	6.87	6.00	5.88	5.89	6.18	6.05	6.23	4.39
SR	-0.07	0.31	0.35	0.61	0.70	0.85	1.02	1.04	1.22	1.47	2.22
Panel C: High ETF Ownership											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.34	0.60	0.77	0.78	0.79	0.96	1.05	1.03	1.29	1.38	1.04
Std	7.94	7.21	6.77	6.57	6.60	6.28	5.98	6.04	6.14	6.38	4.69
SR	0.15	0.29	0.39	0.41	0.41	0.53	0.61	0.59	0.73	0.75	0.77

Table 5: Alphas for Net Portfolios

This table reports alphas of decile portfolios sorted based on the CZ Net score for low and high ETF ownership stocks. We report alphas based on CAPM, Fama and French (2015) with momentum (FF6), Hou, Xue, and Zhang (2015) (HXZ), Stambaugh and Yuan (2017) (SY), and Daniel, Hirshleifer, and Sun (2020) (DHS). The mean and standard deviation are calculated from monthly returns in percentage and the Sharpe ratio is annualized. All portfolios are equal-weighted. The sample period is from January 2000 to December 2020. The CZ Net column represents the decile 10 - decile 1 long-short portfolio return.

Panel A: Low ETF Ownership											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
α_{CAPM}	-0.93	0.02	0.06	0.61	0.67	0.93	1.23	1.33	1.60	2.10	3.04
	(-2.80)	(0.06)	(0.22)	(2.04)	(2.63)	(3.58)	(4.63)	(4.79)	(6.02)	(7.62)	(12.07)
α_{FF6}	-0.80	0.22	0.03	0.63	0.71	0.91	1.18	1.31	1.49	1.90	2.70
	(-2.72)	(0.76)	(0.11)	(2.30)	(3.11)	(3.77)	(5.03)	(5.22)	(6.36)	(7.91)	(11.51)
α_{HXZ}	-0.46	0.46	0.30	0.88	0.86	1.09	1.40	1.49	1.76	2.17	2.63
	(-1.46)	(1.49)	(1.15)	(3.12)	(3.68)	(4.42)	(5.75)	(5.88)	(7.48)	(8.95)	(10.44)
α_{SY}	-0.48	0.45	0.35	0.85	0.86	1.09	1.37	1.42	1.66	2.10	2.58
	(-1.59)	(1.48)	(1.34)	(3.07)	(3.67)	(4.44)	(5.65)	(5.56)	(6.82)	(8.19)	(10.58)
α_{DHS}	-0.40	0.52	0.39	0.97	0.91	1.17	1.40	1.53	1.79	2.22	2.62
	(-1.23)	(1.57)	(1.37)	(3.19)	(3.46)	(4.36)	(5.09)	(5.36)	(6.49)	(7.71)	(10.72)
Panel B: High ETF Ownership											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
α_{CAPM}	-0.51	-0.18	0.03	0.06	0.08	0.29	0.41	0.39	0.66	0.73	1.24
	(-2.27)	(-0.89)	(0.18)	(0.34)	(0.44)	(1.56)	(2.41)	(2.13)	(3.33)	(3.42)	(4.48)
α_{FF6}	-0.20	-0.01	0.13	0.12	0.05	0.22	0.23	0.14	0.38	0.35	0.55
	(-1.50)	(-0.10)	(1.24)	(1.21)	(0.42)	(1.95)	(2.26)	(1.51)	(4.28)	(3.32)	(3.65)
α_{HXZ}	0.07	0.16	0.20	0.23	0.15	0.29	0.31	0.20	0.37	0.43	0.36
	(0.39)	(1.14)	(1.71)	(2.11)	(1.24)	(2.43)	(2.75)	(1.71)	(3.02)	(3.03)	(1.91)
α_{SY}	0.04	0.14	0.13	0.12	0.01	0.18	0.21	0.18	0.37	0.37	0.33
	(0.25)	(1.07)	(1.08)	(1.07)	(0.06)	(1.46)	(2.04)	(1.71)	(3.19)	(2.67)	(1.80)
α_{DHS}	0.06	0.23	0.37	0.31	0.29	0.39	0.44	0.38	0.59	0.60	0.54
	(0.32)	(1.25)	(2.16)	(1.83)	(1.47)	(2.04)	(2.44)	(2.00)	(2.92)	(2.76)	(2.47)

