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 discover 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, leading to reduced mispricing and increased informational efficiency. We document similar results when we match the two groups based on size, volume, book-to-market, and momentum. Our results remain robust to different matching methods and a wide array of controls in Fama-MacBeth regressions. Using Russell index reconstitution as a natural experiment, we uncover causal evidence that ETF ownership attenuates anomaly returns.

JEL classifications: G11, G12, G14, G23

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1. Introduction

ETFs were first introduced in the 1990s, and they have demonstrated significant growth over the past 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 US 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 intraday 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 commonality in the 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 ETFs reduce post-earnings announcement drift (PEAD) and improve market efficiency for stocks with high industry risk exposure. In contrast to their study, 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 (2022).

First, we investigate the effect of ETF ownership on anomalies one at a time. For each anomaly, we partition stocks in the long and short legs into three groups based on ETF ownership and form long-short portfolios using low and high ETF ownership stocks, respectively. If there were no effect of the ETF ownership, the difference should be theoretically zero and empirically indistinguishable. Our analysis reveals that among all 205 anomalies considered, the anomaly portfolios formed by low ETF stocks consistently outperform those formed by high ETF stocks, indicating that ETF ownership has a substantial impact on all anomalies and high ETF ownership weakens the returns.

Second, we move on to aggregate all the information from the 205 individual anomalies by constructing a Net measure following Engelberg, McLean, and Pontiff (2018). This 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 is associated with much higher average returns, Sharpe ratios, and highly significant alphas across all leading factor models. The results hold after we match stocks by size, volume, and propensity score trained on stock characteristics, and remain robust to alternative measures of the ETF activity.

Third, we demonstrate the attenuation effect of ETF ownership on anomaly mispricing through Fama and MacBeth (1973) cross-sectional regressions. We regress one-month ahead stock return on ETF ownership, Net, and the interaction between Net and ETF ownership with common control variables. Our finding is that the interaction term is highly negative and significant across all regression specifications, implying that for higher ETF ownership stocks, the typical anomaly variables no longer have predictive power for future stock returns. The effect is not subsumed by the typical size and volume amplification effect highlighted in Han et al. (2022) and Hou, Xue, and Zhang (2020).

Fourth, we explore the potential mechanism through which ETF attenuates stock mispricing. Our analysis reveals that high ETF ownership group stocks have significantly lower price delay by Hou and Moskowitz (2005), yielding more prompt response of stock returns to market-wide news. This suggests that ETFs propagate macro information more easily to individual stocks so that the impacted stock prices better reflect the macro information. As a result, mispricing declines. We also discover that active ETFs play a more significant role in attenuating returns generated by anomaly strategies. Our results are similar when we focus on style ETFs. Lastly, ETFs attenuate build-up anomalies more than resolution anomalies, leading to a reduction of overall mispricing in the market.

Fifth, we zoom in on the high-frequency news release and earnings announcement days to examine whether ETFs affect stock return predictability during public information announcements. 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 the 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 returns on news release days decrease by 82.1%. This evidence suggests that 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 indices reconstitute their constituents every June following mechanical rules. They rank 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 indices. Therefore, stocks around the cutoff can be viewed 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 discover 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 ETFs, arguably the most important disruptive innovation in the asset management industry over the last 30 years, have 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 ETFs can influence systematic mispricing. Section 3 summarises our data, including ETF and stock return data, anomalies and the construction of the Net portfolio, firm-news and earnings announcements, as well as Russell index constituents. Section 4 presents the key empirical results of our study, focusing on how ETFs impact market efficiency by analyzing stock market anomalies. Section 5 zooms in on the high-frequency evidence from news releases and earnings announcements. Section 6 reports the Russell index reconstitution natural experiment results. Section 7 concludes. The Internet Appendix provides additional summary statistics and robustness checks.

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 ETFs instead of individual stocks because ETFs have better liquidity and provide more direct exposure to the systematic factor the traders have information about. 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 ETFs can alleviate this market incompleteness friction, it enables smooth, systematic information flow from the informed traders to the stock price. Due to 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 as they offer instant liquidity to the market. Noise trading combined with limits to arbitrage can cause the underlying security price to deviate further from its fundamental value. Specifically, ETF trading would 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. Consequently, stock returns can be more predictable based on ex-ante characteristics.

Studying the effect of ETFs on anomaly returns can resolve this tension: whether this financial innovation mitigates frictions, facilitates arbitrage trading, and enhances price discovery, or it increases 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 prices, we can further decompose the effect of ETFs 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 incorporation 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 prices 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 more incentive to acquire information ex-ante. Therefore, stock prices will incorporate a greater amount of accessible systematic information, leading to reduced price reactions during news releases. Consequently, the ratio of the price jump at the announcement to the cumulative return prior to the announcement will be diminished.

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 prices. 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 utilized in our study. We first introduce the ETF and stock data in our analyses. Next, we describe our equity market anomaly dataset from Chen and Zimmermann (2022) and outline the construction of the Net strategy following Engelberg, McLean, and Pontiff (2018), which aggregates information from all anomalies. Lastly, we summarize the news and earnings announcement data, along with the Russell index constituents data, which we rely on to demonstrate the underlying 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 of CRSP as the existing time period for each ETF. Next, we merge the ETFs identified with the CRSP mutual fund database, which contains the detailed names of each ETF. Following Ben-David et al. (2023), we restrict our sample to equity-focused ETFs that hold US stocks in their portfolios, which allows closely benchmarking the ETF portfolios to broad-based US stock indices. Specifically, we exclude non-equity, foreign equity, leveraged and inverse-leveraged, and active ETFs. Our sample includes 1,509 unique US equity ETFs with the inception and ending dates for each ETF over the period between January 2000 and December 2020.

ETF Holdings Data. We utilize the ETF metadata to retrieve 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. Our entire sample covers the period from January 2000 to December 2020. In many cases, the first reporting dates of the holdings differ between the two sources. We follow Ben-David et al. (2023) and take one source per ETF as the reference for its holdings; if an ETF has holdings information in both sources, we use the one with the start date that is closer to the launch date in CRSP. 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.[1]

Stock Market Trading and Characteristics Data. We collect the monthly trading data (return, market cap, and 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 price delay variables directly from Chen and Zimmermann (2022). When constructing these variables, Chen and Zimmermann (2022) adhere to the principle of replicating the original studies that initially proposed these cross-sectional return predictive characteristics as much as possible, and successfully demonstrate significant replication performance compared to the original studies. In order to avoid encountering non-standard errors highlighted in Menkveld et al. (2021), we directly utilize the readily available data from Chen and Zimmermann (2022). We consider these variables because of their documented ability in the literature to either attenuate or amplify the profitability of anomalies.

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 (2022). 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 (2022).[2] The authors compiled a comprehensive dataset of anomalies and provided an open-source

[1] In Section B of the Appendix, we consider an alternative measure of ETF activity, ETF Volume Induced Trading.

[2] https://www.openassetpricing.com/. We rely on the first version of the data "April 2021 Data Release (v1.1.0)" consisting of 205 anomalies in total.

version of anomaly construction code. Therefore, we have detailed data on each anomaly's underlying stock characteristics and the portfolio constituents for different anomalies. Because 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 (2022) 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.[3] 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.[4] 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

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

[4]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.

