Retail Trading of Leveraged ETFs

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Abstract

In this paper, I study retail investor use of Leveraged ETFs. Increased retail adoption of these securities provides an opportunity to understand the explicit and implicit costs that retail investors are paying in order to access leverage and complication. This paper shows that embedded leverage leads to mostly negative alphas. Additionally, I find evidence that more complicated payout structures see lower risk-adjusted returns. Lastly I document that retail investor trading in leveraged ETFs does not exhibit contrarian patterns observed in stock investments, suggesting that a liquidity provision is not a dominant motive for trading in these securities.

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1 Introduction

Classic portfolio theory tells investors to invest in the tangency portfolio on the Efficient Frontier, the set of portfolios offering the best risk-return payoff. Investors with a relatively low degree of risk aversion should borrow in order to invest more capital in the tangency portfolio. In order to attain a higher expected return, investors must lever up and invest more, past the weights of the tangency portfolio. Practically, however, this may be difficult for investors not able to borrow at attractive rates. However, leveraged exchange-traded funds have now provided a way for retail investors to obtain an increase in market exposure through financial instruments that embed the leverage through the use of financial derivatives.

These leveraged ETFs can take on many forms but primarily use either options or swaps to amplify or modify their returns. The purpose mainly includes amplifying the returns of a predetermined index. Examples include SPXL or TQQQ which aim to return 3 times the return of the SP 500 and Nasdaq, respectively. They can also work in the opposite direction, going short an index, returning the inverse of the underlying's performance. These instruments give retail investors the opportunity to take leveraged positions on popular indices, but also entire sectors, countries and asset classes. In that order, example tickers/names include: SDP- ProShares Short Utilities Sector, XXCH- Direxion Daily MSCI Emerging Markets China Bull 2x Shares, and TMF- Direxion Daily 20+ Year Treasury Bull 3X Shares.

An additional purpose of these structured products is to alter the payout structure, by capping and amplifying cutoffs at different points. Essentially, they serve as tradeable options portfolios on either single stocks or broader indices. There are two main objectives for these Defined Payout ETFs.

The first are ETFs designed to protect investors against downside in exchange for a capped upside. One version of this type of ETF protects fully against downside, eliminating losses after a certain period. This ETF is constructed either by holding the underlying or synthetically recreating the payoffs by buying a call and put at the same strike price. Then, a call is sold out of the money to cap the upside at a predetermined limit and a put is bought out of the money to cap the downside. A more complicated variation of the downside upside trade off ETF is where investors are only protected from the downside up to a certain point, at which they will start losing again. These are constructed in the same way, except an extra put is sold out of the money to end the protection period. Since the caps are predetermined, the options often have very specific strike prices. For this purpose, the funds will use FLEX options as opposed to standard options which allow for penny increments in the strike price, flexible expiry on any business day, and American or European expiry.

The second most common variation is a covered call ETF, where the asset manager will sell one, or multiple, out of the money call options depending on the underlying assets, to cap the upside in exchange for extra income from the sold calls. These can be written on either single stocks or broad indices.

These new instruments that have increased in popularity provide the opportunity to better understand the costs and risks that are posed to retail investors, beyond the expense ratios that are significantly large. The first section asks if leveraged ETFs have negative alphas, and whether this result is amplified with the increased leverage of the ETFs. This measures the cost to retail investors in terms of under performance with respect to models such as the CAPM, and 3/4 Factor models. Are investors sacrificing return in order for easier access to leverage? Are investors additionally sacrificing return in exchange for access to more complicated options based strategies? The second section relates to behavioral costs that is dependent on retail investor behavior. Do investors trend-chase, meaning they buy after periods of good return? Or do retail investors act in a contrarian manner, buying after stretches of negative returns and selling after stretches of positive returns?

Existing literature provides context on the questions asked above. **Frazzini and Pedersen (2021)** find that options and leveraged ETFs had increased return volatility in proportion to the embedded leverage. The increase in leverage also leads to lower risk adjusted returns. Additionally, they find that "Betting Against Beta" portfolios that are long low-embedded leverage and short high-embedded leverage have abnormal returns with Sharpe ratios greater than 1.