Table 6: Match Sample Sharpe Ratio Difference Test

This table reports the number of observations and average stock characteristics (size, trading volume, book-to-market, 12-month momentum) in the whole sample and matched samples. The '-H' variable refers to the values in the high ETF ownership group, and the '-L' variable refers to the values in the low ETF ownership group. We also report the p-value for the Sharpe ratio test for the difference in Sharpe Ratios between the high-ETF Net LS portfolio and the low-ETF Net LS portfolio using Ledoit and Wolf (2008) procedure (the 'p for SR diff' column). All portfolios are equal-weighted. We consider three different matching procedures: (1) 'size matched' matches stocks based on their market cap; (2) 'size, vol matched' matches stocks based on the Euclidean distance between standardized size and volume tuples; (3) 'propensity score matched' pairs stocks based on the propensity score from a logit model. The logit model includes size, volume, book-to-market, and 12-month momentum as the x variables. The details of the matching algorithm are presented in section 4.4.

	N	Size-H	Size-L	Vol-H	Vol-L	BM-H	BM-L	Mom-H	Mom-L	p for SR diff
Whole Sample	364046	20.99	17.95	19.13	14.69	-0.88	-0.42	0.12	0.08	0.000
Size Matched	85788	19.73	19.73	17.64	16.85	-0.58	-0.85	0.05	0.30	0.016
Size, Vol Matched	88198	19.72	19.62	17.48	17.32	-0.58	-0.91	0.06	0.35	0.003
Propensity Score Matched	75538	19.73	19.74	17.44	17.40	-0.76	-0.70	0.16	0.20	0.036

Table 7: Net Portfolio Performance of the Size Matched Sample

This table reports the decile portfolio performance sorted based on Net for two matched samples: high ETF ownership stocks and low ETF ownership stocks. The matching criterion is market cap. The mean and standard deviation are calculated from monthly returns in percentage and the Sharpe ratio is annualized. All portfolios are equal-weighted. The time period is from January 2000 to December 2020. The CZ Net column represents the decile 10 - decile 1 long-short portfolio return.

Panel B: Low ETF Ownership, Size Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	-0.04	0.52	0.88	1.20	1.68	1.44	1.36	1.29	1.41	2.22	2.26
Std	8.21	7.86	6.55	6.73	8.37	6.13	5.51	5.91	5.80	6.40	5.53
SR	-0.02	0.23	0.47	0.62	0.70	0.82	0.86	0.76	0.84	1.20	1.41
Panel A: High ETF Ownership, Size Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.30	1.06	0.76	1.12	1.06	1.34	1.30	1.55	1.54	1.63	1.33
Std	11.34	11.26	10.25	9.98	10.08	9.09	9.02	8.49	8.20	8.37	8.27
SR	0.09	0.33	0.26	0.39	0.36	0.51	0.50	0.63	0.65	0.67	0.56

Table 8: Alphas for Net Portfolios, Size Matched Sample

This table reports alphas of decile portfolios sorted based on the CZ Net score for low and high ETF ownership stocks. Each month, we sort stocks based on their CZ Net measure. We match low and high ETF ownership stocks based on size. We report alphas of CAPM, Fama and French (2015) with momentum (FF6), Hou, Xue, and Zhang (2015) (HXZ), Stambaugh and Yuan (2017) (SY), and Daniel, Hirshleifer, and Sun (2020) (DHS). The mean and standard deviation are calculated from monthly returns, and the Sharpe ratio is annualized Sharpe ratio. All portfolios are equal-weighted. The time range is from 2000:01 to 2020:12. The CZ Net column represents the decile 10 - decile 1 long-short portfolio return.

