The Rise of Single-Stock ETFs and More Volatile Stock Prices

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Abstract

I investigate the novel instrument of single-stock ETFs. I propose that single-stock ETFs gain popularity because they satisfy retail investors' demand for taking short-term leveraged long and short positions on popular stocks at a low cost. I show that flows, turnover ratios, and retail buy-sell imbalance of both long and short single-stock ETFs are positively related to the retail attention on the underlying stock. This suggests that single-stock ETFs are mainly used by retail investors to circumvent leverage and short-selling constraints. Furthermore, I find that following the launch of the first short single-stock ETF on a stock, the underlying stock experiences a significant and long-lasting increase in the idiosyncratic volatility.

Keywords: single-stock ETFs; retail trading; retail attention; idiosyncratic volatility; short-selling

1. Introduction

In the last three decades, ETF industry is home to many financial innovations, given its ease to trade and its flexible structure. All investors who have access to a brokerage account can trade any ETF listed on the US equity markets whenever the market is open, just as they can trade public stocks. This allows ETF sponsors to directly sell their products to a broader set of potential customers at a lower cost, as compared to traditional mutual fund sponsors. ETFs are also extremely flexible, because they are essentially a vehicle that comprises a set of underlying assets, which can be almost any asset specified by the fund sponsor. Despite initially proposed as equity index-based passive products, ETFs have now been designed to incorporate many strategies, including but not limited to active stock-picking, smart beta, industry-specific, and thematic (Ben-David, Franzoni, Kim, and Moussawi, 2023). However, all these ETFs had one thing in common: they have dozens, if not hundreds, of securities holdings in their portfolios. This changed in July 2022, when a novel type of ETF comes to the US market: single-stock ETFs. The portfolios of these single-stock ETFs only have exposure to a single stock. There are two types of single-stock ETFs: long and short. For a long single-stock ETF, it holds a leveraged long position in one underlying stock and promises a daily return that is equal to a pre-specified positive multiple of the daily return of the underlying stock. For a short single-stock ETF, it holds a short position in one underlying stock and promises to deliver a daily return that is a negative multiple of the daily return of the underlying stock. It's important to note that long single-stock ETFs are always leveraged in my data sample, whereas short single-stock ETFs do not necessarily involve leverage.

These single-stock ETFs have gained popularity very quickly, as demonstrated by the explosion in their sizes. Within around two years after the introduction of the first single-stock ETF in the US markets, the aggregate total market capitalization of all single-stock ETFs has reached 20 billion dollars in the US. Considering the fact that the aggregate total market capitalization of all single-stock ETFs was 17 million dollars on the first trading day of the first group of single-stock ETFs, the industry grew more than 1000 times in two years. Unlike index-based ETFs that have hundreds or even thousands of portfolio holdings, all single-stock ETFs in my sample data track 24 US stocks in total. In the beginning, the stocks tracked by single-stock ETFs are mainly mega-cap stocks, such as AAPL and TSLA. In 2024 and 2025, the scope of single-stock ETFs expanded to smaller stocks, such as MU, CRWD, and DJT, which are popular among retail investors. If the growth of single-stock ETFs maintains at such a high pace, they will control a sizeable portion of some of the largest stocks in the world, whereas we still do not understand these investment vehicles very well. Regulators are also calling for studies to understand this novel type of instrument[1]. To author's knowledge, this paper is the first academic research to study single-stock ETFs. With this paper, I wish to fill the gap in our understanding of this financial innovation and its impact on the underlying stocks. Specifically, I aim to answer the following two questions in this paper. First, why single-stock ETFs exist and grow so rapidly. Second, how the launch of single-stock ETFs affects the trading of underlying stock.

Given that the single-stock ETFs essentially provide leveraged long and short

[1]See SEC commissioner statement at https://www.sec.gov/newsroom/speeches-statements/crenshaw-single-stock-etfs-20220711.

exposures to individual stocks, the natural question to ask is why investors buy single-stock ETFs, instead of buying the stock on margin or short-selling the stock. To answer this question, I first investigate the underlying mechanism and some of the characteristics of the single-stock ETFs. I document that single-stock ETFs are expensive. The annual expense ratio for single-stock ETFs averaged 1.13% as of June 2024, which is about three times as high as the average expense ratio for broad-based ETFs as documented in the literature (Ben-David et al., 2023). I found that most shares (around 83% of market capitalization) of single-stock ETFs are held by individual investors, and the average holding period is as short as two days, which is around 20 times shorter than the average holding period for the index ETFs in my sample period. These results suggest that single-stock ETFs could mainly be held by short-term oriented individual investors, who are willing to pay the hefty fee for some reason. I rationalize their behaviors by noting that although single-stock ETFs charge a higher fee than most other ETFs, trading single-stock ETFs is still very likely the cheapest, if not the only, way for most individual investors to take on leveraged long or short positions on the underlying stocks.

I further investigate the relation between single-stock ETF trading and retail investors by focusing on the role of retail investor attention. Adopting Da, Engelberg, and Gao (2011) retail investor attention measure constructed from Google Trends search volume index, I show that the flows into both long and short single-stock ETFs are high when the underlying stock receives abnormally high attention from retail investors. The same pattern exists for the turnover ratios of both long and short single-stock ETFs. I also use Barber, Huang, Jorion, Odean, and Schwarz

(2024) algorithm to directly identify retail buy and sell trades of the single-stock ETFs and compute retail investors' buy-sell imbalance measure, similar to that in Barber and Odean (2008). I show that when retail attention on the underlying stock increases, the buy-sell imbalance ratio of retail investors increases for both long and short single-stock ETFs. Moreover, for long single-stock ETFs, both attention-driven buying and attention-driven selling from retail investors are positive and significant. These findings fit the limited attention theory of retail investors (Seasholes and Wu, 2007; Barber and Odean, 2008; Barber, Huang, Odean, and Schwarz, 2022): Retail investors do not always attend to the information about the public firms and financial markets, and they are more likely to make the trades when their attention is drawn to the stocks. The evidence discussed so far points to an answer to the question that why single-stock ETFs exist and grow: these ETFs cater to the retail investors' demand for short-term leverage and short-selling by providing them with a cheap and accessible way to do so.

After answering the first question, I move on to investigate how the launch of single-stock ETFs affects the trading of the underlying stocks. In this paper, I focus on the idiosyncratic volatility of the underlying stocks, because if retail trading are driven by attention, rather than risks, more retail trading should lead to higher volatility in stock return, after controlling for risk factors. This hypothesis is similar to the story of Ben-David, Franzoni, and Moussawi (2018), where they show that ETFs attract a new group of short-term traders, resulting in an increase in the volatility for stocks in the ETF basket. I compute the idiosyncratic volatility for each stock in each month as the standard deviation of the residuals from CAPM regression. I find that following the launch of the first short single-stock ETF on an underlying stock, the idiosyncratic volatility of the stock increases, and this increase lasts for at least 12 months. Following the launch of the first long single-stock ETF, the increase in the stock idiosyncratic volatility is positive but insignificant, and the increase reverts to zero in the eighth month after the long ETF launch.

This article is mainly related to three topics in literature: ETF innovation, impact of ETFs on underlying assets, and retail trading. First, this article contributes to the ETF innovation literature by investigating a new type of ETF and explaining its rapid growth since initial launch. Many authors have attempted to explain the rise of non-index-based ETFs. Cong, Huang, and Xu (2024) argue that ETFs that are not fully index-based allow investors to use their factor-specific information to make trading profits. They suggest that in equilibrium, the weight of each asset in the portfolio should be proportional to its exposure to a factor to facilitate "factor investing". Ben-David et al. (2023) investigate the rise of sector-based and thematic ETFs and suggest that these ETFs mainly target sectors that have high investor attention and sentiment in recent months. My argument is in a similar spirit to that of Ben-David et al. (2023). I show that another type of novel ETF, single-stock ETF, is also a popular vehicle that facilitates trading of attention-grabbing stocks. I argue that single-stock ETF relaxes the leverage and short-selling constraints faced by retail investors when trading attention-grabbing stocks, resulting in single-stock ETFs' popularity and rapid growth. Second, this article contributes to the literature on the impact of ETFs on underlying assets. Scholars have shown that ETFs make underlying stock returns more correlated (Da and Shive, 2018), and widens bid-ask spread of underlying stocks (Evans, Moussawi, Pagano, and Sedunov, 2024). There has also been conflicting evidence on how ETFs affect the informativeness of underlying stock prices (Israeli, Lee, and Sridharan, 2017; Buss and Sundaresan, 2023). There has been articles showing that ETFs raise the volatility of underlying stocks (Ben-David et al., 2018; Cheng and Madhavan, 2009). In this paper, I add support to this strand of literature by demonstrating that following the introduction of short single-stock ETFs, there is a long-lasting increase in the idiosyncratic volatility of the underlying stock. This finding could be explained by the theory that single-stock ETFs attract attention-driven retail investors, whose trading adds noise to the underlying stock price. Third, this article contributes to the literature of retail investor trading by exploring a new instrument that could serve as a useful arena for observing retail behaviors. I show that trading in single-stock ETFs exhibits many patterns that are typical of retail trading, suggesting that the majority of investors trading these single-stock ETFs are retail investors. In particular, I apply retail attention measure from Da et al. (2011) to single-stock ETFs and show that this measure predicts trading in single-stock ETFs. I also confirm the finding of Barber and Odean (2008) that attention-driven retail buying is greater than attention-driven retail selling, in the context of single-stock ETFs. Moreover, I find that both long and short single-stock ETFs experience similar magnitudes of increase in retail buy-sell imbalance when retail attention is high. This supports the explanation proposed in Barber and Odean (2008) that asymmetry in attention-driven buying and selling is due to short-selling constraint of retail investors, instead of because retail investors are more likely to long the stock when attention is high than to short the stock.

The remainder of the paper is organized in the following way. Section 2 introduces the sources of the data I use in this paper. Section 3 is a general overview of the single-stock ETFs. In section 4, I investigate the relation between retail investor attention and single-stock ETF trading. Section 5 investigates how idiosyncratic volatility of the underlying stock evolves around the launch of the first single-stock ETFs. Section 6 concludes the paper.

2. Data

First of all, there is no complete list of all single-stock ETFs provided by any data vendor. Therefore, I manually read through the list of all US dollar-denominated ETFs that have ever been traded (totaling 9344 ETFs as of March 2025) from Refinitiv Eikon. Because this list also includes the ETFs that have stopped trading, there is no survivor bias in my final sample of single-stock ETFs. I identify all single-stock ETFs by the inclusion of any stock ticker in the name of the ETF. For example, "GraniteShares 2x Short NVDA Daily ETF" is a short single-stock ETF on stock NVDA. It's a convention that single-stock ETFs need to include the ticker of the underlying stock in their names. However, there are many ETFs with stock tickers in their names, but that are not the standard single-stock ETFs I want to focus on in this paper. Specifically, there are many option income strategy ETFs, which hold the publicly traded stock options to create a hedged portfolio that generates streams of monthly incomes for investors. These option income ETFs mostly adopt covered option strategies, and thus have very different underlying mechanism from the single-stock ETFs that I wish to study in this paper, so I exclude these option income ETFs from my sample. I further exclude the ETFs that had never been traded on any US exchanges by the end of 2024. After this screening process, I am left with 72 single-stock ETFs on 24 underlying stocks. Out of the 72 single-stock ETFs, 47 are long ETFs, and 25 are short ETFs. Note that only 66 out of 72 single-stock ETFs were still being traded as of December 2024. The list of the names and tickers for all single-stock ETFs in my sample can be found in Appendix C. The earliest trading day of any single-stock ETF was July 13th, 2022. Therefore, the sample period for single-stock ETFs is from July 13th, 2022 to Dec 31st, 2024.