With regards to pay-out structure complexity, **Célérier and Vallée (2017)** study retail structured products using text analysis on their payoff structure. Over the 8 year period they found that headline rates for products were positively correlated with their risk and level of complexity. My research builds upon this by studying whether complexity in options-based ETFs, which as mentioned earlier alter the payout structure, leads to lower risk adjusted returns.

Egan, Mackay, and Yang (2022) use data on the demand for leveraged SP&500 ETFs to create a model based on revealed preference that tracked changes in expectations of future returns across investors. Their model reveales that following a downturn in the markets, investors become more pessimistic on average but disagreement increases due to contrarian investors in the market. While previous research suggests that retail investors are contrarian in the stock market, the degree of which can be influenced by factors such as age and attentiveness to the market **(Luo, Ravina, Sammon, Viceria (2022))**, research suggests that this trend is not consistent across all asset classes. **Kogan, Makarov, Niessner, and Schoar (2022)** find that investors in cryptocurrency do not act in a contrarian manner and instead employ momentum-following strategies. Additionally, retail investors broadly speaking tend to follow contrarian trading patterns across commodities, with retail traders entering both short and long positions nearly an equal amount **(Ferko, Mixon, Onur (2024))**. I attempt to establish what the nature of retail trades are when it comes to ETFs with embedded leverage and derivatives by using a dataset that indicates retail buys and sells.

For the analysis, three data sets are needed. First, I obtain daily return data from the Center for Research in Security Prices that spans from the start of 2005 to the end of 2022. This is the data used when analyzing the risk adjusted returns of the fund group mentioned earlier.

The second data set contains information on the retail initiated buys and retail initiated sells on a daily basis for the predetermined ticker pool. Additionally, it contains a field for non retail volume, of which the direction is not specified. This data set is constructed by observing price improvements in Trade and Quote (TAQ) data, which is publicly available. Since regulatory structure requires price improvement on retail, but not institutional, order flow, one can determine which trades are retail initiated. The methodology is explored in more detail in **Boehmer, Jones, Zhang, and Zhang (2020)**.

Lastly, I construct a list of tickers for leveraged ETFs using Bloomberg Terminal's ETF Screener to select leveraged funds only. However, this did not include funds that used options to modify the payout structure. I augment this list by selecting the derivatives based filter as well, and remove any ETFs that used futures to track the performance of commodities. This was done because they do not either alter or amplify the payouts, which is the ultimate goal. This leaves a list of options based ETFs which is added to the earlier list of leveraged ETFs.

This paper will begin with a comprehensive profile of the funds included. Then I will explore the relationship between risk and return for these specific instruments with a specific focus on the leverage and complication of the funds. After, I examine the retail trading behavior of leveraged ETFs to determine whether investors are trend chasing, or not.

2 Fund Profile

2.1 Growing Popularity

ETFs with embedded leverage and defined payout structures have been increasing in popularity over the years. Taking the CRSP data which contains returns from as far back as 2005 up to 2022, I graph the amount of tickers for leveraged ETFs that actively traded in the year. It is important to note, however, that the tickers at the end of 2022 do not match the total number included in the generated list of tickers from Bloomberg's fund filter for a few reasons. First, defined payout and leveraged ETFs can often be delisted if the product is not widely adapted enough or ran into regulatory issues. Additionally, Bloomberg's Fund Filter generated a list of ETFs that matched criteria in 2023, but the CRSP data only goes up to 2022, so there are tickers that are not included in the chart.