Panel A: Low ETF Ownership, Size Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
α_{CAPM}	-0.80	-0.17	0.31	0.60	1.04	0.91	0.88	0.75	0.90	1.67	2.47
	(-2.45)	(-0.49)	(1.09)	(2.12)	(2.54)	(3.39)	(3.69)	(3.08)	(3.58)	(5.91)	(7.40)
α_{FF6}	-0.71	-0.01	0.20	0.41	0.74	0.81	0.62	0.54	0.68	1.36	2.07
	(-2.34)	(-0.04)	(0.70)	(1.51)	(1.85)	(3.23)	(2.91)	(2.60)	(3.21)	(5.68)	(6.33)
α_{HXZ}	-0.51	-0.19	0.33	0.62	1.33	0.95	0.85	0.65	0.82	1.52	2.03
	(-1.63)	(-0.54)	(1.17)	(2.23)	(3.26)	(3.64)	(3.79)	(2.99)	(3.69)	(6.08)	(5.96)
α_{SY}	-0.45	-0.12	0.32	0.50	1.04	0.83	0.74	0.54	0.71	1.40	1.85
	(-1.49)	(-0.35)	(1.15)	(1.81)	(2.60)	(3.22)	(3.34)	(2.55)	(3.27)	(5.60)	(5.71)
α_{DHS}	-0.37	0.04	0.41	0.76	1.28	1.01	0.91	0.80	0.92	1.63	2.00
	(-1.13)	(0.10)	(1.39)	(2.57)	(3.03)	(3.61)	(3.64)	(3.12)	(3.51)	(5.53)	(6.06)
Panel B: High ETF Ownership, Size Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
α_{CAPM}	-0.77	0.10	-0.21	0.18	0.17	0.48	0.48	0.76	0.78	0.87	1.64
	(-1.70)	(0.19)	(-0.53)	(0.45)	(0.39)	(1.34)	(1.29)	(2.22)	(2.36)	(2.48)	(3.28)
α_{FF6}	-0.25	0.54	0.18	0.45	0.50	0.67	0.49	0.63	0.51	0.40	0.65
	(-0.77)	(1.44)	(0.62)	(1.44)	(1.71)	(2.39)	(1.75)	(2.81)	(2.10)	(1.57)	(1.66)
α_{HXZ}	0.05	0.82	0.38	0.61	0.69	0.73	0.75	0.68	0.53	0.54	0.49
	(0.14)	(1.93)	(1.13)	(1.84)	(2.00)	(2.40)	(2.37)	(2.37)	(1.97)	(1.84)	(1.12)
α_{SY}	0.10	0.96	0.37	0.64	0.71	0.75	0.74	0.81	0.62	0.57	0.47
	(0.26)	(2.25)	(1.11)	(1.83)	(2.01)	(2.41)	(2.37)	(3.18)	(2.36)	(1.98)	(1.06)
α_{DHS}	0.22	0.99	0.50	0.76	0.82	0.78	0.80	0.96	0.80	0.77	0.55
	(0.53)	(2.06)	(1.33)	(1.99)	(1.91)	(2.13)	(2.10)	(2.73)	(2.34)	(2.13)	(1.25)

Table 9: CZ Net Portfolio Performance based on Other Matching Criteria

This table reports the decile portfolio performance sorted based on Net for 2 alternative matching methods: match based on size and volume, and match based on propensity score calculated from size, volume, BM, and momentum. The size, volume matched sample has 88,198 observations, 24.1% of the whole sample. The propensity score matched sample has 75,538 observations, 20.6% of the whole sample. All portfolios are equal-weighted. The time range is from 2000:01 to 2020:12. The CZ Net column represents the decile 10 - decile 1 long-short portfolio return.