I download all daily data on single-stock ETFs from CRSP. These daily data include price, return, trading volume, net asset value, etc. However, the daily net asset value data from CRSP mutual fund dataset contain many missing values for some single-stock ETFs, and thus I focus on the market capitalization of these ETFs as the main measure of sizes. This measure of size is warranted by the small daily price premia in these single-stock ETFs, computed from the limited net asset value data. Moreover, I download the daily data on underlying stocks from CRSP. Quarterly institutional ownership data on single-stock ETFs are from Thomson Reuters 13-F database. Earnings announcement dates for stocks are accessed from IBES. I use Bloomberg to download the cross-sectional data on fees and expense ratios for single-stock ETFs as of June 2024. I am unable to download panel data on ETF fees and expense ratios from CRSP, because of the incompleteness of such data on CRSP. As a result, I am unable to include ETF fees and expense ratios as control variables in my panel regressions presented later in the paper. The fees and expense ratios for single-stock ETFs will be used for informational purpose only. Following literature (Boehmer, Jones, Zhang, and Zhang, 2021; Barber et al., 2024), I download trade-level data from NYSE Trade and Quote (TAQ) to measure retail trading of single-stock ETFs.

Lastly, I download historical Google Search Volume Index (SVI) from Google Trends, as in Da et al. (2011). Following Da et al. (2011), I manually search the stock ticker for each of the underlying stocks. For example, for "Apple Inc.", I query for the keyword "AAPL" on Google Trends. As argued by Da et al. (2011), the practice of searching for stock ticker is less ambiguous, because people searching for the stock ticker is very likely to be attentive to the information about the stock, which is exactly the attention I want to measure. Da et al. (2011) find strong empirical support for the reliability of this retail attention measure. I construct two time series of retail attention measure (Abnormal SVI, or ASVI) for each underlying stock at two different frequencies. First, I construct the weekly time series of SVI in the same way as Da et al. (2011). The query time period is from Jan 1st, 2020 to Dec 31st, 2024. I limit the geographical region to the United States. Then I query for the ticker symbols for the underlying stocks to get the weekly SVI data[2]. Second, I construct the daily time series of SVI. Because any query with a period longer than a few months will return weekly SVI values, rather than daily SVI, I write a scraper program to query the stock ticker for 31 days at a time. There are two caveats with Google Trends SVI data that will affect my variable preparation. The first caveat

[2]Google Trends performs random sampling to produce SVI index for each query, and thus the results will be slightly different for the same query parameters if the query is repeated. Da et al. (2011); Cebrián and Domenech (2024) show that such sampling errors are small.

is that for each query, Google automatically performs linear rescaling on the SVI data such that the maximum value in the returned time series is always 100. The second caveat is that SVI values are rounded to the nearest integer. To mitigate the misaligned scales and rounding errors resulted from these two caveats, I leave a 5-day overlap window between each pair of adjacent query periods for the same stock. Then I re-align the scales of the SVI series returned by two adjacent queries by linearly scaling the two series such that the greatest SVI value in the 5-day overlap window for each series is equal. I choose to align the scale based on the greatest value in each series in the overlap window to minimize rounding errors. For example, suppose I only have a 1-day overlap and align the SVI series by setting the SVI value on that overlapping day equal in both series. If the actual precise SVI value on that overlap day is 1.4 in the earlier series and 1.5 in the later series, then the SVI value after rounding will be 1 in the earlier series and 2 in the later series. Because I can only access the rounded SVI value, I would have to scale all observations in the earlier series by a factor of 2, whereas the actual scaling factor should have been 1.07 (1.5/1.4). As one can see, the rounding error will be very significant in this case. To minimize the rounding error, I choose to adopt a 5-day overlap period and scale the series based on the greatest value in that window. One can argue for other lengths of the overlapping window, I choose 5 days to strike a balance between the rounding error minimization and the total scraping time minimization. Similarly, using a query period of 31 days at a time is also the result of balancing these two problems. Using a longer query period will reduce the time needed for scraping, whereas it will compress the SVI values in the series downwards, because the maximum value is always 100. After setting the daily SVI values to the same scale for each stock, I concatenate them together and perform the final rescaling such that the maximum daily SVI value is 100 for each underlying stock. Now I have got a daily panel of SVI measure for each underlying stock from Jan 1^{st}, 2020 to Dec 31^{st}, 2024, and each time series is on the same scale. Then, I only keep daily SVI observations on the trading days. Note that, for some tickers that went public in the middle of my sample period, Google Trends does not give any SVI values before the firm went public. This makes sense, because the character combinations in many stock tickers were meaningless before the stock went public.

The weekly SVI data from Google Trends corresponds to each week from Monday to Sunday. There is concern that the retail attention reflected in Google searches over the weekend will not have an impact on the trades in the same week. This bias will have a big impact on the construct validity of the weekly SVI index, only if SVI index is high on the weekend. However, an inspection of the daily SVI index will mitigate this concern, because the daily SVI measure on Saturdays and Sundays is usually close to zero. Therefore, the weekly SVI measure I obtain mainly captures the retail investor attention during the workdays in the week, and most workdays are trading days when the investors can trade the stocks and ETFs. After getting SVI measures on both daily and weekly frequencies, I need to compute abnormal SVI (ASVI) values as proxies for retail attention. As the first step, I subtract the median of weekly SVI values in the past eight weeks from the current weekly SVI, as in Da et al. (2011). For daily SVI, I subtract the median daily SVI in the past 42 trading days from current daily SVI. Following Da et al. (2011), I then standardize each series at both weekly and daily frequencies obtained from the previous step to get the final retail attention measure (Abnormal SVI, or ASVI).

Because I download SVI measures ticker-by-ticker, there is no cross-sectional comparability between SVI values for different underlying stocks. This is the rationale behind standardization by each stock. The daily ASVI values for each underlying stock are plotted in figure 1. There are regular spikes in the ASVI for most stocks, and I confirm almost all spikes happen around the time of quarterly earnings announcements. There is a concern that ASVI might also capture some institutional attention as well, because institutions are also attentive to company earnings announcements. I will address this concern in the next section, and I will show that the main contributor to stock ASVI and single-stock ETF trading is retail investors. The spikes in ASVI could also raise concern that the regression results in the following sections might be driven by outliers around earnings announcements. To alleviate this issue, I conduct (unreported) robustness tests by running all the following regressions again, but with 10 daily observations around each earnings announcement date dropped from the sample. The results from these robustness tests are qualitatively similar to the regression results reported in the following sections.

3. Overview of Single-Stock ETFs

This section introduces the underlying mechanisms, institutional backgrounds and characteristics of single-stock ETFs in greater details.

3.1. Underlying Mechanisms of Single-Stock ETFs and Implications

All single-stock ETFs in my sample aim to provide a pre-specified multiple of the daily returns of the underlying stock by using derivatives. This pre-specified multiplier can be positive or negative. If the multiplier is positive, it's called a long ETF. If the multiplier is negative, it's a short ETF. The name of a single-stock ETF always contains the information about both its multiplier and its direction. Long ETFs can be identified by relevant keywords, such as "Long" and "Bull", in the ETF names. The names of Short ETFs usually contain keywords like "Short", "Bear", and "Inverse". For example, "GraniteShares 2x Short NVDA Daily ETF " is a short ETF tracking Nvidia stock with a multiplier of -2. If the multiplier is positive, it's always greater than 1. In other words, long ETFs are always leveraged. There is no value for investors to hold a long single-stock ETF with a multiplier of 1, because holding such an ETF is always inferior to holding the underlying stock. On the other hand, the leverage ratios of all short single-stock ETFs in my sample range from 1 to 2. This implies that some investors are willing to buy unlevered short single-stock ETFs, possibly because they face short-sale constraints or high short-selling fees.

Single-stock ETFs track a multiple of the daily return of underlying stocks by signing swap agreements with a group of large investment banks. At the end of each trading day, the management team of a single-stock ETF adjusts the notional value of the swaps to maintain the correct level of multiplier on the next trading day. This practice is known as "daily rebalancing". All single-stock ETFs in my sample perform daily rebalancing, and thus they are required by SEC to include the word "daily" in their names[3]. This daily rebalancing feature might also be a reason for the popularity of these single-stock ETFs, because it would be inconvenient, if not impossible, for retail investors to accurately rebalance their portfolios every day. The cost and benefit of daily rebalancing to investors will be an issue that is worth future exploration. Conventional index-based leveraged and inverse ETFs also perform daily rebalancing through financial derivatives. Over an extended investment horizon, daily rebalancing makes the holding period return of leveraged and inverse ETFs significantly deviate from the specified multiple of holding period return of the underlying stock or index. This brings a nuanced difference between holding a leveraged ETF and margin trading. Suppose two investors achieve a leverage of x (x>1) on the same stock through buying-on-margin and long single-stock ETFs respectively. Each of them has endowment M. Both investors hold the position for T trading days. The holding-period return for the investor who buys the stock on margin, assuming zero interest, will be given by:

$$r_{Margin,T} = \frac{xM\prod_{t=1}^{T}(1+r_t) - xM}{M} = x(\prod_{t=1}^{T}(1+r_t) - 1) \tag{1}$$

where r_t is the underlying stock return on day t.

The holding-period return for the investor who buys a long single-stock ETF will be the following:

$$r_{ETF,T} = \frac{M\prod_{t=1}^{T}(1+xr_t) - M}{M} = \prod_{t=1}^{T}(1+xr_t) - 1 \tag{2}$$

[3]See question 20 at SEC correspondence https://www.sec.gov/Archives/edgar/data/1587982/000139834422010342/filename1.htm

The holding-period return for holding the underlying stock without leverage is:

$$r_{Stock,T} = \prod_{t=1}^{T}(1 + r_t) - 1 \tag{3}$$

We can see that for a holding period $T > 1$, the return of buying-on-margin will be different from the return of holding a single-stock ETF. This difference will be larger for longer holding periods. In summary, buying the stock on margin yields an accurate multiple of holding period stock return, whereas buying single-stock ETFs provides an accurate multiple of daily stock return to the investor every day.

3.2. Institutional background

Single-stock ETFs were introduced in Europe slightly earlier than in the US. The first single-stock ETF was introduced to the US market in 2022. The launch in 2022 may be partly due to a 2021 SEC regulation[4] that modified rules 6c-11 and 18f-4 in Investment Company Act and significantly reduced the regulatory burden on leveraged and inverse ETFs. Under the old regulation, every leveraged and inverse ETF needs to obtain an exemptive order from SEC before it can be introduced to the market. Under the new regulation, leveraged and inverse ETFs are automatically exempted, significantly lowering the costs and uncertainty associated with launching new leveraged and inverse ETFs. ETF sponsors can now launch leveraged and inverse ETFs much quicker and cheaper than before. Since the introduction of the first single-stock ETF in the US, the aggregate total market capitalization for all single-stock ETFs have been expanding rapidly, as illustrated in figure 2. Within around

[4] Accessed at https://www.sec.gov/files/rules/final/2019/33-10695.pdf

two years, the aggregate total market capitalization increased from 0 to more than 20 billion dollars.

3.3. Characteristics of Single-Stock ETFs and Underlying Stocks

Table 1 summarizes the key characteristics of single-stock ETFs. The first four rows are summary stats at ETF-daily level. As we can see from table 1, the ETF-daily level average total market capitalization is around 143 million dollars. Note that the total market capitalization of almost every single-stock ETF increases throughout the sample period, and thus the average total market capitalization at the end of the sample period is much higher than the sample mean in table 1. On average, long ETFs are roughly 7.5 times larger in size than short ETFs. The size discrepancy between long and short single-stock ETFs grew throughout the sample period. One of the most important results in the summary statistics is that the daily turnover ratios are very high for both long and short ETFs. The investors' average holding period for long ETFs is about 4 days. For short ETFs, investors only hold them for around 1.2 days on average. As a comparison, the average daily turnover ratio for all ETFs in CRSP dataset in the same sample period is 2.08%. The 90-th percentile of average ETF daily turnover ratio is 3.20%. Average daily turnover ratios for single-stock ETFs are more than ten times higher than the average for all ETFs. This observation points to the insight that most investors of single-stock ETFs use them as a short-term trading tool, rather than a long-term investment vehicle. I compute daily proportional flows of single-stock ETFs in a similar way as in Sirri and Tufano (1998). On average, long single-stock ETFs acquire 2% inflow every day in my sample, while short single-stock ETFs enjoy a slightly higher inflow of around 3% every day. These daily average proportional flows are large, and corroborates with the rapidly growing sizes of single-stock ETFs. The standard deviations of these proportional flows are also very high, with 17% for long ETFs and 132% for short ETFs, signifying that daily flows are very volatile. These patterns hold true for daily dollar flows of single-stock ETFs. Single-stock ETFs are usually traded at a price that's very close to their net asset values, as illustrated by the small premium. This suggests that market makers of these single-stock ETFs excelled in arbitraging and providing liquidity to these instruments.