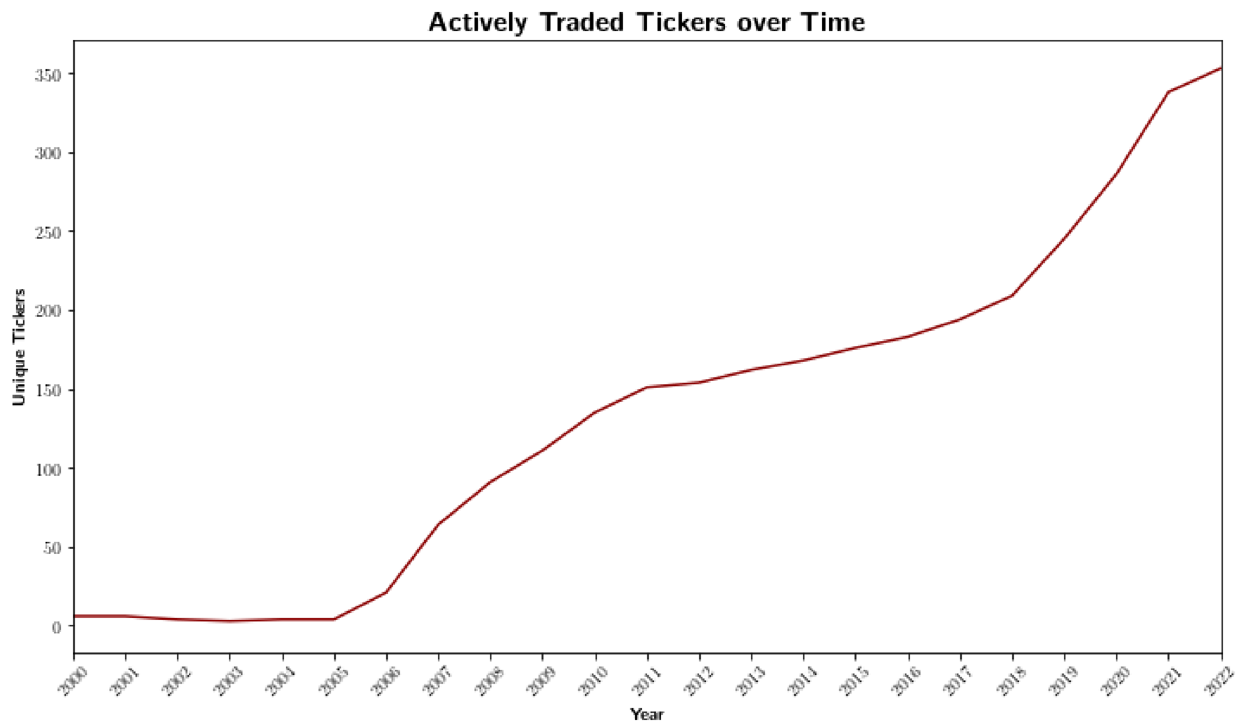

Figure 1: This figure depicts the steadily increasing number of leveraged ETFs and defined payout ETFs throughout the sample's span.

Volume in the sample has also increased over the last 5 years. Using the CRSP return data, I aggregate and average the daily volume across all tickers in the sample, and then took the average of that value per year. The past 5 years show a strong increase from 2021 to 2022.

2.2 Categorization

The sample used consists of several different variations of ETFs, mentioned in the Introduction. Table 1 depicts an overview of funds contained in the sample. The Full Sample can be separated into Options/Structured ETFs that alter payouts with floors, caps, and buffers on returns. Leveraged ETFs enhance the returns of an index or strategy either by increasing returns at different levels (Long ETFs) or returning the inverse to varying degrees (Short ETFs).

Options/Structured ETFs are identified through the derivatives based filter mentioned in Section 1. All ETFs not marked as structured are then classified as Leveraged ETFs. The distinction between