Panel A: Low ETF Ownership, Size Vol Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	-0.15	0.23	0.76	0.91	1.57	1.62	1.62	1.47	1.64	2.33	2.48
Std	9.36	7.81	7.33	7.29	7.68	7.29	6.63	6.36	7.21	7.31	6.38
SR	-0.05	0.10	0.36	0.43	0.71	0.77	0.85	0.80	0.79	1.11	1.35
Panel B: High ETF Ownership, Size Vol Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.34	0.54	0.54	1.14	0.62	1.12	1.18	1.58	1.66	1.78	1.44
Std	11.44	10.77	9.88	9.70	8.28	8.47	7.85	7.89	7.83	8.01	8.68
SR	0.10	0.17	0.19	0.41	0.26	0.46	0.52	0.70	0.73	0.77	0.58
Panel C: Low ETF Ownership, Propensity Score Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	-0.12	0.56	0.43	1.21	1.41	1.56	1.31	1.41	1.38	2.08	2.20
Std	8.98	8.14	7.57	7.90	7.91	7.00	6.65	6.55	6.98	7.11	6.43
SR	-0.05	0.24	0.20	0.53	0.62	0.77	0.68	0.75	0.69	1.02	1.19
Panel D: High ETF Ownership, Propensity Score Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.18	0.34	0.60	0.83	0.57	1.17	1.05	1.65	1.29	1.57	1.39
Std	10.37	9.66	9.45	9.11	7.93	8.30	7.36	7.54	7.61	7.88	7.65
SR	0.06	0.12	0.22	0.32	0.25	0.49	0.49	0.76	0.59	0.69	0.63

Table 10: ETF Ownership and CZ Net: Fama-MacBeth Regressions

This table reports the Fama and MacBeth (1973) regression of returns at time $t+1$ on characteristics at time t. The regression specification is laid out in equation 2. For ease of interpretation, all individual variables (ETF ownership, CZ Net, Size, Volume, Book-to-market ratio (BM), and 12-month momentum (MOM)) are cross-sectionally transformed into their ranks mapped into the interval $[-1, 1]$. All regression coefficients are expressed in percentages. We report Newey and West (1987) t-statistics in squared brackets. *, **, and *** denote significance at 10%, 5%, and 1%, repectively. The predictive regression R^2s are reported in the last row. We calculate the R^2s by taking an average of the cross-sectional regression R^2s

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ETF Ownership	-0.17				0.03	0.25*	0.10	0.12	0.10
	[-1.11]				[0.17]	[1.67]	[0.63]	[0.91]	[0.75]
CZ Net		0.95***			0.86***	0.78***	0.79***	0.79***	0.74***
		[4.93]			[4.85]	[4.06]	[4.64]	[4.79]	[5.84]
Size			-0.46*			-0.37		-0.79	-0.49
			[-1.85]			[-1.12]		[-0.91]	[-0.70]
Volume				-0.40**			-0.11	0.58	0.38
				[-2.39]			[-0.62]	[0.82]	[0.62]
ETF Ownership×CZ Net					-0.76***	-0.48***	-0.69***	-0.56***	-0.58***
					[-10.79]	[-3.54]	[-5.77]	[-4.76]	[-5.28]
Size×CZ Net						-0.53***		-1.41***	-1.34***
						[-2.61]		[-4.09]	[-3.93]
Volume×CZ Net							-0.12	1.05***	1.02***
							[-0.57]	[3.47]	[3.35]
BM									0.20
									[1.45]
MOM									0.01
									[0.07]
R^2	0.62%	0.63%	0.78%	0.59%	1.35%	2.10%	1.76%	3.17%	3.99%

Table 11: Performance of Controlled Portfolios Sorted by Net: Active ETF Ownership vs Passive ETF Ownership