At the quarterly level, we can see that most of the shares (83%) of single-stock ETFs are held by individual investors. Figure 3 further shows that the institutional ownership percentage are decreasing over time for both long and short single-stock ETFs. This pattern remains true for most of the individual single-stock ETFs. However, because the total market capitilization of most of the single-stock ETFs are increasing rapidly, institutions are increasing the value of their single-stock ETF holdings, despite the drop in the ownership percentage. These ownership data are recorded at the end of each calendar quarter. There is no daily data on institutional ownership, and the quarterly ownership data may not reflect the actual institutional ownership within the quarter.

The last six rows in table 1 are at ETF-level. For each single-stock ETF, I compute its tracking error using two measures. Elton, Gruber, and Busse (2004) propose two types of tracking error for index funds in their case. The first type of tracking error is the random deviation of fund performance from underlying index performance due to imperfect replication. They measure this type of tracking error using 1 minus R-squared for the following daily level time series regression:

$$r_{t,NAV} = \alpha + \beta \cdot r_{t,index} + \epsilon_t \tag{4}$$

where $r_{t,NAV}$ is the daily percentage change in the fund's net asset value on day t, and $r_{t,index}$ is the daily percentage return of the target index of the fund. I replicate this measure by regressing the daily percentage change in net asset value of each single-stock ETF on the daily percentage return of the underlying stock. In my sample, the average R-squared is around 99% for both long and short single-stock ETFs. This R-squared is slightly smaller than the average R-squared (99.99%) for all S&P 500 index mutual funds in Elton et al. (2004). Therefore, single-stock ETFs have larger random variations in their net asset values than S&P 500 index funds. This tracking error may be attributed to the use of derivatives in managing these ETFs, as opposed to holding underlying stock baskets in most index mutual funds. The second type of tracking error proposed by Elton et al. (2004) is the systematic deviation of net asset value from the underlying return. They capture this type of tracking error by using $|1 - \hat{\beta}|$, where $\hat{\beta}$ is the point estimate of the coefficient in the above regression equation. This measure is not applicable to single-stock ETFs, because all single-stock ETFs are levered, inverse, or both. Therefore, desired β for all single-stock ETFs will not be 1. Hence, I modify my second tracking error measure to capture the spirit of systematic deviation of net asset value, as envisioned by Elton et al. (2004). I run the following daily regression for each single-stock ETF:

$$r_{t,NAV} - k \cdot r_{t,stock} = \alpha + \beta \cdot r_{t,stock} + \epsilon_t \tag{5}$$

where k is the pre-specified return multiplier for this single-stock ETF. This way, I can use the estimate for the coefficient β to measure the systematic deviation of the ETF net asset value return from the pre-specified multiple of the underlying stock return. Running regressions in this form deals with the issue above such that my measure is applicable to all single-stock ETFs, despite their wide range of multipliers. Unlike in Elton et al. (2004), the $\hat{\beta}$ in the above regression should have been 0, if there is no systematic tracking error. Therefore, I use $|\hat{\beta}|$ as the measure for systematic tracking error. From table 1, one can see that long single-stock ETFs have slightly higher systematic tracking errors than short single-stock ETFs, both of which have higher systematic tracking errors than S&P 500 index funds (Elton et al., 2004).

Expense ratios and management fees data were downloaded from Bloomberg terminal in early June 2024. Due to data limitation of Bloomberg terminals, these expense and fee data are all cross-sectional as of the date of download. Thus, expense ratios and management fees are not included as control variables in panel regressions in the following sections. All long and short ETFs have similar expense ratios and management fees. On average, single-stock ETFs charge 1.13% of their total net asset every year. The average management fee of single-stock ETFs is 0.93%. These fees are extremely high compared to the fees charged by index ETFs, which commonly have annual expense ratios at around a few basis points. One of the possible reasons for their high expense ratios is that single-stock ETFs perform daily rebalancing, which demands the use of expensive swaps. The important thing to keep in mind is that despite the high costs, trading single-stock ETFs is still likely the cheapest and the most convenient way for retail investors to leverage or short-sell many stocks, compared to other means[5]. Finally, both long and short single-stock ETFs have average leverage ratios greater than 1, and long single-stock ETFs have higher leverage ratios than short single-stock ETFs on average. These findings are consistent with the earlier observation that all long single-stock ETFs are levered, while some short single-stock ETFs do not use leverage.

In addition to characteristics of single-stock ETFs, I also present the characteristics of all underlying stocks of single-stock ETFs in table 2. There are 24 US stocks that ever had a tracking single-stock ETF as of end of December 2024. On a daily level, the average market capitalization of these 24 underlying stocks is 480 billions dollars, indicating that most of the underlying stocks are mega-cap stocks. The average daily stock return is 0.15% in my sample. The stock turnover ratio is 1.98% on average, much smaller than the turnover of single-stock ETFs. The average book-to-market ratio for underlying stocks is 0.27, implying that most of the underlying stocks fall into the growth category. I compute daily Amihud illiquidity measure for stocks by scaling daily absolute return in decimal by daily trading volume in billion dollars. On an average day, the underlying stock price moves by 9% for every billion dollar traded in the stock. The last four rows in table 2 compare the size of single-stock ETF and the size of underlying stocks. I aggregate all the long or short single-stock ETFs tracking a specific stock to stock-daily level, and then compare it to underlying stocks. The aggregate market capitalization of both long and

[5] See Robinhood margin trading and short-selling policy (https://robinhood.com/us/en/support/articles/margin-rates/)

short single-stock ETFs are still very small compared to the market capitalization of underlying stocks, as most of the underlying stocks are large stocks. Despite the relatively small market capitalization of single-stock ETFs, the dollar trading volumes of single-stock ETFs are significant relative to the trading volumes of underlying stocks. On average, the dollar amount of long single-stock ETFs traded every day stands around 0.84% of underlying stock trading volume, while the trading volume of short single-stock ETFs is 0.17% of stock trading volume. More importantly, this ratio is highly positively skewed, especially for long ETFs. 90th percentile of this ratio for long single-stock ETFs is 1.97%, and there are dozens of daily observations of this ratio above 10%, with the maximum standing around 20%. This suggests that on some days, the amount of capital trading single-stock ETFs is very significant, compared to the underlying stocks. Therefore, it's very likely that the arbitraging demand between single-stock ETFs and underlying stocks may have a huge impact on the underlying stock price, and the leveraged nature of single-stock ETFs only adds to this impact even further.

In sum, results in tables 1 and 2 allude to a story that single-stock ETFs are mainly used by short-term oriented individual investors to take on leveraged or inverse positions on some of the largest and most popular stocks in the US market. This story could explain the emergence and the rapid growth of single-stock ETFs in the last two years. To provide further support for this story, I attempt in the next section to show that there is significant retail trading in single-stock ETFs.

4. Single-Stock ETF Trading and Retail Investor Attention

The results in the last section point to the idea that single-stock ETFs exist to facilitate short-term leveraging and short-selling of retail investors. If this story is true, then single-stock ETFs should be traded mainly by retail investors. In this section, I am going to test this hypothesis by focusing on the retail attention. I test how retail attention on underlying stock is related to three characteristics of single-stock ETFs: flows, turnover ratios, and retail trades.

4.1. Single-Stock ETF Flows and Retail Attention

I resort to the investor attention literature (Seasholes and Wu, 2007; Barber and Odean, 2008; Barber et al., 2022) to uncover the relation between retail attention and single-stock ETF trading. Literature has shown that retail investors have the tendency to trade attention-grabbing stocks. Therefore, I will test whether retail investor attention on the underlying stocks positively affect the turnover ratios, flows, and retail trades of single-stock ETFs in this section.

I follow Da et al. (2011) to measure retail investor attention using Abnormal Search Volume Index (ASVI) from Google Trends. They have shown that this measure captures the attention of retail investors and correlates with their trading behaviors. Da et al. (2011) also argue that this ASVI measure is superior to other common investor attention measures, such as extreme stock turnover and returns, because it is more "active" than other measures. Even if a stock has extreme turnover or return on one day, it's not guaranteed that this extreme phenomenon will be noticed by many retail investors, since retail investors usually do not pay attention to the stock market every day. In contrast, searching on Google can only happen after investors are already attentive to the stock. Therefore, Google search volume is a less noisy measure for the attention of retail investors than common trading-based measures.

First, I investigate the relation between retail investor attention and single-stock ETF flows. I measure the daily (weekly) proportional flow of each single-stock ETF by using formula from Sirri and Tufano (1998), except that I use market capitalization of ETFs, instead of total net assets:

$$Flow_t = \frac{MktCap_t - MktCap_{t-1} \cdot (1 + r_t)}{MktCap_{t-1}} \tag{6}$$

where $MktCap_t$ is the market capitalization of the single-stock ETF at the end of period t, and r_t is the price return of this ETF in period t. I use market capitalization of ETFs, instead of total net assets of ETFs, mainly because CRSP reports many missing daily observations of total net assets for single-stock ETFs, while very few observations of market capitalization are missing.

I run the following weekly panel regression to investigate the relation between retail attention on the underlying stock and proportional flow of the single-stock ETF:

$$Flow_{it} = \alpha + \beta_1 \cdot ASVI_{i,t-1} + \beta_2 \cdot Controls_{i,t-1} + \delta_t + \gamma_i + \epsilon_{it} \tag{7}$$

where $ASVI_{i,t-1}$ is the standardized abnormal search volume index of the underlying stock of single-stock ETF i in week $t-1$. I use lagged stock ASVI as my main independent variable, because using concurrent retail attention would make it difficult to interpret the direction of the effect, even if β_1 is significant. Control variables include other common retail attention measures and the variables known to affect ETF flows. Researchers (Barber and Odean, 2008; Barber et al., 2022) have shown that stocks with high absolute value of return and high turnover ratio will attract more retail investor attention, which will induce them to trade the stocks more. Highly volatile daily price movements usually make the news and attract investor attention. I use ASVI as my main variable of interest, because Da et al. (2011) show that ASVI is a better investor attention proxy than these control variables, in that ASVI contains more useful information about investor attention. Moreover, Da et al. (2011) provide evidence that ASVI measures the attention of retail investors specifically, who are the main group of investors related to my story. It's well-known that fund return, fund size, and fund age are related the fund flow (Sirri and Tufano, 1998; Spiegel and Zhang, 2013), so I include these as controls. All control variables are lagged by 1 week, because most of these variables are related to the trading of underlying stocks, and thus can potentially be affected by the trading of single-stock ETFs in the same week through arbitrage channel. The standard error is double-clustered at ETF and weekly level. I run the above regression on all ETFs, long ETFs, and short ETFs respectively. The output of the regression above is presented in table 3.

The main observation in table 3 is that the weekly flows of both long and short ETFs are positively predicted by the retail attention in the previous week. This means that both long and short single-stock ETFs experience higher weekly flow when the underlying stock attracts higher attention from retail investors. Another finding in table 3 is that sizes of long and short ETFs are negatively related to the ETF flows, even after controlling for retail attention. This observation is consistent with the traditional findings in mutual fund literature (Sirri and Tufano, 1998).

My hypothesis is that retail attention on the stock induces flow into the corresponding single-stock ETFs, which is supported by findings in table 3. Nevertheless, one might expect that retail attention is short-lived and does not last a week. This suggests that the effect I found in table 1 should also be present at higher frequencies. Thus, I rerun the regression on daily frequency with lagged ASVI:

$$Flow_{it} = \alpha + \beta_1 \cdot ASVI_{i,t-1} + \beta_2 \cdot Controls_{i,t-1} + \delta_t + \gamma_i + \epsilon_{it} \tag{8}$$

where all variables are at daily level, and all independent variables are lagged by 1 day.