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 corporate 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 conduct our main empirical analyses on how ETFs impact market efficiency through the lens of stock market anomalies. Section 4.1 provides an overview of the summary statistics for the stocks and ETFs in our sample. Section 4.2 presents initial evidence on the return difference between individual anomaly portfolios formed by high and low ETF ownership stocks. Section 4.3 compiles the information from all anomalies into a comprehensive Net measure, and provides the summary statistics for the CZ Net strategy constructed using stocks with low and high ETF ownership. Section 4.4 reports results based on high and low ETF ownership stocks with similar characteristics. 4.5 provides Fama-MacBeth regression results. The last three sections inspect the potential mechanism through which ETFs affect market efficiency. Section 4.6 examines the information efficiency of stocks with different levels of ETF ownership by utilizing the price delay measure. Section 4.7 classifies ETFs into active and passive ones and explores their impact on anomaly returns separately. Section 4.8 performs additional test on whether ETF ownership attenuates build-up anomalies more than resolution anomalies.

4.1. Summary Statistics

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

Table 1 provides the results for low ETF ownership (Panel A) and high ETF ownership (Panel B) stocks, respectively. 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. Panel (a) of Figure 1 illustrates the number of ETFs in our sample from January 2000 until December 2020. Notably, the ETF industry experiences substantial growth during this period. Initially, there were only a few ETFs, but by 2020, the number of ETFs exceeds 800. In Panel (b) of Figure 1, we observe the proportion of the equity market owned by ETFs over time. This proportion demonstrates a consistent upward trend, reaching over 8% by December 2020. Panel (c) of Figure 1 presents the proportion of stocks held by ETFs throughout the sample period. We find that ETFs encompass almost all available stocks by the end of our sample period. In particular, there is a significant surge in ETF coverage between 2000 and 2004, with ETFs eventually covering over 80% of US equities. Panel (d) of Figure 1 shows that the total Net Asset Value (NAV) of ETFs continuously increases over time, reaching around $3 trillion in December 2020. Collectively, these results underscore the growing significance of ETFs as a prominent 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 equally partition each portfolio into three groups by ETF ownership. The high ETF ownership group consists of the top 1/3 of stocks, while the low ETF ownership group comprises the bottom 1/3 of stocks. We form 205 long-short portfolios using low and high ETF ownership stocks, respectively, and calculate the return difference between the high and low ETF ownership anomalies. Our findings reveal that the anomalies exhibit greater strength in the low ETF ownership group. Among the 205 anomalies studied, none of them exhibit significantly higher mean returns in the high ETF ownership group compared to the low ETF ownership group at 5% significance level under Benjamini and Hochberg (1995) multiple testing adjustment. However, 26 of these anomalies demonstrate significantly lower mean returns in the high ETF ownership group compared to the low ETF ownership group.

Table 2 reports the 26 anomalies with significant return differences at 5% level between high and low ETF ownership groups after the Benjamini and Hochberg (1995) adjustment. Additionally, we present the category to which each anomaly belongs. Our analysis reveals that ETF ownership has a notable impact on anomalies belonging to the following categories: earnings event, earnings growth, earnings forecast, external financing, and momentum, all of which reflect ETFs' significant role in more swiftly incorporating fundamental information into the stock price and reducing the medium-term momentum of stock price movements.

4.3. CZ Net Strategy

To examine the relationship between ETF ownership and anomalies, we aggregate the information of all anomalies 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, as well as the CZ Net score (defined as *Long* - *Short*), for the entire 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. These results suggest that, on average, low ETF ownership stocks are more likely to be included in the long leg of the anomaly portfolios.

CZ Net Performance. Table 4 further provides summary statistics of the mean, standard deviation, and Sharpe ratio for CZ-Net-score-sorted portfolios. P1 denotes stocks in the lowest decile (e.g., overvalued stocks), and P10 denotes stocks in the highest 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 the results for all stocks, low ETF ownership stocks, and high ETF ownership stocks, respectively.[5]

[5] In the main body of our paper, we focus on the equal-weighted portfolio strategy. Our findings remain robust when using log value weights, as in Green, Hand, and Zhang (2017) and Han et al. (2022). We provide these results in Tables A1, A2 and A3 in the Appendix for reference.

For the long-short portfolio formed by different stock samples, we observe that high ETF ownership group stocks exhibit a mean return spread of 1.04% per month with an annualized Sharpe ratio of 0.77. In stark contrast, low ETF ownership stocks demonstrate a much higher mean of 2.81% and a Sharpe ratio of 2.22. This significant disparity reinforces our previous finding that anomalies are attenuated among stocks with high ETF ownership.

Alphas. In order to gain further insights, we run time-series regressions of the CZ Net portfolio returns against various 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), and present the results in Table 5. We find that the anomalies almost completely "reside" among the low ETF ownership group. Irrespective of the factor model specifications employed, the low ETF ownership group consistently exhibits highly significant alphas with t-statistics above ten, while for the high ETF ownership group, the alphas are considerably weaker in both magnitude and economic significance. Based on the new threshold set by Harvey, Liu, and Zhu (2016), we find that the three new factor models (HXZ, SY, and DHS) can effectively account for the mispricing present within 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 potentially contributes to 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, may contribute to attenuating anomaly profitability among high ETF ownership stocks. To isolate the impact of ETFs on stock mispricing, we report results based on high and low ETF ownership stocks with similar characteristics. Specifically, we employ three stock matching procedures: matching by size, matching by size and volume, and propensity score matching, which takes into account multiple characteristics simultaneously. Our main focus is on the results based on matching with size, and our findings remains robust to different matching methods.

Matching procedure. To balance the number of matched stocks, we employ a nearest neighbor without replacement matching algorithm. The matching procedure is carried out iteratively. In each iteration, we aim to match each stock in the treatment group (high ETF ownership) with the closest matching stock from the control group (low ETF ownership) based on a specified 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 matching variable can vary significantly between the treatment and control groups. Therefore, we only match observations that fall within the common support of the distributions. Observations outside this common support would be too dissimilar to form meaningful pairs. As our matching algorithm iterates, we gradually exhaust the observations within the common support. If there is no observations sharing a similar matching variable, nearly all observations in the treatment group would be matched to the same observation in the control group, resulting in only one pair of matches. Such an extreme scenario is undesirable as the matched pair would exhibit vastly different characteristics. To avoid this, we halt the iteration process when the marginal increase in the number of matched pairs falls below 100, which indicates the overlap in the distribution support between the treatment and control groups is approaching zero. In our empirical setting, we find that the algorithm typically completes in fewer than ten iterations.

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 begin with fitting a logit model of the ETF ownership binary variable on size, volume, book-to-market, and 12-month momentum, where high ETF ownership is labeled as 1 while low ETF ownership is 0. We then perform stock matching based on the propensity score from the fitted logit model.

Table 6 displays the results of the matching process, including the number of matched stocks and the characteristics before and after matching. As can be seen, the successfully matched pairs range from 20.7% (75,538/364,046) to 24.2% (88,198/364,046) across different matching methods. The similarity between the characteristics before and after matching provides strong evidence that our research design effectively addresses key confounding variables, such as size and volume.

Matching results. Table 7 presents the CZ Net decile portfolios for the low and high ETF ownership groups. As can be seen, the average monthly return for the long-short portfolio is 2.26% (with an annual Sharpe ratio of 1.41) for the low ETF ownership group, whereas it is 1.33% (with an annual Sharpe ratio of 0.56) for the high ETF ownership group. To assess the significance of the difference in Sharpe rations, we perform a statistical test based on the approach of Ledoit and Wolf (2008) and report the results in the last column of Table 6. The difference in Sharpe ratio is significant at 5% level with a p-value of 0.016.