This table reports the performance of controlled portfolios based on active ETF ownership and passive ETF ownership. Following Easley et al. (2021), we calculate an activeness index for each ETF as in equation 5. We define active (passive) ETFs as ETFs with an activeness index above (below) 0.5. We then calculate active and passive ETF ownership for each stock using equation 1. After this, we redo the controlled portfolio analysis. Panel A reports results using all ETFs and panel B (C) reports results using only active (passive) ETFs. Within each panel, we report 5 sets of portfolio results: (1) 'Whole Sample EW' is the baseline result using all stocks with equal-weighted portfolios. (2) 'Whole Sample VW' is the result using only anomalies that are 5% significant under the value-weighting scheme and considers value-weighted portfolios. (3) 'Size Matched' is the result using matched sample based on market cap. (4) 'Size, Vol Matched' matches stocks with the Euclidean distance between standardized size and volume tuples. (5) 'Propensity Score Matched' pairs stocks based on the propensity score from a logit model. The logit model includes size, volume, book-to-market, and 12-month momentum as x variables. The details of the matching algorithm are presented in section 4.4. For each set of results, we present the total number of observations for the tercile ETF ownership groups, average monthly Net long-short portfolio return in high and low ETF groups (LS mean High (Low) ETF columns), annualized Sharpe ratio for the Net long-short portfolios in the high and low ETF groups (LS SR High (Low) ETF columns) and the p-value for the difference of the Sharpe Ratios between the two groups using the Ledoit and Wolf (2008) procedure. The sample period is from January 2000 to December 2020.

Panel A: All ETF ownership						
	Observations	LS mean High ETF	LS mean Low ETF	LS SR High ETF	LS SR Low ETF	p for SR diff
Whole Sample EW	364046	1.04	2.81	0.77	2.22	0.000
Whole Sample VW	364046	0.67	2.18	0.47	1.13	0.011
Size Matched	85788	1.33	2.26	0.56	1.41	0.016
Size, Vol Matched	88198	1.44	2.48	0.58	1.35	0.003
Propensity Score Matched	75538	1.39	2.20	0.63	1.19	0.036
Panel B: Active ETF ownership						
	Observations	LS mean High ETF	LS mean Low ETF	LS SR High ETF	LS SR Low ETF	p for SR diff
Whole Sample EW	364046	0.99	2.78	0.68	2.25	0.000
Whole Sample VW	364046	0.68	1.78	0.49	0.87	0.130
Size Matched	90413	1.13	1.90	0.46	1.19	0.027
Size, Vol Matched	87402	1.59	2.12	0.66	1.19	0.047
Propensity Score Matched	83229	0.88	2.21	0.41	1.20	0.003
Panel C: Passive ETF ownership						
	Observations	LS mean High ETF	LS mean Low ETF	LS SR High ETF	LS SR Low ETF	p for SR diff
Whole Sample EW	364046	1.37	2.55	1.01	1.92	0.001
Whole Sample VW	364046	1.07	1.38	0.77	0.95	0.453
Size Matched	117415	1.60	1.84	0.81	1.26	0.149
Size, Vol Matched	111616	1.60	1.88	0.78	1.07	0.219
Propensity Score Matched	106458	1.66	2.05	0.88	1.20	0.294

Table 12: Effect of ETF on Anomaly Returns on News and Earnings Announcement Days