The output of this regression is presented in table 4. Because the regression is at daily level, I do not have stock volatility as a control variable. As seen in table 4, ASVI of the underlying stock on the previous day positively predicts the flow into both long and short single-stock ETFs, despite the positive relation being insignificant for short ETFs this time. This daily-level result from table 4 corroborates with the weekly-level result from table 3, in that both tables suggest the flows of both long and short single-stock ETFs are positively related to retail attention on the underlying stock of the ETFs.

4.2. Single-Stock ETF Turnover and Retail Attention

Besides ETF flow, turnover ratio is also an important indicator of the intensity of ETF trading. I further investigate the relation between stock retail attention and ETF turnover ratio. I run the same regression as above, with dependent variable changed to the turnover ratio of the single-stock ETFs. Again, I run this regression on both weekly and daily level. The output of the weekly regression is shown in table 5, and the daily results are in table 6. The results for turnover ratios are qualitatively identical to the results for fund flows. On weekly level, the lagged retail attention on the underlying stock positively predicts the turnover ratios of both long and short single-stock ETFs in the following week. In daily panel regressions, the lagged retail attention on the underlying stock positively predicts the turnover ratios of both long and short single-stock ETFs on the following day.

Tables 3, 4, 5, and 6 demonstrate that flows and turnover ratios of both long and short single-stock ETFs are positively related to the retail investor attention on the underlying stock. This finding corroborates my story that single-stock ETFs are vehicles mainly traded by retail investors. Note that the flows and turnover ratios of both long and short single-stock ETFs are symmetrically influenced by investor attention. This symmetric influence on trading of ETFs in both directions is different from the finding of Barber and Odean (2008). Barber and Odean (2008) show that retail investors are net-buyers of attention-grabbing stocks, and they explain this phenomenon with the short-sale constraint faced by retail investors. They argue and empirically show that retail investors only sell the stocks that they already own. In the case of single-stock ETFs, since a short equity position on the underlying stock is achieved by buying short ETFs, retail investors' short-selling behavior is no longer restricted by short-sale constraint posed by their brokers. Retail investor can buy both long and short single-stock ETFs when their attention is drawn to the underlying stock, as shown in tables 3 and 4. As a result, despite different from empirical findings of Barber and Odean (2008) on face value, my findings above are consistent with and provide support to their investor attention theory. Furthermore, my results allude to that short single-stock ETFs effectively relax short-selling and leverage constraints on retail investors, allowing them to magnify their influence on the underlying stocks, especially when the underlying stocks are smaller in size.

I have interpreted the positive relations between retail attention and ETF flow and turnover as supporting evidence for the retail trading story. However, one may challenge my story by asserting that Google search volume is correlated to fundamental news and thus is also related to institutional trading. I would like to refute this alternative hypothesis both logically and empirically. Logically, I want to make two points to argue that this alternative hypothesis is not likely to be true. First, Da et al. (2011) establish that Google search volume mainly captures the attention of uninformed retail investors. Their reasoning is that unlike retail investors who tend to use Google, institutional investors use more sophisticated tools, such as Bloomberg terminals, to gather information. They further segregate retail investors into informed and uninformed groups. They empirically show that Google search volume index correlates more to the order flows of uninformed retail investors than to orders of informed retail investors. Therefore, the retail attention measure I use in my analysis is not likely to be correlated to informed retail trading, not to mention institutional trading. Second, the institutional trading story cannot explain the empirical finding that flows of both long and short single-stock ETFs are positively correlated to Google search volume. Suppose that ASVI is correlated to the institutional attention through channels like fundamental news, then rational institutions would adjust their valuations for the firm following the news and make trading decisions based on the relation between current share price and the institutions' updated firm valuation. In this case, most rational institutions would trade in the same direction, either long or short. Thus, after fundamental news, institutional flows of long and short single-stock ETFs should always be asymmetric in direction, contradicting with the symmetric findings in tables 3 and 4. To further dismiss the alternative hypothesis that my findings above are driven by institutional trading, instead of retail trading, I empirically measure retail trading using the algorithm from Barber et al. (2024), and test for the relation between retail attention on underlying stock and retail trading of single-stock ETFs.

4.3. Retail Trading of Single-Stock ETF and Retail Attention

In this subsection, I directly identify the retail trades in NYSE Trade and Quote (TAQ) data using the algorithm in Barber et al. (2024). Then I investigate how the retail trades of single-stock ETFs are related to the retail attention drawn to the underlying stocks of the ETFs.

Boehmer et al. (2021) propose an algorithm to both measure and sign retail investor trading using NYSE Trade and Quote (TAQ) data. Barber et al. (2024) further improve this algorithm to increase the accuracy rate for the computed signs of retail trades. However, Barber et al. (2024) also experimentally show that both their algorithm and Boehmer et al. (2021) algorithm can correctly identify only one third of all retail trades as retail trades, and this identification rate decreases with bid-ask spreads. Since the bid-ask spreads of single-stock ETFs are large, the identification rate of Barber et al. (2024) algorithm may be even lower than one third for single-stock ETF trades. Therefore, Barber et al. (2024) retail buy and sell volumes computed below only serve as proxies, instead of accurate accounts, for retail trading in each direction. An implication of this caveat is that all retail trading results in this subsection does not provide any information on institutional trading, because institutional trades cannot be identified as the complement set of the identified retail trades.

In my sample period, I obtain trade-level data from NYSE TAQ database for all single-stock ETFs in my sample. I implement Barber et al. (2024) algorithm to identify and sign retail trades. For each single-stock ETF, I compute the daily total dollar volumes of all retail buy trades and all retail sell trades respectively. It's important to note that Barber et al. (2024) show that their algorithm does not identify all retail trades, and thus these retail dollar volumes are a proxy, instead of an accurate measure, for the intensity of retail trades. Then, I scale the dollar volumes of both retail buy trades and retail sell trades by the market capitalization of the single-stock ETF at the end of the previous trading day. This gives me two dependent variables that measure retail buy activity and retail sell activity for each single-stock ETF on each trading day. This process to compute the dependent variables are summarized in the formulae below:

$$RetailBuy_{i,t} = \frac{\sum_{b \in B_{i,t}} Size_b \times Price_b}{MarketCap_{i,t-1}} \tag{9}$$

$$RetailSell_{i,t} = \frac{\sum_{s \in S_{i,t}} Size_s \times Price_s}{MarketCap_{i,t-1}} \tag{10}$$

where $B_{i,t}$ is the set of all retail buy trades, as identified by Barber et al. (2024), of single-stock ETF i on day t, and $S_{i,t}$ is the set of all retail sell trades, as identified by Barber et al. (2024), of single-stock ETF i on day t. $Size_b$ is the number of shares traded in trade b, and $Price_b$ is the execution price of trade b.

To compare the differences between retail buying and retail selling for single-stock ETF i on day t, I also compute a buy-sell imbalance (BSI) measure similar to that in Barber and Odean (2008), but with dollar volume of retail trades, instead of number of trades:

$$BSI_{i,t} = \frac{\sum_{b \in B_{i,t}} Size_b \times Price_b - \sum_{s \in S_{i,t}} Size_s \times Price_s}{\sum_{b \in B_{i,t}} Size_b \times Price_b + \sum_{s \in S_{i,t}} Size_s \times Price_s} \tag{11}$$

After computing all dependent variables, I run the daily panel regressions below:

$$RetailTradeMeasure_{i,t} = \alpha + \beta_1 \cdot ASVI_{i,t} + \beta_2 \cdot Controls_{i,t} + \delta_t + \gamma_i + \epsilon_{it} \tag{12}$$

where $RetailTradeMeasure_{i,t}$ is one of the three dependent variables above for single-stock ETF i on day t. All independent variables are the same as in previous regressions, except that I do not lag independent variables in this regression. This is because the dependent variable in this regression is a direct measure of retail trades. Retail trades are usually both small and not observable by most investors, and thus retail trades are not likely to affect the independent variables, alleviating the reverse causality concern. This concurrent specification is also adopted by Da et al. (2011) in their regression of retail order on retail attention. Standard errors are again double-clustered at ETF and daily level. The result of this regression is presented in table 7.

The first three columns show that retail investors' buying behaviors of long single-stock ETFs are significantly positively related to the retail attention on the underlying stock, while retail buying for short single-stock ETFs is positively but insignificantly related to attention. The next three columns demonstrate a similar pattern for the retail investors' selling behaviors, except that retail selling of short single-stock ETFs is negatively but insignificantly related to retail attention. Therefore, the first six columns show that retail investors both buy and sell more long single-stock ETFs when they are more attentive to the underlying stocks, while the retail buying and selling of short single-stock ETFs do not seem to significantly relate to retail attention.

Comparing the point estimates for coefficients in columns 2 and 5, one can see that the retail buying of long ETFs increases more than retail selling of long ETFs does when retail attention increases. Columns 3 and 6 also suggest that attention-driven retail buying is greater than attention-driven retail selling of short single-stock ETFs. To formally test this proposition, I regress Buy-Sell-Imbalance (BSI) measure from Barber and Odean (2008) on retail attention, and present the results in the last three columns. Columns 7 to 9 confirm that the retail buying increases more than retail selling, when retail attention on underlying stock is higher. Moreover, this increase in buy-sell imbalance is present for both long and short single-stock ETFs, consistent with findings in Barber and Odean (2008).

Combining the findings from all nine columns of table 7, one can get to the following conclusion: for long single-stock ETFs, higher retail attention on the underlying stock leads to increases in both retail buying and retail selling of the ETF. For both long and short single-stock ETFs, the retail buying increases relative to retail selling, when retail attention is higher. My findings are consistent with Barber and Odean (2008) story that due to the short-sale constraints of retail investors on single-stock ETFs, attention-driven retail buying is greater than attention-driven retail selling.

In this section, I have shown that the retail investor attention on the underlying stocks is positively related to the flows and turnover ratios of both long and short single-stock ETFs. I further show that retail buy-sell imbalance of both long and short single-stock ETFs are positively related to retail attention on the underlying stock, consistent with retail attention literature. Although I do not directly measure institutional trading of single-stock ETFs, the fact that retail trading and aggregate trading exhibit similar patterns provides further support to my story that single-stock ETFs are mainly traded by retail investors, instead of institutional investors.

5. Single-Stock ETFs and Stock Price Idiosyncratic Volatility

After showing that single-stock ETFs mainly attract short-term retail investors, I ask the follow-up question that how the introduction of single-stock ETFs affects the stock price. Ben-David et al. (2018) have shown that the inclusion in an ETF's portfolio results in an increase in the stock price volatility. They explain this relation by a theory that ETFs attract short-term oriented liquidity traders, who raises the volatility of ETF prices, and this increase in volatility is propagated to the underlying stock price by the arbitraging activities. Since I have shown that single-stock ETFs mainly attract attention-driven retail investors, the story in Ben-David et al. (2018) is expected to apply to single-stock ETFs as well. To formally test the hypothesis that the launch of single-stock ETFs raises the volatility of underlying stock prices, I conduct event study with staggered launch of single-stock ETFs to different underlying stocks. In this section, I conduct the staggered event study with two approaches. First, I apply Callaway and Sant'Anna (2021) estimator to estimate the dynamic treatment effect of the introduction of the first long and short single-stock ETFs on an underlying stock. Second, I follow Baker, Larcker, and Wang (2022) and Deshpande and Li (2019) to conduct difference-in-differences analysis on a stacked dataset to estimate the treatment effect of single-stock ETF launch.