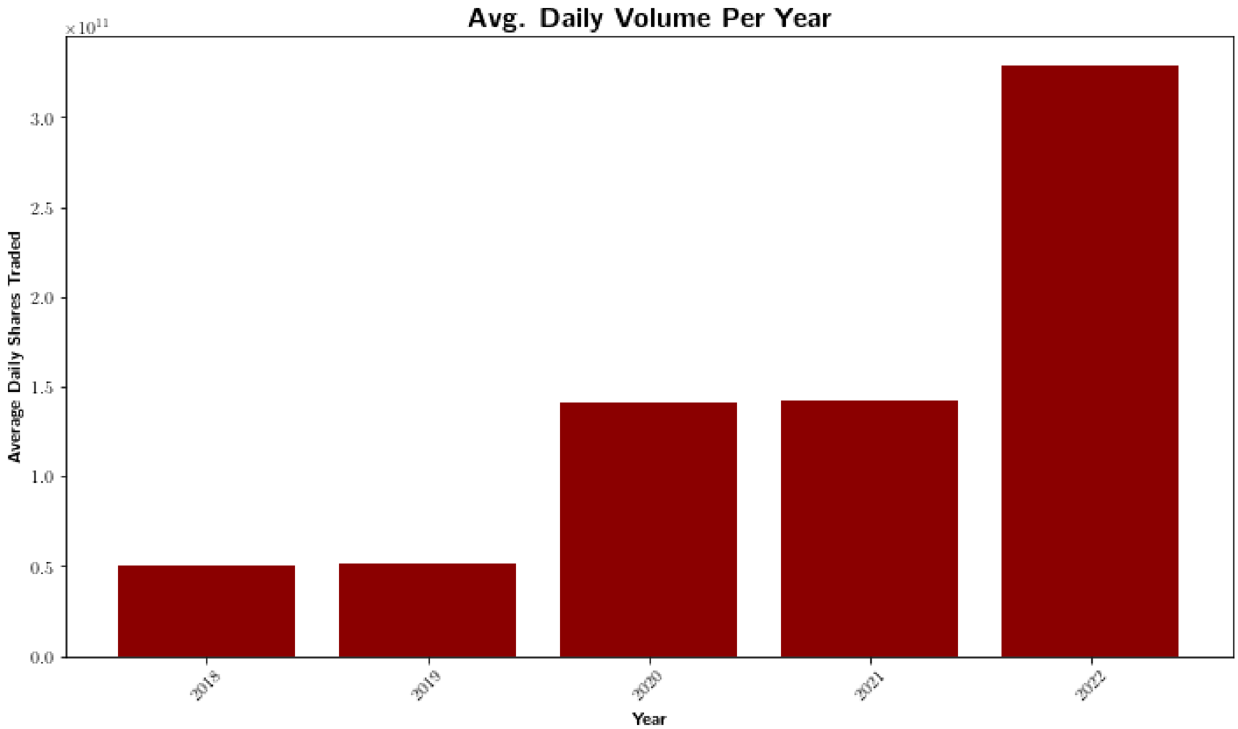

Figure 2: This figure depicts the increasing volume in the sample over the last 5 years.

Short and Leveraged ETFs is made by initially seeing if it is depicted in the name of the ETF. For example, ProShares UltraPro Short QQQ (SQQQ) was classified as a "Short ETF". After this iteration of classification was finished, the last filter was to read the ETF investment purpose on Bloomberg and from there determine the ETFs direction.

Table 1: Sample Profile

Category	Number of Funds	Total AUM, MLN USD	Average Expense Ratio
Full Sample	532	181,396	0.84%
Options/Structured	198	42,937	0.77%
Non-Structured	334	138,459	0.87%
Short ETFs	105	23,340	1.03%
Long ETFs	229	115,120	0.79%

As shown below in Table 1, Leveraged ETFs currently have a significantly larger AUM with slightly higher expense ratios than Structured ETFs. Amongst the Leveraged ETFs, Short ETFs have lower AUM but higher expense ratios.

2.3 Risk Adjusted Returns

In order to analyze the risk adjusted returns, I use the CAPM and Fama-French 3 Factor and 4 factor regressions which are the following:

$$\textbf{CAPM:}\ R_i = R_f + \beta_i(R_m - R_f) + \alpha \tag{1}$$

$$\textbf{3 Factor:}\ R_i = R_f + \beta_i(R_m - R_f) + \beta_{smb}(SMB) + \beta_{hml}(HML) + \alpha \tag{2}$$

$$\textbf{4 Factor:}\ R_i = R_f + \beta_i(R_m - R_f) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + +\beta_{MOM}(MOM) + \alpha \tag{3}$$

The relationship between leverage and alpha is expected to be negative, meaning that the higher the embedded leverage, the more negative the alpha. What this would imply is that retail investors would be sacrificing more return in order to get access to leverage they would not have otherwise. Additionally such a finding would be consistent with the results from Frazzini and Pedersen (2021). In addition to lower alphas, it is expected to see higher volatility with higher leverage which would also be consistent with previous findings.

As a proxy for leverage levels, I use the CAPM Betas generated from equation 1. This is due to the fact that the level of leverage is either explicitly mentioned in the ETF Name or Description (ex: SPXL Direxion Daily S&P 500 Bull 3X) , or it is vague (ex: BBEM JPMorgan Betabuilders Emerging Markets Equity ETF). The second classification is more common.

Plotting each ticker's CAPM beta against their CAPM alpha results in Figure 3. It shows how an increase in leverage, specifically in long ETFs tend to generate lower alphas following an increase in leverage.