This table reports the regression results of equation 6. *Eday* and *Nday* are indicator variables that take a value of 1 on earnings announcement and news release days. All other individual variables (CZ Net, ETF ownership, market cap, book-to-market ratio, past 12-month momentum, Amihud illiquidity, and short interest) are cross-sectionally transformed into their ranks mapped into the interval $[-1, 1]$. Our lagged control variables include market cap, book-to-market ratio, past 12-month momentum, Amihud illiquidity, and short interest. Following Jiang, Li, and Wang 2021b, we divide news into fundamental news and non-fundamental news groups. We report regression results with all the news in panel A and regression with fundamental (non-fundamental) news in panel B (C). In all our regressions, we include a day-fixed effect and cluster the standard errors at the daily level. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Dependent Variable:	Ret					
	Panel A: All		Panel B: Fundamental		Panel C: Non-fundamental	
Net	0.034***	0.018***	0.033***	0.018***	0.037***	0.023***
	(5.87)	(3.82)	(5.80)	(3.82)	(6.36)	(4.69)
Eday	0.195***	0.191***	0.276***	0.277***	0.254***	0.254***
	(9.71)	(9.52)	(13.83)	(13.82)	(12.74)	(12.69)
Nday	0.162***	0.174***	0.304***	0.313***	0.124***	0.136***
	(24.61)	(26.79)	(26.36)	(27.39)	(16.34)	(18.19)
ETF	−0.007	0.006	−0.004	0.009	−0.004	0.008
	(-0.97)	(0.86)	(-0.54)	(1.32)	(-0.53)	(1.15)
Eday × Net	0.272***	0.270***	0.302***	0.301***	0.299***	0.299***
	(10.03)	(9.98)	(11.15)	(11.14)	(11.06)	(11.05)
Nday × Net	0.067***	0.069***	0.177***	0.180***	0.024***	0.026***
	(9.62)	(9.96)	(14.21)	(14.46)	(2.73)	(3.02)
Eday × ETF × Net	−0.083***	−0.082***	−0.098***	−0.097***	−0.098***	−0.097***
	(-2.71)	(-2.70)	(-3.22)	(-3.17)	(-3.23)	(-3.20)
Nday × ETF × Net	−0.055***	−0.054***	−0.129***	−0.129***	−0.011	−0.011
	(-6.10)	(-6.09)	(-8.27)	(-8.31)	(-0.97)	(-0.99)
Lagged Controls	No	Yes	No	Yes	No	Yes
Day Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,724,268,300		3,724,268,300		3,724,268,300	

Table 13: Quasi-Natural Experiment Based on the Russell Index Reconstitution

This table reports the first-stage and second-stage IV regression results from equation 7 and 8. Columns (1) - (3) report regressions with different bandwidths. R2000 is an indicator variable that takes a value of 1 if the stock belongs to the Russell 2000 index. Controls include size, momentum, book-to-market, illiquidity, short interest, and index fund ownership. All non-indicator individual variables except ETF ownership (CZ Net, Size, 12-month momentum (MOM), Book-to-market (BM), Amihud Illiquidity, Short Interest, Index Ownership) are cross-sectionally transformed into their ranks mapped into the interval $[-1, 1]$. Panel A (B) reports the first-stage (second-stage) estimation results. *, **, and *** denote significance at 10%, 5%, and 1%, respectively. The sample period is from January 2000 to May 2007.

Panel A: First-Stage Estimation

Dependent Variable:	ETF ownership		
	(1)	(2)	(3)
R2000	0.277***	0.228***	0.204***
	(7.55)	(6.90)	(6.59)
CZ Net	0.090***	0.071***	0.071***
	(7.99)	(8.28)	(10.06)
Size	−0.183***	−0.080**	−0.099*
	(-5.09)	(-2.01)	(-1.94)
MOM	−0.033**	−0.032***	−0.028***
	(-2.54)	(-3.13)	(-2.91)
BM	0.062***	0.070***	0.072***
	(4.85)	(6.57)	(6.80)
Illiquidity	−0.443***	−0.347***	−0.303***
	(-12.05)	(-13.65)	(-13.12)
Short Interest	−0.099***	−0.098***	−0.108***
	(-6.19)	(-6.98)	(-7.85)
Index Ownership	0.627***	0.576***	0.554***
	(14.20)	(13.08)	(13.06)
Month Fixed Effect	Yes	Yes	Yes
Bandwidth	200	300	400