Additionally, we examine the presence of portfolio alpha in Table 8. It is evident that all long-short (LS) portfolios within the low ETF ownership group exhibit significant alpha across all factor models. Conversely, the LS portfolio returns for the high ETF ownership group can be fully explained by nearly all the models. These findings suggest that ETF ownership introduces an additional mitigating effect on trading profits of anomalies, even after controlling for size.

Robustness Check. In addition to matching based on size alone, we also perform matching based on size and volume, as well as propensity score matching. Across different specifications, our portfolio return and alpha results remain robust. Table 9 presents the portfolio results for size and volume matching, along with propensity score matching. In both cases, we observe that low ETF ownership stocks exhibit higher Sharpe ratios compared to stocks with high ETF ownership.

4.5. Cross-sectional Regressions

Alongside the portfolio analyses, we provide additional support to our hypothesis via Fama and MacBeth (1973) cross-sectional regression by regressing next-month stock returns in percentage on CZ Net, ETF ownership, the interaction between CZ Net and ETF ownership, and a number of controls. According to our hypothesis, ETF ownership would have an attenuation effect on the mispricing from the anomalies. Therefore, we expect to observe a significant negative regression coefficient for the interaction term between CZ Net and ETF ownership.

The full 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 on anomaly mispricing (Hou, Xue, and Zhang (2020), Han et al. (2022)). We also include typical characteristics related to expected stock returns, such as BM and 12-month momentum. 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 ranked and then mapped to the $[-1, 1]$ interval.

Table 10 presents full and nested version of the regression results. The interaction term between ETF ownership and CZ Net remains highly significant and substantial in magnitude across different regression specifications, suggesting that ETF ownership exhibits an incremental dampening effect on anomaly profits beyond the effect of control variables.

4.6. Price Delay and ETF Ownership

To investigate the mechanism through which ETFs mitigate the trading profit of anomalies, we present preliminary evidence of informational efficiency based on the price delay measure proposed by Hou and Moskowitz (2005). This measure assesses whether there is a delay in a stock's response to market-wide news. Following Hou and Moskowitz (2005), at the end of June of each calendar year, we run a regression of each stock's weekly returns on contemporaneous and four weeks of lagged returns on the market portfolio over the prior year:

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

The price delay is defined as:

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

where $R^2_{\delta_i^{-j}=0, \forall j \in [1,4]}$ denotes the R^2 of the regression in Eq. (3) when setting $\delta_i^{(-1)}$, $\delta_i^{(-2)}$, $\delta_i^{(-3)}$, and $\delta_i^{(-4)}$ to 0. PD measures the decrease in R^2 when the regression coefficients on lagged market returns are set to 0. If a stock price instantaneously incorporates systematic market information, its return would have zero loadings on past market returns, resulting in a price delay of 0. Conversely, if there is a delayed response of stock return to systematic information, the PD measure would be positive.

Our objective is to utilize this measure to examine whether ETFs improve the systematic information flow to the underlying securities. Figure 3 presents the evolution of price delay

(PD) over time for the high and low ETF ownership groups. Notably, the low ETF ownership group exhibits a considerably higher price delay in comparison to the high ETF ownership group. Moreover, the high ETF ownership group experiences a significant decrease in PD during the initial phase of the ETF rollout from 2000 to 2004. To provide a comprehensive overview, we also present the summary statistics of price delay for both groups in Table 1. The findings indicate that ETF ownership enhances the connection between stocks and market fundamentals, facilitating the incorporation of market-wide systematic information into stock prices at a faster rate.

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 the activeness index for each ETF j in each month t as:

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

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.[6] By construction, 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. While type (1) ETFs adhere to fixed rules, they usually serve as building blocks for active trading strategies. The study by Huang, O'Hara, and Zhong (2021) highlights hedge funds' inclination to engage in arbitrage behaviors involving longing the stock and shorting the

[6]We obtain similar results when calculating the absolute difference between the weight of a stock in the ETF and its weight in the market portfolio.

industry ETF. Hence, the definition of active ETFs captures their contribution to active trading strategies.

Table 11 reports the number of observations and summary statistics on the mean and Sharpe ratio for the whole sample and the matched samples based on all (Panel A), active (Panel B), and passive ETF ownership (Panel C).

The results reveal that active ETFs exhibit a more pronounced influence on anomaly returns when compared to passive ETFs. Specifically, considering active ETF ownership, we observe a larger disparity in the spread between average returns (Sharpe Ratios) for the low and high ETF ownership groups, compared to the spread observed for passive ETF ownership. This underscores the significant role that active ETFs play in enhancing market efficiency.

One important trend in the ETF space is the rise of style ETFs. Rather than betting on individual stocks or certain industries, style ETFs follow a specific investment style or strategy, such as value, growth, momentum, etc.[7] This approach provides investors with exposure to a unique investment style within an asset class. By examining style ETFs, we can delve into a specific aspect of active ETFs that pertains to factor investing.

To pinpoint style ETFs, we select those whose names contain specific keywords: value, growth, momentum, small, mid, large, beta, factor, volatility, dividend, quality, ESG, social, environmental, and responsible. These terms represent a broad range of ETFs tilted toward certain equity strategies. Subsequently, we ascertain the ownership based on these style ETFs and proceed with our portfolio analysis using the ownership data derived from the style ETFs. Table reports the decile portfolio performance sorted based on Net for all stocks, high style-ETF ownership stocks, and low style-ETF ownership stocks. We observe that the long-short anomaly portfolio formed by stocks with low-style ETF ownership yields notably higher returns (2.84%) than that formed by stocks with high-style ETF ownership (0.93%), and the disparity is more pronounced than the comparison using all ETF ownership

[7] https://www.justetf.com/en/etf-lists.html offers a comprehensive list of ETFs and their strategies.

in Table 4 (2.81% vs 1.04%). The evidence indicates that style ETFs play a pivotal role in reducing the profitability of exploiting asset pricing anomalies.

4.8. Build-up vs Resolution Anomalies

Apart from the heterogeneity of ETFs, it is also intriguing to explore the heterogeneity of anomalies that ETFs have an attenuation effect on. Binsbergen et al. (2023) classify anomalies into two broad categories: build-up anomalies that exacerbate mispricing and resolution anomalies that alleviate mispricing. Thus far, we have established that ETFs diminish anomaly profits, but it remains crucial to determine whether they attenuate resolution anomalies. If ETFs do attenuate resolution anomalies, they could potentially exacerbate mispricing in the stock market. In this section, we present evidence demonstrating that ETFs primarily mitigate build-up anomalies, thereby exerting an overall positive impact on market efficiency for stocks.

Following Binsbergen et al. (2023), the price wedge measure is constructed to quantify the deviation of a stock price from benchmark factor models:

$$PW_{i,t} = -\log\left(\frac{\tilde{P}_{i,t}}{P_{i,t}}\right) , \tag{6}$$

where $\tilde{P}_{i,t}$ represents the stock price implied by a model and $P_{i,t}$ denotes the actual stock price in the market. A positive value of $PW_{i,t}$ would indicate overpricing of the stock, and vice versa.

If ETFs attenuate build-up anomalies more than resolution anomalies, all else being equal, high ETF ownership stocks would have lower mispricing levels. Conversely, if they attenuate resolution anomalies more than build-up anomalies, the opposite would be true. To test this hypothesis, we regress the absolute value of the price wedge in month t on previous-month ETF ownership and control variables:

$$|PW_{i,t}| = \beta \text{ETF Ownership}_{i,t-1} + \eta \text{Controls}_{i,t-1} + \alpha_t + \delta_i + \epsilon_{i,t} \ , \tag{7}$$

where $|PW_{i,t}|$ denotes the absolute value of price wedge, ETF ownership is our key variable of interest, and the controls include market cap, 12-month momentum, book-to-market ratio, Amihud illiquidity, short interest, and institutional ownership. Like before, all independent variables are cross-sectionally ranked and then mapped into the $[-1, 1]$ interval.