The dependent variable in both analyses are stock-monthly level idiosyncratic volatility, which is defined as the standard deviation of the residuals from the CAPM regression. For each stock-month, I regress the daily excess return of the stock on the daily market risk premium, and then take the root mean square of the daily residuals from this regression as the stock-monthly idiosyncratic volatility. I use the idiosyncratic volatility, instead of volatility of raw stock return, because if retail investor behaviors are purely driven by attention, rather than risks, their trading would lead to an increase in the volatility that is not explainable by the market risks. By removing the stock price movement component related to market risks, I could more accurately capture the potential impact of attention-driven trading of retail investors. For the main specification, I do not use factor models with more factors, such as Fama-French 3 factor model, because the treated stocks are mainly growth and large stocks, as shown in table 2, and controlling for growth and size factors may lead to biases. In unreported specifications, I also use idiosyncratic volatility from Fama-French 3 and 5 factor models, and the results are quantitatively weaker but qualitatively similar. For both event study analyses, I compute the monthly idiosyncratic volatility up to March 2025, because the last treatment month in my sample of single-stock ETFs is December 2024. Ideally, I should have more recent idiosyncratic volatility observations, but March 2025 is the most recent data from CRSP as of the time of this writing. For both event study analyses, the stock sample I use are the union of the set of stocks that ever had a tracking single-stock ETF as of December 2024 and the set of the largest 500 US stocks by market capitalization on the first trading day of 2022. I use the never-treated largest US stocks as control groups, because the treated firms are mainly large-cap stocks, as shown in table 2.

In the first event study analysis, I apply the estimator from Callaway and Sant'Anna (2021) to estimate the dynamic treatment effect of the staggered launch of first long or short single-stock ETFs on each underlying stock. I use the doubly-robust method of Sant'Anna and Zhao (2020), as suggested in Callaway and Sant'Anna (2021). I conduct the event study on the launch of the first long single-stock ETF and the first short single-stock ETF respectively. Although in some cases, the first long single-stock ETF and the first short single-stock ETF on a stock are introduced in the same month, there are significant variation between these two treatment events. In my sample, each underlying stock remains treated once it's treated.

The resulting event study plot from the Callaway and Sant'Anna (2021) estimator is presented in figure 4. The first thing we can observe from both panels in figure 4 is that there is no significant pre-trend before the treatments of both long and short single-stock ETFs. The top panel shows an increase in idiosyncratic volatility starting from the second month after the launch of first long ETF, but this increase is not significant at 5% level, and this increase reverts to 0 in the eighth month after the treatment. On the other hand, the bottom panel illustrates a larger and longer-lasting increase in the stock idiosyncratic volatility following the treatment of first short single-stock ETF launch.

Besides the staggered event study with Callaway and Sant'Anna (2021) approach, I also conduct a stacked difference-in-differences analysis as in Baker et al. (2022) and Deshpande and Li (2019) to arrive at an estimate on the static treatment effect, because the size of effect on idiosyncratic volatility seems to be permanent in figure 4, at least for short single-stock ETFs. For long and short single-stock ETFs respectively, I create one stacked dataset by stacking all sub-experiments together. Each sub-experiment is defined by the treatment month, in which the first single-stock ETF starts trading. For each sub-experiment, I include the monthly observations, from 3 months before treatment to 3 month after treatment, for all never-treated firms and all firms treated in this specific sub-experiment. I choose 3 month windows before and after treatment month for the stacked difference-in-differences analysis mainly because of data availability issue. There are many treatment events in the last quarter of 2024, whereas the stock price data is updated to the first quarter of 2025 as of the time of this writing. The following regression is estimated on each stacked dataset:

$$IdiosyncraticVolatility_{i,t,j} = \alpha + \beta_1 \cdot Post_{t,j} + \beta_2 \cdot Post_{t,j} \cdot Treated_{i,j} + \beta_3 \cdot Controls_{i,t} + \delta_t + \gamma_i + \epsilon_{i,t,j} \tag{13}$$

where $Treated_{i,j}$ is a dummy equal to 1 if stock i is treated in sub-experiment j. $Post_{t,j}$ is the post dummy equal to 1 if month t is after treatment month of sub-experiment j, and equal to 0 if month t is before treatment month of sub-experiment j. I exclude the monthly observations for the treatment month of each sub-experiment from regression, because the exact treatment day in the month may vary for each treated stock. I include stock-monthly level control variables that may be related to stock volatility, including stock return, Amihud illiquidity measure, and the log of stock market capitalization at the end of the month. I also control for stock and month fixed effects. Because for each sub-experiment, I only include never-treated stocks and stocks that are treated in this sub-experiment, a treated dummy would have been subsumed by the stock fixed effect. The standard errors are double-clustered at stock and monthly level, because treatment assignment is at stock level.

The results of this stacked difference-in-differences analysis are presented in table 8. Similar to the event study plots in figure 4, table 8 shows that the treatment effect of the first short single-stock ETF on stock idiosyncratic volatility is significantly positive, whereas the treatment effect of long single-stock ETF is positive but insignificant. One can also observe that stock market cap is negatively related to the impact of treatment on the stock idiosyncratic volatility, likely because retail trading is too small to significantly move the prices of large stocks.

In this section, I conduct event study analyses to investigate the treatment effect of the launch of the first long or short single-stock ETF on the idiosyncratic volatility of the underlying stocks. Both the event study plot from Callaway and Sant'Anna (2021) estimator and the stacked difference-in-differences analysis as in Baker et al. (2022) and Deshpande and Li (2019) illustrate similar patterns: stock idiosyncratic volatility increases after the launch of first short single-stock ETF, whereas the launch of first long single-stock ETF has an insignificantly positive effect. In general, these results are consistent with the story in Ben-David et al. (2018) that ETFs attract a new group of short-term liquidity traders, whose trading contributes to higher volatility in the underlying security price.

6. Conclusion

This paper is the first to investigate the novel instrument of single-stock ETFs. US single-stock ETFs have enjoyed rapid growth in size and popularity since their recent advent. I introduce the underlying mechanisms of single-stock ETFs, and reveal the fundamental characteristics of this instrument. I show that single-stock ETFs are mainly held by individual investors and that investors only hold single-stock ETFs for 2 days on average. Moreover, single-stock ETFs charge 1.13% annually on average, much higher than index-based ETFs. I propose to explain the single-stock ETFs' rapid growth and popularity among retail investors, despite their hefty fees, by the argument that single-stock ETFs satisfy the retail investors' demands for taking short-term leveraged long and short positions on popular stocks. These demands were previously unmet or very expensive for retail investors.

To support this hypothesis, I show that flows and turnover ratios of both long and short single-stock ETFs are all positively correlated to the retail attention on the underlying stocks. I also find that buy-sell imbalance in retail trades of single-stock ETFs increases with retail attention. These findings are consistent with the investor attention theory in literature (Barber and Odean, 2008). The symmetric relations between retail attention and retail trading in both long and short single-stock ETFs suggest that single-stock ETFs, especially short ETFs, relax the retail investors' trading constraints on underlying stocks by allowing them to short-sell and take leverage. Thus, single-stock ETFs serve the purpose of leveling the playing ground between retail and institutional investors. The fact that ETF overall flows and turnover ratios exhibit similar pattern as the retail trades of ETFs provide further support to my story that single-stock ETFs are mainly traded by retail investors to meet their demands for leverage and short-selling.

I further investigate how the introduction of single-stock ETFs affects the idiosyncratic volatility of the underlying stocks. I show that the idiosyncratic volatility of underlying stock price increases following the launch of the first short single-stock ETF tracking this stock. This increase lasts for at least 12 months after the first short single-stock ETF starts trading. Following the launch of the first long single-stock ETF, the increase in idiosyncratic volatility of the underlying stock is positive but insignificant, and it reverts to 0 in 8 months after the treatment.

Although the sizes of underlying stocks are much larger than the sizes of single-stock ETFs as of December 2024, the impact of single-stock ETFs could continue to grow in the future, as single-stock ETF industry is expected to grow rapidly and start to cover smaller and less liquid stocks. As documented in this paper, the daily aggregate trading volume of single-stock ETFs has even reached 20% of daily trading volume of the underlying stock on some stock daily observations. Therefore, understanding and continuously monitoring the impact of single-stock ETFs on financial market could be an important task for both academics and policymakers. This paper serves as the starting point for single-stock ETF research, and more research will be needed to better understand this novel instrument.

Appendix A. Figures

Fig. 1. Daily Standardized ASVI for All Underlying Stocks

This figure plots daily standardized abnormal SVI values for all 24 underlying stocks of single-stock ETFs. The sample period is from Jan 1st, 2020 to Dec 31st, 2024. The ticker symbols of the stocks are given above each subfigure. The series for META is obtained by combining the values for FB before its change in ticker and the values for META after its change in ticker.

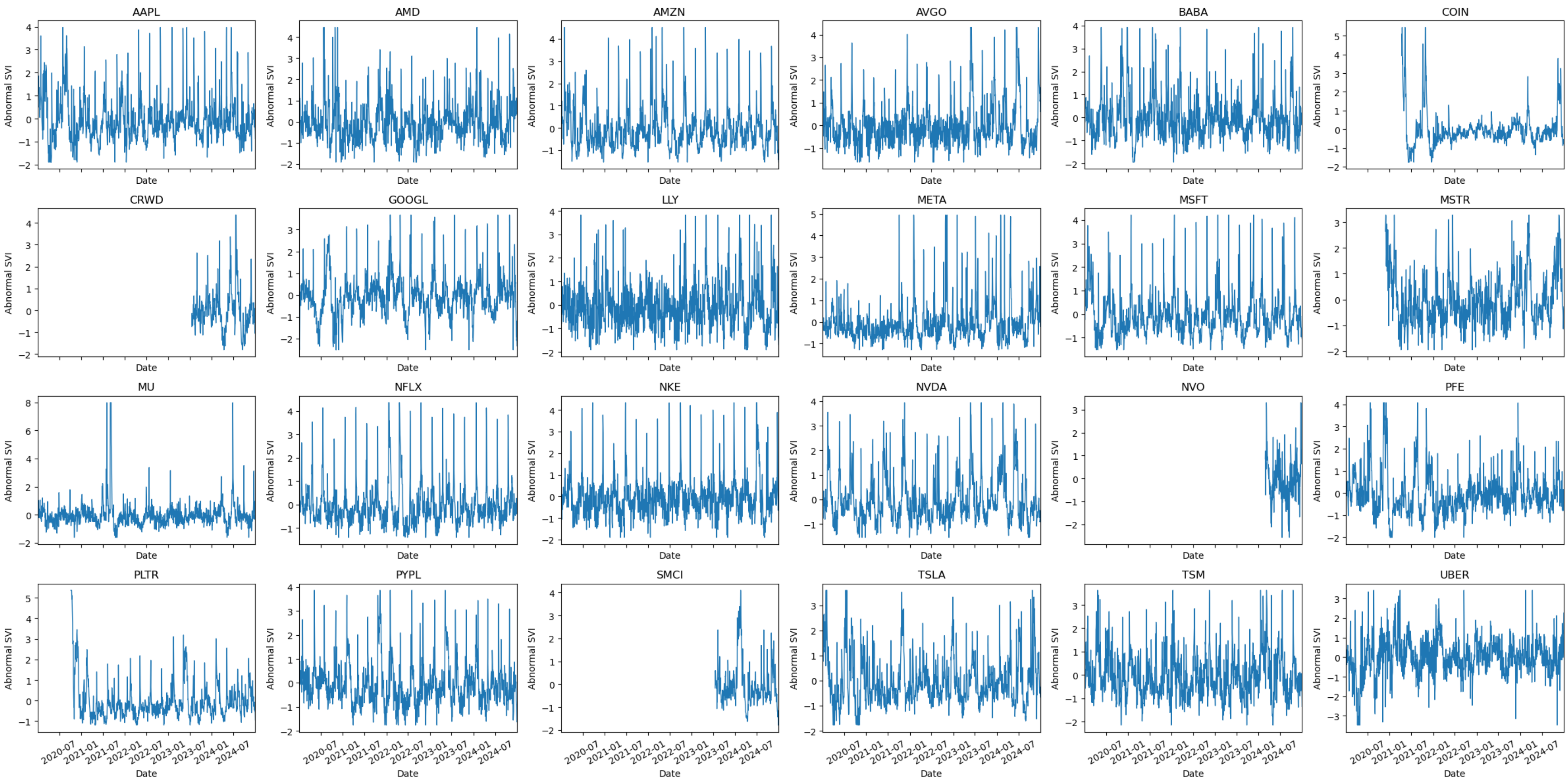


Fig. 2. Growing Size of Single-Stock ETF Industry

This figure plots the time series of daily total market capitalization for all single-stock ETFs in aggregate. The sample period is from July 13th, 2022 to Dec 31st, 2024. The blue line is the daily aggregate total market capitalization for all single-stock ETFs trading in the market, including both long and short ETFs. The orange line is the daily aggregate total market capitalization for all long single-stock ETFs. The green line is the daily aggregate total market capitalization for all short single-stock ETFs. The aggregate size of all single-stock ETFs (blue line) is the sum of the aggregate sizes of all long single-stock ETFs (orange line) and all short single-stock ETFs (green line). Y-axis is the total market capitalization of single-stock ETFs in billions of US dollars.