Panel B: Second-Stage Estimation

Dependent Variable:	Ret		
	(1)	(2)	(3)
ETF ownership	0.295	−0.792	−1.405
	(0.22)	(-0.40)	(-0.57)
CZ Net	0.012**	0.015**	0.016**
	(2.06)	(2.29)	(2.56)
ETF × Net	−0.974**	−1.099*	−1.211**
	(-2.03)	(-1.95)	(-2.17)
Size	−0.037	−0.028	−0.026
	(-1.03)	(-0.80)	(-0.75)
MOM	0.008	0.006	0.006
	(1.57)	(1.21)	(1.21)
BM	0.003	0.003	0.005
	(0.97)	(0.94)	(1.48)
Illiquidity	0.001	−0.002	−0.004
	(0.11)	(-0.19)	(-0.37)
ShortInterest	0.004	0.001	−0.001
	(0.76)	(0.28)	(-0.17)
Index Ownership	−0.005	0.000	0.003
	(-0.50)	(0.03)	(0.18)
Month Fixed Effect	Yes	Yes	Yes
Bandwidth	200	300	400
Observations	26503	43529	60653

Internet Appendix for

"ETFs, Anomalies and Market Efficiency"

Not for Publication

Table 1: Top 30 Anomalies with Higher Returns in High ETF ownership group

This table reports the top 30 anomalies ranked by the t-stat of the average return difference between the high ETF ownership group and the low ETF ownership group, i.e. they have higher returns in the high ETF ownership group. None of them are significant at 5% level under Benjamini and Hochberg (1995) multiple testing adjustment. We report average return differences (Diff column), t-statistics (t-stat column), average anomaly returns using high (low) ETF ownership stocks (H-ETF column and L-ETF column respectively), and the average anomaly return using all stocks (Original column). The 'Acronym' and 'Category' columns follow directly from Chen and Zimmermann (2020).

Acronym	Category	Diff	t-stat	H-ETF	L-ETF	Original
RDcap	asset composition	0.60	2.54	0.59	-0.01	0.41
RD	R&D	0.81	2.46	1.06	0.25	0.84
fgr5yrLag	earnings forecast	0.53	2.45	0.43	-0.10	0.13
BetaLiquidityPS	liquidity	1.00	2.44	0.59	-0.41	0.29
PatentsRD	profitability alt	0.25	2.32	-0.02	-0.27	-0.15
Price	other	0.75	2.31	0.73	-0.02	0.42
BetaFP	other	0.71	2.22	-0.02	-0.73	-0.24
grcapx3y	investment growth	0.45	2.19	0.21	-0.24	0.12
Leverage	leverage	0.51	1.98	0.19	-0.32	0.07
Tax	other	0.49	1.98	0.73	0.24	0.46
BidAskSpread	liquidity	0.71	1.96	0.22	-0.50	-0.12
MomSeason06YrPlus	other	0.59	1.74	0.62	0.03	0.44
MomSeason11YrPlus	other	0.57	1.72	0.51	-0.07	0.32
AbnormalAccruals	accruals	0.40	1.63	-0.16	-0.55	-0.17
ChInvIA	investment growth	0.29	1.60	0.26	-0.03	0.27
AnalystValue	valuation	0.37	1.59	0.50	0.13	0.35
FirmAge	info proxy	0.28	1.45	0.26	-0.01	0.09
RIO_Disp	short sale constraints	0.47	1.44	0.86	0.38	0.61
NOA	asset composition	0.41	1.36	0.51	0.11	0.70
MomOffSeason11YrPlus	other	0.49	1.31	0.42	-0.08	0.18
Activism2	ownership	1.57	1.31	1.61	0.04	1.26
AOP	other	0.21	1.29	0.08	-0.14	0.02
STreversal	short-term reversal	0.35	1.23	0.99	0.64	0.94
ChNNCOA	investment alt	0.20	1.23	0.08	-0.12	0.08
MRreversal	long term reversal	0.31	1.23	0.09	-0.21	0.11
Size	size	0.19	1.04	0.24	0.06	0.10
Coskewness	risk	0.27	0.94	0.41	0.13	0.22
ChEQ	investment	0.19	0.93	0.36	0.16	0.46
ConsRecomm	recommendation	0.38	0.93	0.56	0.17	0.20
PayoutYield	valuation	0.30	0.90	0.05	-0.25	0.12