Table 13 presents the regression results with different fixed effects. Our analysis reveals that ETF ownership consistently exhibits significant negative regression coefficients across various specifications, indicating that stocks with high ETF ownership tend to have a reduced level of mispricing compared to stocks with lower ETF ownership. These findings align with the hypothesis that ETFs primarily mitigate build-up anomalies rather than resolution anomalies.

5. News and Earnings Announcement

Our previous analyses have primarily focused on low-frequency monthly observations and highlight the significant attenuation effects ETFs have on the profitability of anomaly returns. In this section, we extend our analysis to encompass the high-frequency resolution of uncertainty surrounding earnings announcements and news release days for companies, utilizing daily stock return data. When there is more ex-ante mispricing for stocks, anomaly returns would be stronger on these news announcement days. Therefore, news announcements and the corresponding anomaly returns offer a natural setting to examine the effect of ETFs on the ex-ante mispricing of the underlying securities.

Engelberg, McLean, and Pontiff (2018) discover that anomaly returns are 50% higher on news release days and six times higher on earnings announcement days. They provide evidence suggesting that such high returns arise from biased expectations, which are partly corrected at the time of the news release. If ETFs contribute to greater ex-ante efficiency in stock prices, we would expect anomaly variables to have less predictive power for stocks with high ETF ownership on news announcement days.

To investigate whether ETFs mitigate ex-ante biased expectation by incorporating more systematic information into the stock price, we conduct the following regression analysis:

$$\begin{aligned} Ret_{it} =& \alpha + \beta_1 Net_{i,t-1} + \beta_2 Eday_{it} + \beta_3 Nday_{it} + \beta_4 ETF_{i,t-1} + \beta_5 Net_{i,t-1} \times Eday_{it} \\ &+ \beta_6 Net_{i,t-1} \times NDay_{it} + \beta_7 Net_{i,t-1} \times ETF_{i,t-1} \times Eday_{it} \\ &+ \beta_8 Net_{i,t-1} \times ETF_{i,t-1} \times Nday_{it} + Controls_{i,t-1} + \delta_t + \epsilon_{it} \end{aligned} \tag{8}$$

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 constructed in our previous settings. Our controls include market cap, 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 the coefficients of $Eday \times Net$ and $Nday \times Net$. If our hypothesis that ETF improves ex-ante market efficiency holds true, we expect to see significant negative values for β_7 and β_8. Again, all individual variables (CZ Net, ETF ownership, market cap, book-to-market ratio, 12-month momentum, Amihud illiquidity, and short interest) are cross-sectionally ranked and then mapped to the $[-1, 1]$ interval.

Panel A of Table 14 reports the regression results based on Eq. (8). We find that ETF ownership significantly lowers the anomaly returns on earnings announcement days and news release days. As ETF ownership increases from the 25th percentile (-0.5) to the 75th percentile (0.5) within the range of [-1, 1], we observe a substantial decrease in anomaly returns on both news release days and earnings announcement days. Specifically, on news release days, the anomaly returns decrease by 82.1% (the coefficient of $Nday \times ETF \times Net$

divided by that of $Nday \times Net$, or 0.055/0.067). Similarly, on earnings announcement days, the anomaly returns decrease by 30.5% (the coefficient of $Nday \times ETF \times Net$ divided by that of $Nday \times Net$, or 0.083/0.272).

Next, we partition our news data into fundamental news and non-fundamental news and run separate regressions for these two groups. The results are reported in Panels B and C of Table 14, respectively. We observe that ETFs primarily influence anomaly returns by expediting the incorporation of fundamental news into stock prices. The regression coefficient β_8 is significant for two regressions with fundamental news, while it is insignificant for the two non-fundamental news regressions.

6. Russell Reconstitution Quasi-Natural Experiment

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

The Russell 1000 and 2000 indices adhere to predefined, mechanical annual reconstitution rules. On the last Friday of June, FTSE Russell determines which stocks will enter into the Russell 1000 index or the Russell 2000 index based on 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 with market cap around the cutoff on the last Friday of June can be considered as randomly assigned to either the Russell 1000 or 2000 index. As both indices are value-weighted, stocks that are included in the Russell 2000 will have a significantly greater portfolio weight compared to those in the Russell 1000. This is because the stock would rank among the largest holdings within the Russell 2000 portfolio. Given the presence of numerous ETFs that passively track or actively utilize these indices as benchmarks, the randomized assignment of stocks would lead to considerable variations in ETF flow and ownership.

The natural experiment of the Russell reconstitution has been employed by numerous studies to examine various aspects of the stock market. For example, Chang, Hong, and Liskovich (2015) utilize this natural experiment to assess the elasticity of the stock market, and Appel, Gormley, and Keim (2016) exploit this random variation to investigate the effect of passive investors on firms' corporate governance. In the realm of the ETF literature, Ben-David, Franzoni, and Moussawi (2018) and Glosten, Nallareddy, and Zou (2021) employ this technique to demonstrate the causal effect of ETFs on stock volatility and PEAD behaviours, respectively.

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

$$ETF_{it} = \eta + \lambda R2000_{it} + \gamma Net_{it} + Controls_{it} + \delta_t + u_{it} \tag{9}$$

where ETF_{it} represents the ETF ownership of stock i in month t. $R2000_{it}$ equals 1 if stock i is in Russell 2000 in month t and it equals 0 if the stock is in Russell 1000. Our controls include size, Amihud illiquidity, short interest, index fund ownership, book-to-market ratio, and 12-month momentum. 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 ranked and then mapped to the $[-1, 1]$ interval. We keep the original value of ETF ownership to be more consistent with the Russell reconstitution literature.

Panel A of Table 15 presents the first-stage regression with different bandwidths (200, 300, 400). The results indicate a strong relationship between ETF ownership and the assignment to the Russell 2000 index. In particular, the first-stage regression yields t-statistics exceeding the critical value of 4.05 in Stock and Yogo (2002) across all three bandwidth settings, affirming the statistical significance of the relationship.

In the second stage, we run the following regression:

$$Ret_{i,t+1} = \alpha + \beta_1 \widehat{ETF}_{it} + \beta_2 Net_{it} + \beta_3 \widehat{ETF}_{it} \times Net_{it} + Controls_{it} + \delta_{t+1} + \epsilon_{i,t+1} \quad (10)$$

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 aim to examine whether exogenous changes in ETF ownership resulting from Russell reconstitution have an attenuation effect on anomaly returns.

Panel B of Table 15 presents the results from the second-stage regression. We observe a significant negative coefficient for the interaction term $ETF \times Net$ across all three specifications with different bandwidths. A one percent increase in ETF ownership leads to an attenuation of 81.2 percent of anomaly returns based on Net. These estimates remain consistent across the three different bandwidth settings. Thus, based on the evidence from the Russell reconstitution experiment, we establish causal evidence that ETFs have an attenuation effect on anomaly returns.

7. Conclusion

In this paper, we investigate the effect of ETF ownership on stock market anomalies and market efficiency. Our findings reveal a strong attenuation effect of ETF ownership on the profitability of stock market anomalies.