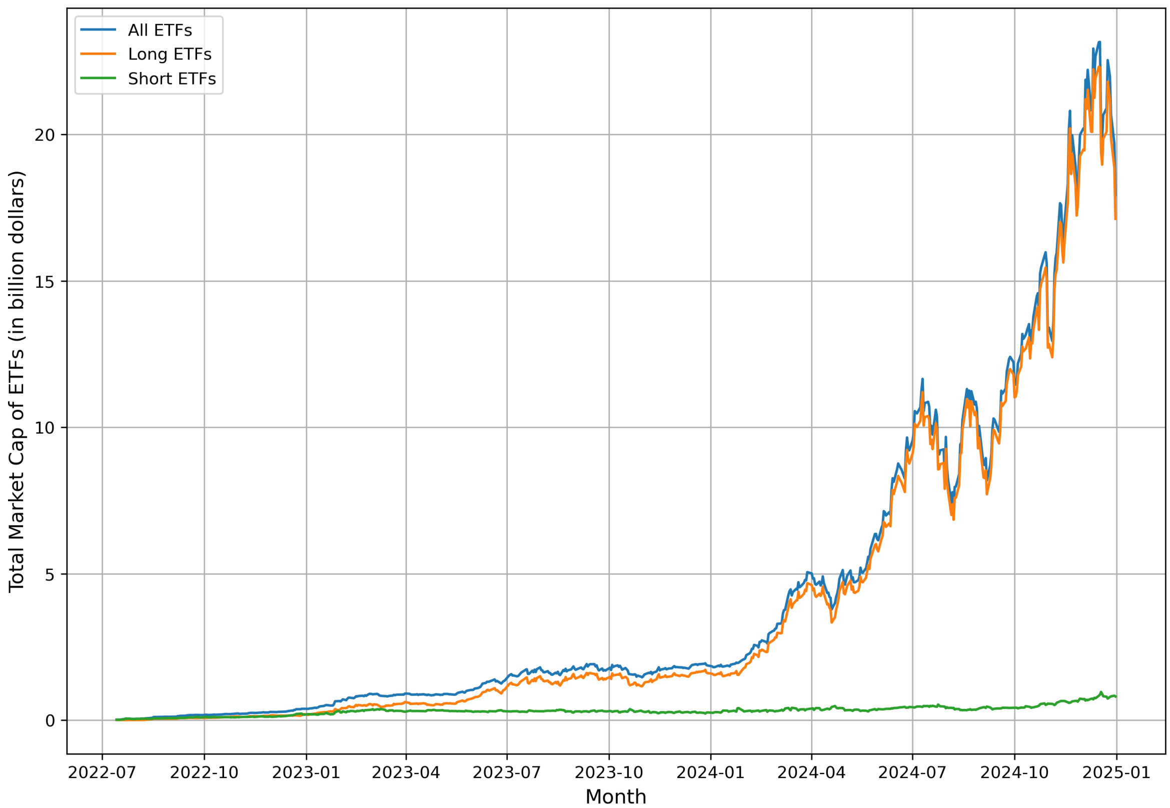


Fig. 3. Institutional Ownership of Single-Stock ETFs
This figure plots the times series of total market capitalization and percentage of single-stock ETFs held by 13-F-reporting institutional investors at a quarterly frequency. The quarterly data are recorded on the last trading day in each calendar quarter. The solid blue line is the aggregate institution-owned total market capitalization of all long single-stock ETFs. The solid orange line is the aggregate institution-owned total market capitalization of all short single-stock ETFs. The aggregate total market capitalizations correspond to the left axis. The dashed blue line is the percentage institutional ownership for long single-stock ETFs in aggregate, computed as aggregate institution-owned total market capitalization for all long single-stock ETFs divided by the sum of total market capitalization for all long single-stock ETFs. The dashed orange line is the percentage institutional ownership for short single-stock ETFs in aggregate, computed as aggregate institution-owned total market capitalization for all short single-stock ETFs divided by the sum of total market capitalization for all short single-stock ETFs. Percentage ownership corresponds to the right axis.

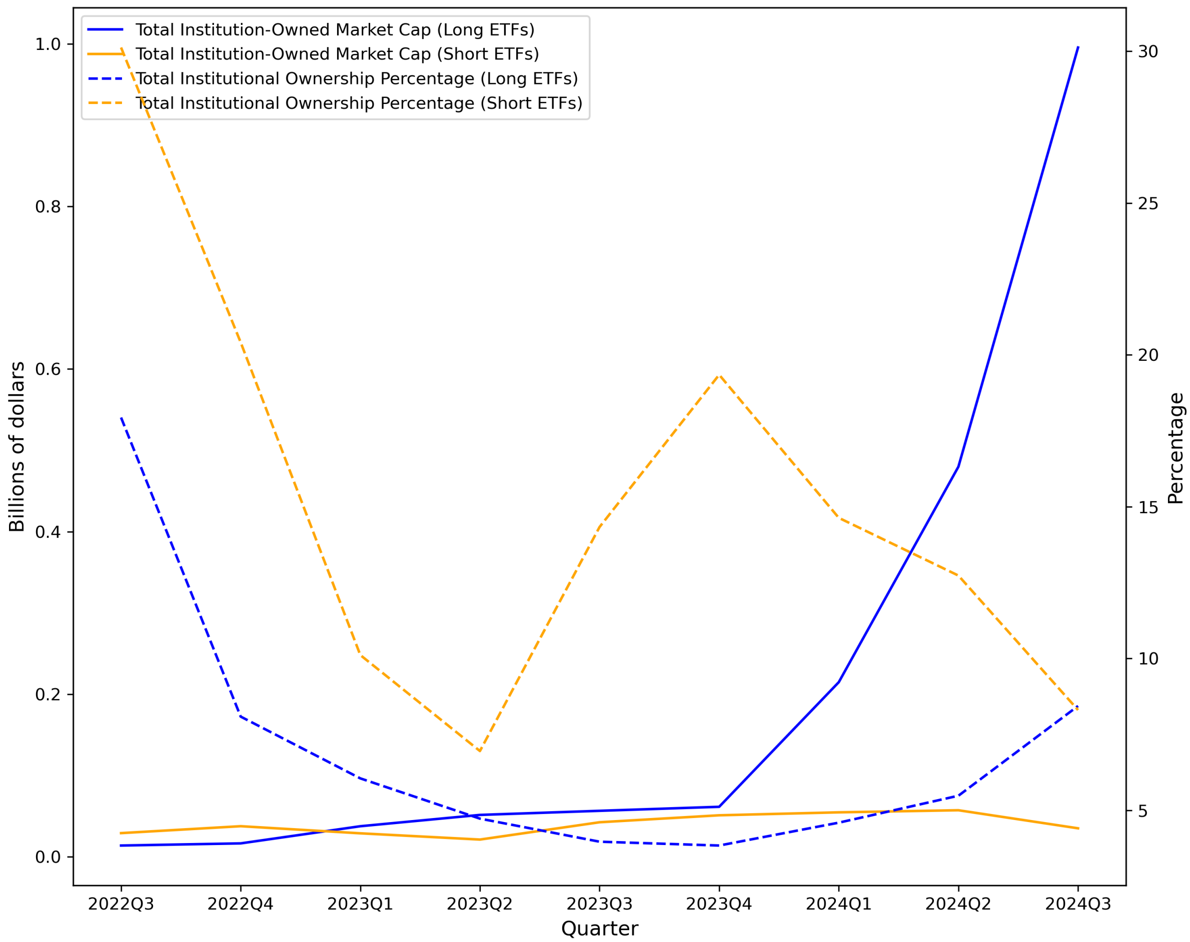
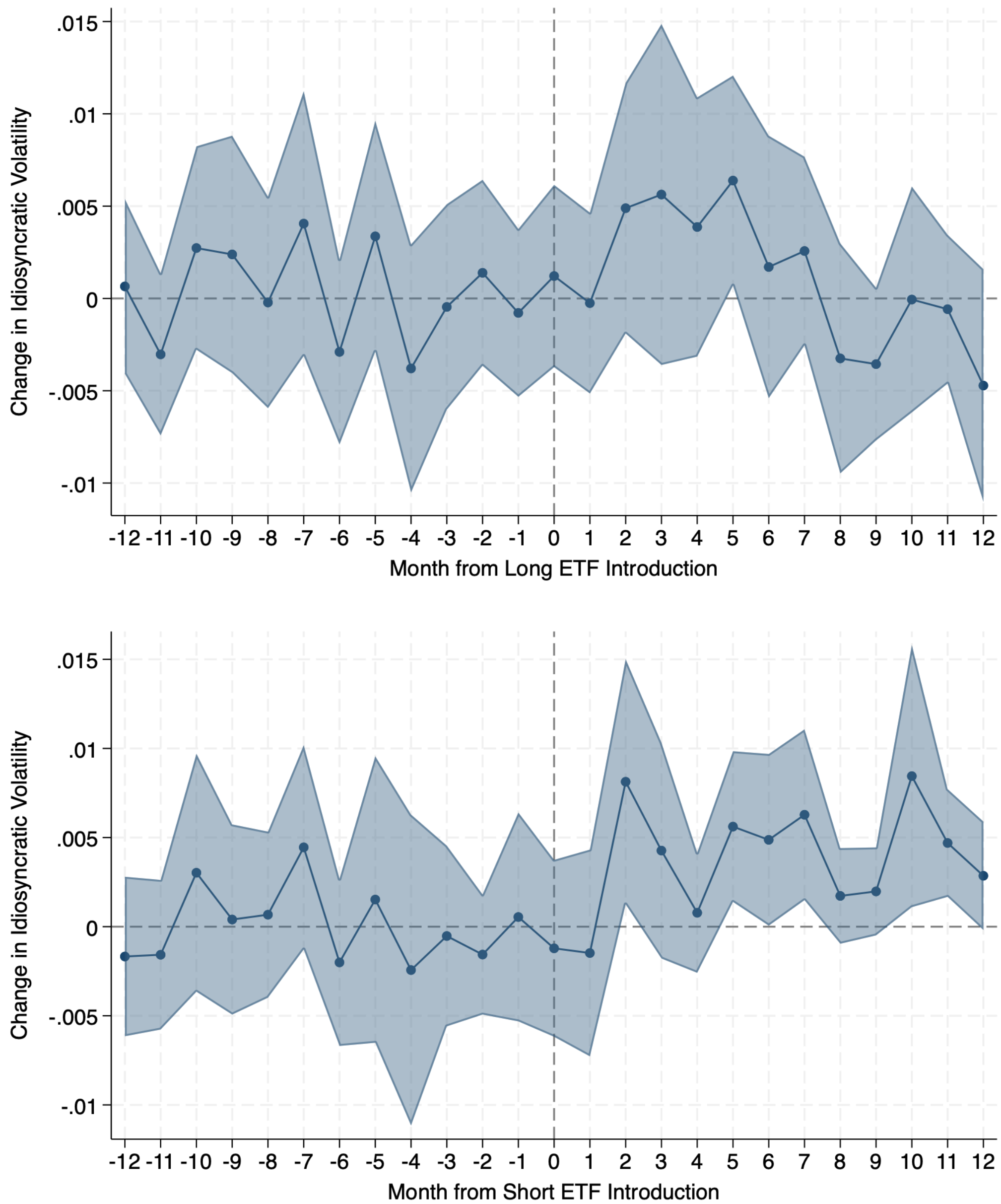


Fig. 4. Stock Idiosyncratic Volatility Around the Launch of First ETF

This figure presents the event study plots on the monthly stock idiosyncratic volatility around the launch of the first long and short single-stock ETF on the stock respectively. Monthly stock idiosyncratic volatility is defined as the standard deviation of the residuals from CAPM regression. y-axis is the regression estimate for the coefficients for each month around the treatment event. x-axis is the number of months from the treatment month, when the first long or short single-stock ETF on the stock starts trading. The top(bottom) panel presents the results from the staggered event study, where the treatment is defined as the launch of the first long(short) single-stock ETF. The event study is conducted as in Callaway and Sant'Anna (2021), using the doubly-robust method from Sant'Anna and Zhao (2020). 95% confidence intervals for the estimates are shaded in blue.