To establish the attenuation effect, we begin by analyzing the profitability of each long-short (LS) anomaly portfolio constructed separately by high and low ETF ownership stocks. After applying multiple testing adjustments, we observe that none of these LS anomaly portfolios exhibit significantly higher returns in the high ETF ownership group compared to the low ETF ownership group. In contrast, we find that 26 out of 205 anomalies demonstrate significantly higher returns in the low ETF ownership group. We then aggregate all information contained in anomalies into a Net variable. Performing portfolio analysis for the LS Net portfolio constructed by high and low ETF ownership stocks separately, we discover that the profitability of the LS Net trading strategy only exists in the low ETF ownership group. This finding suggests that anomalies completely "reside" in the low ETF ownership group. Moreover, we observe no significant alpha for the LS Net portfolios across several leading factor models for the high ETF ownership group. These results also hold for matched stock samples based on size, volume, and propensity scores. Furthermore, we corroborate the attenuation effect of ETFs through Fama-MacBeth regressions and find a negative and highly significant interaction effect between Net and ETF ownership, which is distinct from other anomaly mispricing amplification channels such as size and volume.

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

Furthermore, we investigate the role of active ETFs in mitigating the abnormal returns generated by anomaly strategies. Our analysis reveals that active ETFs have a more significant impact on anomaly returns compared to passive ETFs. Additionally, we explore the impact of ETF ownership on both build-up and resolution anomalies. Our findings indicate that the attenuation effect of ETFs is more pronounced for build-up anomalies than for resolution anomalies, which implies a reduction in overall market mispricing as a result of the presence of ETFs. Last but not least, we uncover a causal effect of ETF ownership on anomaly returns through the natural experiment of Russell index reconstitution. Using Russell 2000 membership as an instrument, we establish 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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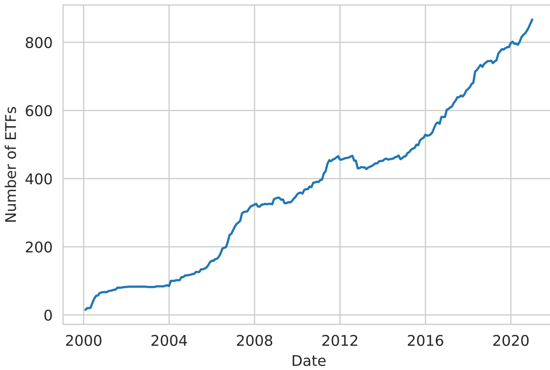
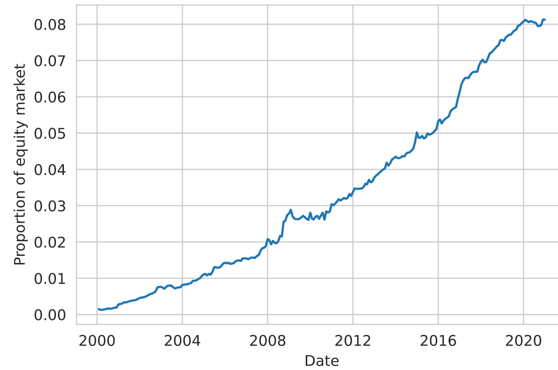
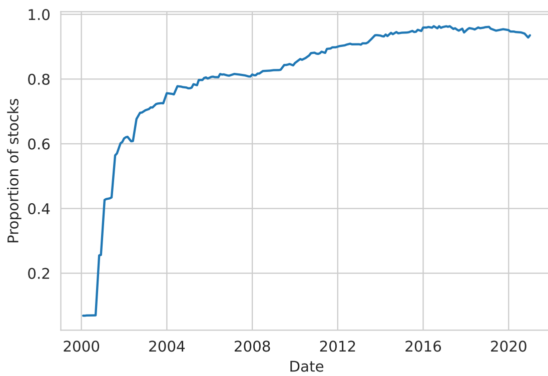


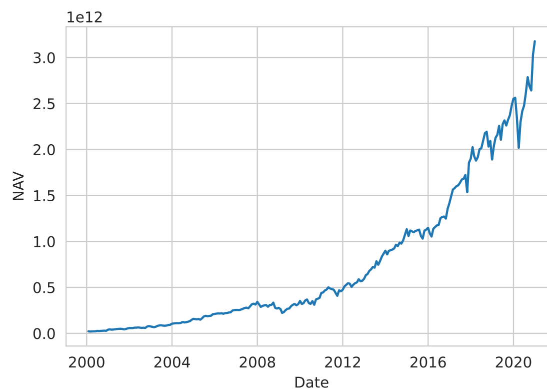
(a) Total Number of US Equity ETFs



(b) Proportion of the Equity Market Owned by ETFs



(c) Proportion of Stocks held by ETFs



(d) Total Net Asset Value of US equity ETFs

Figure 1: ETF Characteristics and Stock Holdings

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

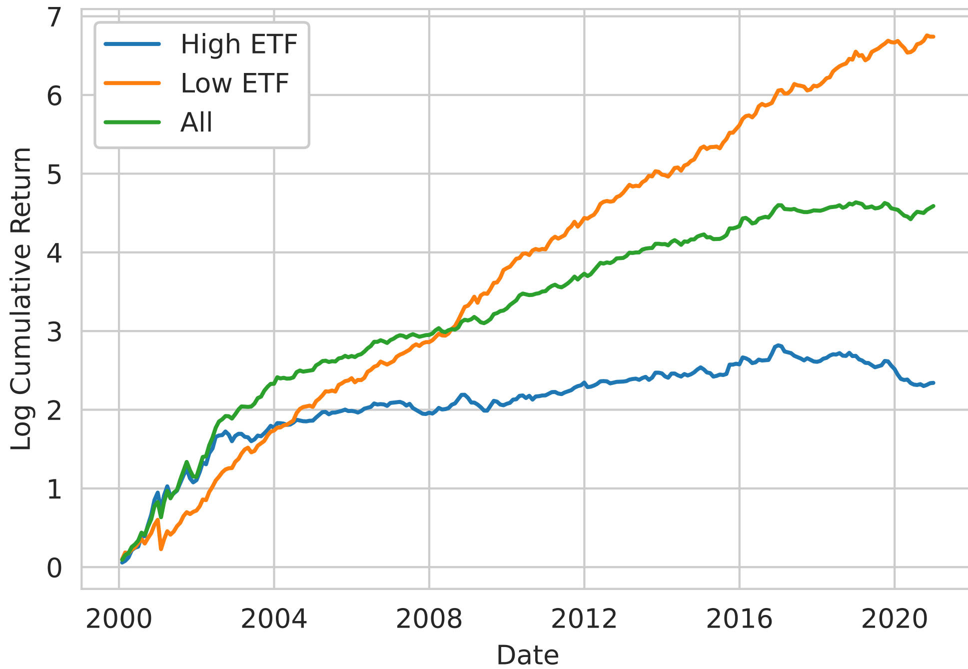


Figure 2: Log Cumulative Return of the long-short CZ Net Portfolios

This figure plots the log cumulative portfolio value from investing in different long-short CZ Net 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 Eq. (1)) ranks in the top (bottom) tercile among all stocks.

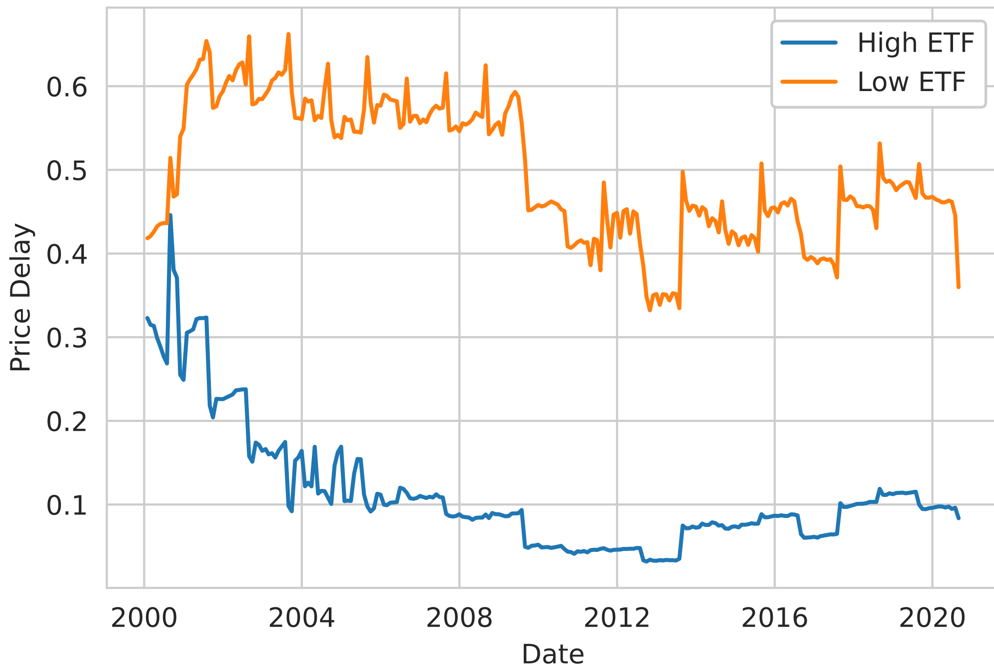


Figure 3: Average Price Delay for High and Low ETF Ownership Groups

This figure plots the cross-sectional average price delay (defined in Eq. (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 Eq. (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 Eq. (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 Eq. (4)) for high and low ETF ownership stocks, respectively.

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 (2022). We then calculate average return differences ("Diff" column) and t-statistics ("t-stat" column) using the two versions of the anomalies. The significance criterion is based on the p-value of the return difference under 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 (2022). There are 26 anomalies with significant return differences between the high ETF ownership group and the low ETF ownership groups. 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 Score), the number of times it occurs on the short side of the anomalies (Short Score), 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 Score	26.36	8.84	0	10	21	26	32	41	71
Short Score	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 Score	27.18	9.85	0	8	22	28	34	42	71
Short Score	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 Score	26.13	7.91	2	14	21	26	31	40	69
Short Score	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 denotes the decile 10 - decile 1 long-short portfolio.

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 CZ 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 monthly alphas in percentage 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). All portfolios are equal-weighted. The sample period is from January 2000 to December 2020. The "CZ Net" column denotes the decile 10 - decile 1 long-short portfolio.

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: Summary Statistics and Sharpe Ratio Difference Test for Matched Sample

This table reports the number of observations and average stock characteristics (size, trading volume, book-to-market, 12-month momentum) for 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 difference test between the high- and the low-ETF Net long-short portfolios using the 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, volume matched" matches stocks based on the Euclidean distance between the standardized size and volume tuples; (3) "propensity score matched" pairs stocks based on size, volume, book-to-market, and 12-month momentum.

	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, Volume 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: CZ Net Portfolio Performance of the Size Matched Sample

This table reports the decile portfolio performance sorted based on the CZ Net score 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 denotes the decile 10 - decile 1 long-short portfolio.

Panel A: 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 B: 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 CZ 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 matched with size. We report monthly alphas in percentage 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). All portfolios are equal-weighted. The sample period is from January 2000 to December 2020. The "CZ Net" column denotes the decile 10 - decile 1 long-short portfolio.

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 the CZ Net score for two alternative matching methods: matching based on size and volume and matching based on a propensity score calculated from size, volume, BM, and 12-month 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 sample period is from January 2000 to December 2020. The "CZ Net" column denotes the decile 10 - decile 1 long-short portfolio.

Panel A: Low ETF Ownership, Size Volume 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 Volume 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 results predicting next-month stock returns in percentage points under the specification of Eq. (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 ranked and then mapped to the $[-1, 1]$ interval. We report Newey and West (1987) t-statistics in squared brackets. *, **, and *** denote significance at 10%, 5%, and 1% levels, respectively.

Dependent Variable:	Monthly Return (%)								
	(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: Summary Statistics and Sharpe Ratio Difference Test for Matched Sample: Active ETF Ownership vs Passive ETF Ownership

This table reports the number of observations and summary statistics on mean and Sharpe ratio for the whole sample and the matched samples based on all, active, and passive ETF ownership. Following Easley et al. (2021), we calculate the activeness index for each ETF as in Eq. (5) and define active (passive) ETFs as those with an activeness index above (below) 0.5. We then compute active and passive ETF ownership for each stock using Eq. (1). Next, we proceed to conduct the matched sample analyses as before. Panel A reports results based on all ETFs and panel B (C) reports results based on only active (passive) ETFs. Within each panel, we report 5 sets of portfolio results: (1) "Whole Sample EW" reports the baseline results using all stocks with equal weights. (2) "Whole Sample VW" reports the results using all stocks with value weights; due to the diminished significance of many anomalies under the value-weighting scheme, the Net score is computed based only on anomalies that are significant at the 5% level. (3) "Size Matched" reports results using matched sample based on market cap. (4) "Size, Volume Matched" reports results using matched sample based on size and volume. (5) "Propensity Score Matched" reports results using matched sample based on size, volume, book-to-market, and 12-month momentum. For each set of the results, we present the total number of observations, average monthly returns in percentage of the long-short CZ Net portfolio within high and low ETF ownership groups ("LS mean High ETF" and "LS mean Low ETF" columns), annualized Sharpe ratios for the long-short CZ Net portfolios within high and low ETF ownership groups ("LS SR High ETF" and "LS SR Low ETF" columns), and the p-value for the Sharpe Ratio difference between the two ETF ownership groups using the Ledoit and Wolf (2008) procedure (the "p for SR diff" column). The sample period is from January 2000 to December 2020.

	N	LS mean High ETF	LS mean Low ETF	LS SR High ETF	LS SR Low ETF	p for SR diff
Panel A: All ETF ownership						
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, Volume 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						
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, Volume 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						
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, Volume 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: CZ Net Portfolio Performance Based on Style ETF Ownership

This table reports the decile portfolio performance sorted based on CZ Net for three different samples: all stocks, high style-ETF ownership stocks, and low style-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 denotes the decile 10 - decile 1 long-short portfolio.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Panel A: All Stocks											
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 Style ETF Ownership											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	-0.25	0.55	0.75	1.25	1.27	1.32	1.58	1.79	2.13	2.58	2.84
Std	8.24	7.70	7.26	6.80	6.34	5.87	6.04	6.13	6.14	6.20	4.49
SR	-0.11	0.25	0.36	0.63	0.70	0.78	0.91	1.01	1.20	1.44	2.19
Panel C: High Style ETF Ownership											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.53	0.78	0.75	0.89	0.78	1.07	1.16	1.19	1.36	1.46	0.93
Std	7.99	7.49	7.40	6.91	6.79	6.29	6.12	6.10	6.18	6.50	4.62
SR	0.23	0.36	0.35	0.45	0.40	0.59	0.66	0.68	0.76	0.78	0.70

Table 13: Effect of ETF Ownership on Build up vs Resolution Anomalies

This table reports the regression results of Eq. (7). The dependent variable is the absolute value of the price wedge, capturing a stock's mispricing level, and ETF ownership is the main variable of interest. If ETFs attenuate build-up anomalies more than resolution anomalies, all else being equal, high ETF ownership stocks would have lower mispricing levels. The control variables include size, momentum, book-to-market ratio, Amihud illiquidity, short interest, and institutional ownership. All independent variables are cross-sectionally ranked and then mapped into the $[-1, 1]$ interval. All standard errors are clustered at the firm level. *, **, and *** denote significance at 10%, 5%, and 1% respectively.