Appendix B. Tables

Table 1: Summary Statistics for Single-Stock ETFs

This table exhibits the summary statistics for the main variables on single-stock ETFs. The sample period is from July 13th, 2022 to Dec 31st, 2024. The first column of numbers is for all long single-stock ETFs. The second column is for all short single-stock ETFs. The last column is data for all single-stock ETFs. The first six rows are variables at ETF-daily level. The seventh to ninth rows are ETF-quarterly level data on institutional ownership of single-stock ETFs. The remaining six rows are ETF-level data. The expense ratio and management fee data are cross-sectional as of June 2024. The first and the last rows are the numbers of observations at ETF-daily level and ETF level respectively. For all other rows, the numbers in front of the parenthesis are the average values, and the numbers in the parenthesis are standard deviations.

	Bet Direction		
	Long	Short	Total
N	11,067 (60.0%)	7,378 (40.0%)	18,445 (100.0%)
Market capitalization (million dollars)	220.64 (707.35)	26.44 (35.40)	142.96 (556.55)
Turnover (percentage)	25.98 (50.43)	83.11 (552.11)	48.83 (352.46)
Proportional flow (decimals)	0.02 (0.17)	0.03 (1.32)	0.02 (0.85)
Dollar flow (thousands)	891.94 (24085.21)	185.85 (4904.16)	609.36 (18912.16)
Premium (percentage)	0.02 (0.26)	0.00 (0.23)	0.01 (0.25)
Quarterly institutional ownership (percentage)	12.63 (18.75)	24.28 (22.31)	17.20 (20.97)
Quarterly individual-owned total market cap (million dollars)	211.82 (618.42)	22.30 (27.93)	135.95 (488.12)
Quarterly institution-owned total market cap (million dollars)	13.72 (59.28)	3.87 (4.04)	9.78 (46.23)
ETF-level tracking error (1 - R-squared)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
ETF-level tracking error (abs(beta))	0.08 (0.13)	0.01 (0.02)	0.06 (0.11)
ETF-level expense ratio (percentage)	1.12 (0.11)	1.15 (0.14)	1.13 (0.13)
ETF-level management fee (percentage)	0.93 (0.15)	0.94 (0.18)	0.93 (0.16)
ETF-level leverage	1.96 (0.15)	1.36 (0.47)	1.75 (0.41)
Number of ETFs	47	25	72

Table 2: Summary Statistics for Underlying Stocks

This table exhibits the summary statistics for the main variables on underlying stocks of the single-stock ETFs. The sample period is from Jan 2nd, 2022 to Dec 31st, 2024. All variables are at underlying stock-daily level. I compute 10th-percentile, mean value, standard deviation, and 90th-percentile across all observations for each variable, except N, and list them in four columns respectively. The first row is the number of underlying stock-daily observations in the sample period, including stock-days when no single-stock ETF is trading on the underlying stock. The second to sixth rows are underlying stock-daily variables on stock characteristics, which are computed for every stock-day in my sample. The seventh to tenth rows are stock-daily variables that compare long(short) single-stock ETF characteristics to underlying stock characteristics, and are only computed for stock-days when there is at least 1 long(short) single-stock ETF trading on the underlying stock. The daily Amihud illiquidity ratio for the stocks is computed as absolute value of stock return in decimal, scaled by trading volume in billion dollars. The single-stock ETF market capitalization and dollar trading volume are summed to underlying stock-daily level, and then expressed as a percentage of stock market capitalization and dollar trading volume.

	p10	Mean	SD	p90
N		29,674		
Stock market cap (billion dollars)	15.44	480.94	727.73	1599.51
Stock return (percentage)	-3.10	0.15	3.26	3.37
Stock turnover ratio (percentage)	0.35	1.98	3.06	4.57
Stock book-to-market ratio	0.03	0.27	0.35	0.63
Stock Amihud illiquidity measure (scaled by volume in billions)	0.00	0.09	0.56	0.06
Long ETF aggregate market cap (as percentage of stock market cap)	0.00	0.00	0.00	0.00
Short ETF aggregate market cap (as percentage of stock market cap)	0.00	0.00	0.00	0.00
Long ETF aggregate trading volume (as percentage of stock trading volume)	0.00	0.84	2.29	1.97
Short ETF aggregate trading volume (as percentage of stock trading volume)	0.00	0.17	0.58	0.54

Table 3: Weekly Single-Stock ETF Flows and Retail Attention

This table presents the results of ETF-weekly panel regressions of single-stock ETF flows on retail attention on the underlying stock. The sample period is from the week of July 13th, 2022 to the week of Dec 31st, 2024. The regression is run on three subsamples: all single-stock ETFs, long single-stock ETFs only, and short single-stock ETFs only. The dependent variable is the proportional flow of single-stock ETFs, computed as in Sirri and Tufano (1998). The main independent variable is lagged weekly abnormal SVI (Google Search Volume Index) on the underlying stock. Control variables include common trading-related investor attention proxies and variables widely known to affect fund flows. Control variables for investor attention are absolute value of stock return, stock volatility, and weekly average of daily turnover ratio of underlying stock. ETF return, ETF size, and ETF age are known to affect future ETF flows. All control variables are lagged by 1 week. ETF fixed effect and week fixed effect are included. Standard errors (in parentheses) are double-clustered at ETF and weekly level. *, **, and *** represent significance at the 10%, 5%, and 1% level respectively.

Dependent Variable:	Weekly Proportional ETF Flow		
	All ETFs	Long ETFs	Short ETFs
Lagged stock weekly standardized ASVI	0.083***	0.067**	0.096**
	(0.021)	(0.027)	(0.041)
Lagged abs(stock weekly return)	0.501	0.235	0.905
	(0.366)	(0.413)	(0.886)
Lagged stock average daily turnover	3.197	-1.196	13.488
	(4.163)	(1.330)	(10.734)
Lagged stock weekly volatility	-5.727	-1.341	-12.194
	(4.847)	(1.297)	(11.793)
Lagged ETF weekly return	-0.152	-0.060	-0.160
	(0.107)	(0.077)	(0.477)
Lagged log(ETF market cap)	-0.290*	-0.194**	-0.774
	(0.162)	(0.074)	(0.557)
Lagged log(ETF age)	0.167	-0.033	0.698
	(0.195)	(0.069)	(0.584)
Constant	4.415**	3.527***	10.193
	(2.063)	(1.114)	(7.043)
Fund FE	YES	YES	YES
Week FE	YES	YES	YES
R-squared	0.15	0.43	0.17
N	3,759	2,251	1,508

Table 4: Daily Single-Stock ETF Flows and Retail Attention

This table presents the results of ETF-daily panel regressions of single-stock ETF flows on retail attention on the underlying stock. The sample period is from July 13th, 2022 to Dec 31st, 2024. The regression is run on three subsamples: all single-stock ETFs, long single-stock ETFs only, and short single-stock ETFs only. The dependent variable is the proportional flow of single-stock ETFs, computed as in Sirri and Tufano (1998). The main independent variable is lagged daily abnormal SVI (Google Search Volume Index) on the underlying stock. Control variables include common trading-related investor attention proxies and variables widely known to affect fund flows. Control variables for investor attention are absolute value of daily stock return and daily turnover ratio of underlying stock. ETF return, ETF size, and ETF age are known to affect future ETF flows. All control variables are also lagged by 1 day. ETF fixed effect and day fixed effect are included. Standard errors (in parentheses) are double-clustered at ETF and daily level. *, **, and *** represent significance at the 10%, 5%, and 1% level respectively.

Dependent Variable:	Daily Proportional ETF Flow		
	All ETFs	Long ETFs	Short ETFs
Lagged stock daily standardized ASVI	0.020**	0.007***	0.036
	(0.009)	(0.002)	(0.023)
Lagged abs(stock daily return)	0.035	0.037	0.646
	(0.207)	(0.120)	(0.488)
Lagged stock daily turnover	-0.312	0.068	-0.639
	(0.437)	(0.082)	(1.359)
Lagged ETF daily return	0.275	0.099**	0.673
	(0.301)	(0.039)	(0.939)
Lagged log(ETF market cap)	-0.058	-0.029***	-0.167
	(0.037)	(0.010)	(0.126)
Lagged log(ETF age)	0.035	-0.007	0.135
	(0.041)	(0.010)	(0.123)
Constant	0.817*	0.529***	2.039
	(0.420)	(0.139)	(1.427)
Fund FE	YES	YES	YES
Day FE	YES	YES	YES
R-squared	0.04	0.12	0.08
N	18,299	10,972	7,327

Table 5: Weekly Single-Stock ETF Turnover Ratios and Retail Attention

This table presents the results of ETF-weekly panel regressions of single-stock ETF turnover ratios on retail attention on the underlying stock. The sample period is from the week of July 13th, 2022 to the week of Dec 31st, 2024. The regression is run on three subsamples: all single-stock ETFs, long single-stock ETFs only, and short single-stock ETFs only. The dependent variable is the weekly average of daily turnover ratio of single-stock ETFs. The main independent variable is lagged weekly abnormal SVI (Google Search Volume Index) on the underlying stock. Control variables include common trading-related investor attention proxies and variables known to affect fund trading. Control variables for investor attention are absolute value of stock return and stock volatility. ETF return, ETF size, and ETF age are known to affect future ETF trading. All control variables are lagged by 1 week. ETF fixed effect and week fixed effect are included. Standard errors (in parentheses) are double-clustered at ETF and weekly level. *, **, and *** represent significance at the 10%, 5%, and 1% level respectively.

Dependent Variable:	Weekly ETF Turnover Ratio		
	All ETFs	Long ETFs	Short ETFs
Lagged stock weekly standardized ASVI	0.003***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)
Lagged abs(stock weekly return)	0.037**	0.028	0.023
	(0.017)	(0.017)	(0.015)
Lagged stock weekly volatility	0.145**	0.124*	0.141
	(0.068)	(0.064)	(0.084)
Lagged ETF weekly return	-0.001	0.010**	-0.031
	(0.004)	(0.004)	(0.019)
Lagged log(ETF market cap)	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)
Lagged log(ETF age)	0.002	0.002	0.003
	(0.001)	(0.002)	(0.002)
Constant	0.018	0.029	0.001
	(0.012)	(0.020)	(0.015)
Fund FE	YES	YES	YES
Week FE	YES	YES	YES
R-squared	0.81	0.81	0.84
N	3,759	2,251	1,508

Table 6: Daily Single-Stock ETF Turnover Ratios and Retail Attention

This table presents the results of ETF-daily panel regressions of single-stock ETF turnover ratios on retail attention on the underlying stock. The sample period is from July 13th, 2022 to Dec 31st, 2024. The regression is run on three subsamples: all single-stock ETFs, long single-stock ETFs only, and short single-stock ETFs only. The dependent variable is the daily turnover ratio of single-stock ETFs. The main independent variable is lagged abnormal SVI (Google Search Volume Index) on the underlying stock. Control variables include common trading-related investor attention proxies and variables known to affect fund trading. Control variables for investor attention are absolute value of stock return and daily turnover ratio of underlying stock. ETF return, ETF size, and ETF age are known to affect future ETF trading. All control variables are also lagged by 1 day. ETF fixed effect and day fixed effect are included. Standard errors (in parentheses) are double-clustered at ETF and daily level. *, **, and *** represent significance at the 10%, 5%, and 1% level respectively.