Dependent Variable:	$\|PW_{i,t}\|$			
	(1)	(2)	(3)	(4)
ETF ownership	-0.024***	-0.014***	-0.013***	-0.008***
	(-11.71)	(-7.80)	(-7.29)	(-4.34)
Size				-0.057***
				(-9.32)
MOM				0.000
				(0.36)
BM				0.029***
				(10.67)
Illiquidity				-0.035***
				(-11.92)
Short interest				-0.004**
				(-2.27)
Institutional ownership				-0.005**
				(-2.03)
Month Fixed Effect	Yes	No	Yes	Yes
Firm Fixed Effect	No	Yes	Yes	Yes
Observations	477935	477935	477935	477935

Table 14: Effect of ETFs on Anomaly Returns: News and Earnings Announcement Days

This table reports the regression results based on Eq. (8). *Eday* and *Nday* are indicator variables that take a value of 1 on earnings announcement and news release days, respectively. All other individual variables (CZ Net, ETF ownership, market cap, book-to-market ratio, 12-month momentum, Amihud illiquidity, and short interest) are cross-sectionally ranked and then mapped to the $[-1, 1]$ interval. Our lagged control variables include market cap, book-to-market ratio, 12-month momentum, Amihud illiquidity, and short interest. Following Jiang, Li, and Wang 2021b, we further partition news into fundamental news and non-fundamental news groups. We report regression results based on all news in Panel A, and fundamental (non-fundamental) news in Panel B (C). In all regressions, we include day-fixed effect and cluster the standard errors at the daily level. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Dependent Variable:	Monthly Return (%)					
	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 15: Quasi-Natural Experiment Based on the Russell Index Reconstitution

This table reports the first-stage and second-stage IV regression results from Eqs. (9) and (10). Columns (1) - (3) report regressions with different bandwidths (200, 300, 400). R2000 is a binary variable that takes a value of one if the stock belongs to the Russell 2000 index. Control variables include size, 12-month momentum, book-to-market, Amihud 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 ranked and then mapped to the $[-1, 1]$ interval. 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:		Monthly Return	
	(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 × CZ 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)
Short interest	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

A. Additional Tables

Table A1: CZ Net Portfolio Performance: Log Market Value Weights

This table reports the log-market-value-weighted decile portfolio performance sorted based on the CZ Net score 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. Due to the diminished significance of many anomalies under the value-weighting scheme, the CZ Net score is computed based only on anomalies that are significant at the 5% level. The sample period is from January 2000 to December 2020. The “CZ Net” column denotes the decile 10 - decile 1 long-short portfolio.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Panel A: All Stocks											
Mean	0.09	0.61	0.74	0.83	1.02	1.19	1.27	1.42	1.51	1.71	1.61
Std	8.65	7.56	6.70	6.25	5.97	5.72	5.48	5.43	5.53	5.82	4.82
SR	0.04	0.28	0.38	0.46	0.59	0.72	0.81	0.91	0.95	1.02	1.16
Panel B: Low ETF Ownership											
Mean	0.04	0.58	0.91	1.24	1.11	1.37	1.68	1.72	1.86	2.36	2.32
Std	8.64	7.71	6.88	6.27	6.14	5.74	5.63	5.63	5.71	6.09	4.83
SR	0.01	0.26	0.46	0.68	0.63	0.83	1.03	1.06	1.13	1.34	1.66
Panel C: High ETF Ownership											
Mean	0.37	0.60	0.66	0.80	0.90	1.00	0.94	1.11	1.27	1.19	0.82
Std	8.81	7.43	6.44	6.38	6.09	5.92	5.77	5.74	5.68	5.84	5.25
SR	0.15	0.28	0.35	0.43	0.51	0.58	0.56	0.67	0.77	0.70	0.54

Table A2: CZ Net Portfolio Performance of Matched Sample Based on Different Matching Criteria: Log Market Value Weights

This table reports the log-market-value weighted decile portfolio performance sorted based on the CZ Net score for varius matched sample based on three matching methods: (1) "Size matched" matches stocks based on their market cap; (2) "Size, volume matched" matches stocks based on size and volume; and (3) "Propensity score matched" pairs stocks based on size, volume, book-to-market, and 12-month momentum. Due to the diminished significance of many anomalies under the value-weighting scheme, the CZ Net score is computed based only on anomalies that are significant at the 5% level. The sample period is from January 2000 to December 2020. The "CZ Net" column denotes the decile 10 - decile 1 long-short portfolio.

Panel A: Low ETF Ownership, Size Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	-0.20	0.84	0.65	0.90	1.17	1.43	1.60	1.37	1.93	2.24	2.44
Std	9.50	8.32	6.95	6.50	6.34	6.12	5.64	5.44	6.04	6.40	7.52
SR	-0.07	0.35	0.33	0.48	0.64	0.81	0.98	0.87	1.11	1.21	1.13
Panel B: High ETF Ownership, Size Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.31	1.06	0.71	1.14	1.00	1.44	1.39	1.72	1.50	1.65	1.35
Std	12.33	10.89	9.54	9.60	9.53	8.63	8.20	7.97	7.95	7.44	8.90
SR	0.09	0.34	0.26	0.41	0.36	0.58	0.59	0.75	0.65	0.77	0.52
Panel C: Low ETF Ownership, Size Volume Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	-0.02	0.46	0.58	1.18	1.29	1.43	1.78	1.91	2.05	2.06	2.08
Std	8.89	7.97	7.79	7.26	7.20	7.00	6.59	6.50	6.99	7.20	6.19
SR	-0.01	0.20	0.26	0.56	0.62	0.71	0.93	1.02	1.02	0.99	1.16
Panel D: High ETF Ownership, Size Volume Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.25	1.03	0.71	0.90	0.71	1.11	1.13	1.52	1.67	1.65	1.40
Std	12.62	10.56	8.89	8.75	8.26	7.68	7.35	7.48	7.54	7.24	9.49
SR	0.07	0.34	0.28	0.36	0.30	0.50	0.53	0.71	0.77	0.79	0.51
Panel E: Low ETF Ownership, Propensity Score Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	-0.10	0.70	0.62	1.29	1.26	1.61	1.64	1.62	1.84	1.85	1.95
Std	9.23	8.81	7.89	7.45	7.17	6.81	6.05	6.59	6.87	7.42	7.24
SR	-0.04	0.27	0.27	0.60	0.61	0.82	0.94	0.85	0.93	0.86	0.93
Panel F: High ETF Ownership, Propensity Score Matched Sample											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.08	0.51	0.60	0.56	0.77	1.07	1.17	1.20	1.49	1.38	1.29
Std	11.69	10.58	8.71	8.40	7.72	7.59	7.23	7.28	7.24	7.03	8.53
SR	0.02	0.17	0.24	0.23	0.35	0.49	0.56	0.57	0.71	0.68	0.52

Table A3: Summary Statistics and Sharpe Ratio Difference Test for Matched Sample: Log Market Value Weighted Portfolios

This table reports the number of observations and average stock characteristics (size, trading volume, book-to-market, 12-month momentum) for the whole sample and matched samples with log market value weights. 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 difference test between the high- and the low-ETF CZ Net long-short portfolios using the Ledoit and Wolf (2008) procedure (the "*p* for SR diff" column). We consider three different matching procedures: (1) "size matched" matches stocks based on their market cap; (2) "size, volume matched" matches stocks based on size and volume; (3) "propensity score matched" pairs stocks based on size, volume, book-to-market, and 12-month momentum. Due to the diminished significance of many anomalies under the value-weighting scheme, the CZ Net score is computed based only on anomalies that are significant at the 5% level.

	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	0.059
Size, Volume Matched	88198	19.72	19.62	17.48	17.32	-0.58	-0.91	0.06	0.35	0.008
Propensity Score Matched	75538	19.73	19.74	17.44	17.40	-0.76	-0.70	0.16	0.20	0.083

B. Alternative Measure of ETF Activity

In this section, we consider an alternative measure of ETF activity. Specifically, instead of leveraging ETF ownership to gauge the ETFs' influence on individual stocks, we employ a different measure which is the total implied trading volume of individual stocks derived from ETF trading volume. The trading activity of each ETF indirectly suggests corresponding trades in its constituent stocks (e.g., via the creation/redemption process), thereby generating an implied trading volume. This volume aligns with the proportion of individual stocks each ETF holds. We refer to this measure as the ETF Volume Induced Trading (ETF VIT) and define it as follows:

$$\text{ETF VIT}_{i,t} = \frac{\sum_j^{J_t} Volume_{j,t} \cdot \frac{shares_{i,j,t}}{shrout_{j,t}}}{shrout_{i,t}}, \tag{11}$$

where $Volume_{j,t}$ is the trading volume of ETF j at month t, $shares_{i,j,t}$ denotes the number of shares of stock i held by ETF j, $shrout_{j,t}$ is the total outstanding shares of ETF j, and $shrout_{it}$ indicates the total outstanding shares of stock i.

The ETF VIT measure captures the cumulative trading volume of stock i attributable to all ETF trades. It can be viewed as a proxy for price discovery in stock i based on ETF trading, as it integrates systematic information into individual stock prices. Variations in ETF VIT can signify different levels of ETF-induced trading activities for individual stocks. It supplements the ETF ownership measure by offering another way to evaluate the ETF's impact on individual stocks.

Table A4 presents analysis of Net portfolios for all stocks as well as stocks with different levels of ETF VIT. The equal-weighted LS portfolio achieves an Sharpe ratio of 1.97 (0.92) for stocks with low (high) ETF VIT. This finding reinforces our previous conclusion that higher ETF activity corresponds to a more pronounced attenuation effect on anomaly profits.

Tables A5 further examines the robustness of our finding using log market cap weight, while Table A6 performs Fama-MacBeth regression analysis predicting next-month stock returns in percentage with alternative ETF activity measure. These results collectively indicate that under the alternative metric of ETF activity using trading volume, ETF activity significantly attenuates the trading profit of asset pricing anomalies.

Table A4: CZ Net Portfolio Performance: Alternative Measure of ETF Activity

This table reports the decile portfolio performance sorted based on CZ Net for three different samples: all stocks, high ETF VIT stocks, and low ETF VIT stocks. ETF VIT denotes ETF Volume Induced Trading defined in Eq. (11). 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 denotes the decile 10 - decile 1 long-short portfolio.

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 VIT											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	0.35	0.92	1.19	1.35	1.52	1.51	1.78	1.93	2.21	2.74	2.39
Std	7.86	7.37	7.09	6.58	6.01	5.69	5.78	6.01	5.98	6.27	4.21
SR	0.16	0.43	0.58	0.71	0.88	0.92	1.07	1.12	1.28	1.51	1.97
Panel C: High ETF VIT											
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Mean	-0.09	0.11	0.37	0.28	0.42	0.64	0.87	0.88	1.20	1.23	1.33
Std	8.62	8.04	7.82	7.27	7.37	6.90	6.57	6.53	6.65	6.79	5.00
SR	-0.04	0.05	0.16	0.13	0.20	0.32	0.46	0.47	0.62	0.63	0.92

Table A5: CZ Net Portfolio Performance: Alternative Measure of ETF Activity and Log Market Value Weights

This table reports the log-market-value-weighted decile portfolio performance sorted based on CZ Net for three different samples: all stocks, high ETF VIT stocks, and low ETF VIT stocks. ETF VIT denotes ETF Volume Induced Trading defined in Eq. (11). The mean and standard deviation are calculated from monthly returns in percentage, and the Sharpe ratio is annualized. Due to the diminished significance of many anomalies under the value-weighting scheme, the CZ Net score is computed based only on anomalies that are significant at the 5% level. The sample period is from January 2000 to December 2020. The "CZ Net" column denotes the decile 10 - decile 1 long-short portfolio.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	CZ Net
Panel A: All Stocks											
Mean	0.20	0.46	0.73	0.84	0.97	1.18	1.28	1.41	1.58	1.99	1.79
Std	7.82	7.12	6.79	6.61	6.01	5.69	5.58	5.62	5.72	5.99	4.25
SR	0.09	0.23	0.37	0.44	0.56	0.72	0.79	0.87	0.96	1.15	1.46
Panel B: Low ETF VIT											
Mean	0.40	0.93	1.17	1.33	1.48	1.47	1.72	1.86	2.10	2.66	2.26
Std	7.59	7.04	6.77	6.37	5.75	5.49	5.56	5.78	5.77	6.14	4.02
SR	0.18	0.46	0.60	0.72	0.89	0.93	1.07	1.12	1.26	1.50	1.95
Panel C: High ETF VIT											
Mean	-0.08	0.14	0.38	0.32	0.45	0.65	0.86	0.89	1.16	1.21	1.29
Std	8.45	7.79	7.53	7.06	7.14	6.71	6.41	6.40	6.50	6.68	4.89
SR	-0.03	0.06	0.18	0.16	0.22	0.34	0.47	0.48	0.62	0.63	0.91

Table A6: ETF VIT and CZ Net: Fama-MacBeth Regressions

This table reports the Fama and MacBeth (1973) regression results predicting next-month stock returns in percentage points under the specification of Eq. (2), where ETF Ownership is replaced by ETF VIT. ETF VIT denotes ETF Volume Induced Trading defined in Eq. (11). For ease of interpretation, all individual variables (ETF VIT, CZ Net, Size, Volume, Book-to-market ratio (BM), and 12-month momentum (MOM)) are cross-sectionally ranked and then mapped to the $[-1, 1]$ interval. We report Newey and West (1987) t-statistics in squared brackets. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Dependent Variable:			Monthly Return (%)			
	(1)	(2)	(3)	(4)	(5)	(6)
ETF VIT	-0.59***				-0.42***	-0.47***
	[-3.71]				[-2.63]	[-3.32]
CZ Net		0.94***			0.79***	0.75***
		[6.11]			[5.12]	[7.61]
Size			-0.46**			-0.49
			[-2.08]			[-0.76]
Volume				-0.40**		0.69
				[-2.33]		[1.22]
ETF VIT×CZ Net					-0.33***	-0.18**
					[-4.06]	[-2.15]
Size×CZ Net						-1.38***
						[-4.16]
Volume×CZ Net						0.83***
						[2.76]
BM						0.20
						[1.54]
MOM						-0.01
						[-0.03]
R^2	0.67%	0.63%	0.77%	0.58%	1.30%	4.06%