Dependent Variable:	ETF Daily Turnover Ratio		
	All ETFs	Long ETFs	Short ETFs
Lagged stock daily standardized ASVI	0.197**	0.073***	0.323*
	(0.090)	(0.009)	(0.157)
Lagged abs(stock daily return)	4.036	1.046***	8.356
	(2.624)	(0.362)	(7.373)
Lagged ETF daily return	-0.806	0.358***	-3.182
	(1.045)	(0.101)	(3.280)
Lagged log(ETF market cap)	-0.469	-0.142**	-1.373
	(0.353)	(0.059)	(1.249)
Lagged log(ETF age)	0.465	0.011	1.406
	(0.382)	(0.046)	(1.176)
Constant	5.866	2.580***	15.660
	(3.939)	(0.833)	(14.276)
Fund FE	YES	YES	YES
Day FE	YES	YES	YES
R-squared	0.30	0.24	0.34
N	18,299	10,972	7,327

Table 7: Daily Retail Trades of Single-Stock ETFs and Retail Attention

This table presents the results of ETF-daily panel regression of retail trades of single-stock ETFs on retail attention on the underlying stock. The sample period is from July 13th, 2022 to Dec 31st, 2024. There are three dependent variables in the regressions: daily total dollar volume of all retail buy trades, daily total dollar volume of all retail sell trades, and buy-sell imbalance (BSI) measure from Barber and Odean (2008). The first two dependent variables are both scaled by the market cap of the ETF at the end of previous trading day. All retail buy trades and retail sell trades are identified by the algorithm introduced in Barber et al. (2024). For each of the dependent variables, I run the regression using daily observations of all ETFs, long ETFs, and short ETFs respectively. The main independent variable is concurrent abnormal SVI (Google Search Volume Index) on the underlying stock. Control variables include common trading-related investor attention proxies and variables known to affect fund trading. Control variables for investor attention are absolute value of stock return and daily turnover ratio of underlying stock. ETF return, ETF size, and ETF age are known to affect future ETF trading. All control variables are concurrent. ETF fixed effect and day fixed effect are included. Standard errors (in parentheses) are double-clustered at ETF and daily level. *, **, and *** represent significance at the 10%, 5%, and 1% level respectively.

Dependent Variable:	Daily Retail Buy			Daily Retail Sell			BSI		
ETFs:	All	Long	Short	All	Long	Short	All	Long	Short
Stock daily standardized ASVI	0.015**	0.009***	0.004	0.011*	0.006***	-0.001	0.011***	0.008*	0.018***
	(0.007)	(0.001)	(0.011)	(0.006)	(0.001)	(0.010)	(0.003)	(0.004)	(0.006)
Abs(stock daily return)	-0.799	0.172***	-1.683	-0.994	0.140***	-1.976	0.568***	0.565***	0.209
	(1.087)	(0.055)	(2.003)	(1.227)	(0.041)	(2.279)	(0.148)	(0.173)	(0.301)
Stock daily turnover	3.937	0.593***	12.470	4.088	0.621***	12.806	-0.185	-0.007	-0.668
	(3.021)	(0.184)	(8.043)	(3.144)	(0.185)	(8.329)	(0.186)	(0.203)	(0.402)
ETF daily return	0.231	0.041**	0.918	0.296	0.022*	1.183	0.155*	0.079	-0.599***
	(0.232)	(0.018)	(0.885)	(0.288)	(0.013)	(0.968)	(0.082)	(0.110)	(0.137)
log(ETF market cap)	-0.044	-0.010***	-0.142	-0.030	-0.005**	-0.099	-0.000	-0.003	0.004
	(0.037)	(0.004)	(0.139)	(0.027)	(0.002)	(0.101)	(0.004)	(0.006)	(0.014)
log(ETF age)	0.040	-0.008**	0.132	0.032	-0.006**	0.100	-0.068***	-0.081***	-0.037**
	(0.039)	(0.003)	(0.111)	(0.029)	(0.003)	(0.081)	(0.011)	(0.015)	(0.017)
Constant	0.520	0.216***	1.511	0.326	0.117***	0.975	0.388***	0.502***	0.170
	(0.397)	(0.056)	(1.618)	(0.266)	(0.035)	(1.148)	(0.067)	(0.071)	(0.192)
Fund FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.32	0.33	0.39	0.32	0.37	0.39	0.07	0.10	0.13
N	18,252	10,974	7,278	18,252	10,974	7,278	18,001	10,861	7,137

Table 8: Monthly Stock Idiosyncratic Volatility Around First ETF Launch

This table presents the results from stacked difference-in-difference regressions on the monthly stock idiosyncratic volatility around the treatment event of the first single-stock ETF launch on the stock. The treatment events include the launch of the first long and short single-stock ETFs on each underlying stock. The stocks in treated group are the underlying stocks ever tracked by any single-stock ETF before Dec 31st, 2024. The stocks in control group are the 500 largest US stocks by market capitalization as of Jan 2nd, 2022 that are not in treated group. For each sub-experiment, 3 monthly observations before treatment month and 3 monthly observations after treatment month are included. The dependent variable is the stock monthly idiosyncratic volatility, defined as the standard deviation of residuals from daily CAPM model regression. Sample period for monthly idiosyncratic volatility is from April 2022 to March 2025. Post dummy is equal to 1 if the stock-monthly observation is after the treatment month in the respective subexperiment, and equal to 0 if it's before the treatment month. Stock fixed effect and month fixed effect are included. Standard errors (in parentheses) are double-clustered at stock and monthly level. *, **, and *** represent significance at the 10%, 5%, and 1% level respectively.

Dependent Variable:	Idiosyncratic Volatility			
ETF Direction:	Long		Short	
Post dummy	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Treated dummy × Post dummy	0.002	0.002	0.003***	0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
Stock monthly return		0.001		0.002
		(0.005)		(0.005)
Stock average daily Amihud illiquidity		-0.001		-0.000
		(0.001)		(0.001)
Stock log(market cap)		-0.005***		-0.004**
		(0.001)		(0.001)
Constant	0.017***	0.067***	0.017***	0.055***
	(0.000)	(0.015)	(0.000)	(0.014)
Stock FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
R-squared	0.50	0.51	0.50	0.50
N	56,274	56,274	51,238	51,238

Appendix C. List of US Single-Stock ETFs

ETF Name	Underlying Stock	Direction	Leverage
GraniteShares 2x Long AAPL Daily ETF	AAPL	Long	2
T-Rex 2X Long Apple Daily Target ETF	AAPL	Long	2
Direxion Daily AAPL Bull 2X Shares	AAPL	Long	2
Direxion Daily AAPL Bear 1X Shares	AAPL	Short	1
GraniteShares 2x Long AMD Daily ETF	AMD	Long	2
GraniteShares 1x Short AMD Daily ETF	AMD	Short	1
Direxion Daily AMZN Bull 2X Shares	AMZN	Long	2
GraniteShares 2x Long AMZN Daily ETF	AMZN	Long	2
Direxion Daily AMZN Bear 1X Shares	AMZN	Short	1
Defiance Daily Target 2X Long AVGO ETF	AVGO	Long	2
Direxion Daily AVGO Bull 2X Shares	AVGO	Long	2
Direxion Daily AVGO Bear 1X Shares	AVGO	Short	1
GraniteShares 2x Long BABA Daily ETF	BABA	Long	2
GraniteShares 2x Long COIN Daily ETF	COIN	Long	2
GraniteShares 1x Short COIN Daily ETF	COIN	Short	1
GraniteShares 2x Long CRWD Daily ETF	CRWD	Long	2
T-Rex 2X Long Alphabet Daily Target ETF	GOOGL	Long	2
Direxion Daily GOOGL Bull 2X Shares	GOOGL	Long	2
Direxion Daily GOOGL Bear 1X Shares	GOOGL	Short	1
Defiance Daily Target 2X Long LLY ETF	LLY	Long	2
GraniteShares 2x Long META Daily ETF	META	Long	2
Direxion Daily META Bull 2X Shares	META	Long	2
Direxion Daily META Bear 1X Shares	META	Short	1
T-Rex 2X Long Microsoft Daily Target ETF	MSFT	Long	2
GraniteShares 2x Long MSFT Daily ETF	MSFT	Long	2
Direxion Daily MSFT Bull 2X Shares	MSFT	Long	2
Direxion Daily MSFT Bear 1X Shares	MSFT	Short	1
Defiance Daily Target 2X Long MSTR ETF	MSTR	Long	2
T-Rex 2X Long MSTR Daily Target ETF	MSTR	Long	2
T-Rex 2X Inverse MSTR Daily Target ETF	MSTR	Short	2
Defiance Daily Target 2X Short MSTR ETF	MSTR	Short	2
GraniteShares 2x Long MU Daily ETF	MU	Long	2
Direxion Daily MU Bull 2X Shares	MU	Long	2
Direxion Daily MU Bear 1X Shares	MU	Short	1
Direxion Daily NFLX Bull 2X Shares	NFLX	Long	2

ETF Name	Underlying Stock	Direction	Leverage
T-Rex 2X Long NFLX Daily Target ETF	NFLX	Long	2
Direxion Daily NFLX Bear 1X Shares	NFLX	Short	1
AXS 2X NKE Bull Daily ETF	NKE	Long	2
AXS 2X NKE Bear Daily ETF	NKE	Short	2
Tradr 1.75X Long NVDA Weekly ETF	NVDA	Long	1.75
Leverage Shares 2X Long NVDA Daily ETF	NVDA	Long	2
Direxion Daily NVDA Bull 2X Shares	NVDA	Long	2
GraniteShares 2x Long NVDA Daily ETF	NVDA	Long	2
T-Rex 2X Long NVIDIA Daily Target ETF	NVDA	Long	2
Direxion Daily NVDA Bear 1X Shares	NVDA	Short	1
Tradr 1.5X Short NVDA Daily ETF	NVDA	Short	1.5
GraniteShares 2x Short NVDA Daily ETF	NVDA	Short	2
T-Rex 2X Inverse NVIDIA Daily Target ETF	NVDA	Short	2
Defiance Daily Target 2X Long NVO ETF	NVO	Long	2
AXS 2X PFE Bull Daily ETF	PFE	Long	2
AXS 2X PFE Bear Daily ETF	PFE	Short	2
Direxion Daily PLTR Bull 2X Shares	PLTR	Long	2
GraniteShares 2x Long PLTR Daily ETF	PLTR	Long	2
Direxion Daily PLTR Bear 1X Shares	PLTR	Short	1
AXS 1.5X PYPL Bull Daily ETF	PYPL	Long	1.5
AXS 1.5X PYPL Bear Daily ETF	PYPL	Short	1.5
Defiance Daily Target 2X Long SMCI ETF	SMCI	Long	2
GraniteShares 2x Long SMCI Daily ETF	SMCI	Long	2
GraniteShares 1.25x Long TSLA Daily ETF	TSLA	Long	1.25
Tradr 1.5X Long TSLA Weekly ETF	TSLA	Long	1.5
Direxion Daily TSLA Bull 2X Shares	TSLA	Long	2
GraniteShares 2x Long TSLA Daily ETF	TSLA	Long	2
Leverage Shares 2X Long TSLA Daily ETF	TSLA	Long	2
T-Rex 2X Long TESLA Daily Target ETF	TSLA	Long	2
Direxion Daily TSLA Bear 1X Shares	TSLA	Short	1
GraniteShares 1x Short TSLA Daily ETF	TSLA	Short	1
Tradr 2X Short TSLA Daily ETF	TSLA	Short	2
T-Rex 2X Inverse TESLA Daily Target ETF	TSLA	Short	2
GraniteShares 2x Long TSM Daily ETF	TSM	Long	2
Direxion Daily TSM Bull 2X Shares	TSM	Long	2
Direxion Daily TSM Bear 1X Shares	TSM	Short	1
GraniteShares 2x Long UBER Daily ETF	UBER	Long	2

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