In order to eliminate directional effect, I recreate the same graph after taking the absolute value of beta which results in the second chart in Figure 3. It shows that, although the data is clouded by outliers, an increase in leverage tends to lead to a decrease in alpha. Figure 4 below shows that Embedded Leverage also increases annualized volatility in an approximately linear relationship.

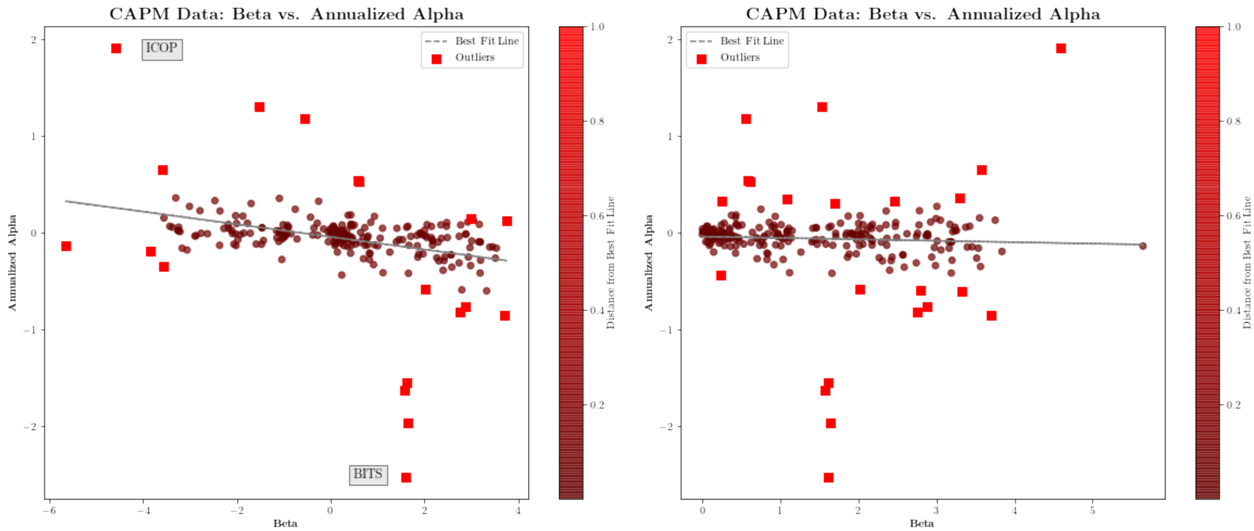

Figure 3: The chart on the left shows the relationship between CAPM Beta, alphas, and the normalized distance from each point to the best fit line. The chart on the right demonstrates the same but with the absolute value of the CAPM Beta.

After limiting the data set to only include tickers that have at least 50 days of trading data, the relationship between leverage and alphas can be seen through five different buckets of ETFs separated by amount of leverage. The table shows that the distribution of short vs. long ETFs is not asymmetric with long leveraged ETFs being much more common than short leveraged ETFs just by count numbers.

Table 2: Alphas with 5 Beta Buckets

Interval		**Beta**				**Alpha Annualized**			
Range	**Count**	**Min**	**Max**	**Mean**	σ	**Mean**	σ	**SEM**	**t**
$[-5.65, -1.09]$	101	-5.65	-1.09	-2.41	0.93	0.11	0.41	0.041	2.68
$[-1.09, 0.26]$	100	-1.09	0.26	-0.24	0.48	0.01	0.25	0.025	0.4
$[0.26, 0.61]$	101	0.26	0.61	0.41	0.09	0.00	0.16	0.016	0
$[0.61, 2.01]$	101	0.61	2.01	1.20	0.50	-0.21	0.57	0.057	-3.68
$[2.01, 3.75]$	101	2.01	3.75	2.76	0.46	-0.23	0.35	0.035	-6.57

Table 2 shows that specifically long high embedded leverage ETFs with high embedded leverage long-ETFs having statistically significant alphas. The alphas represent the explicit cost in terms of returns that retail investors are sacrificing in order to access higher embedded leverage. For example, in order to invest in an ETF classified in the last bucket, they would have to sacrifice 23 basis points of alpha in order to access that leverage.

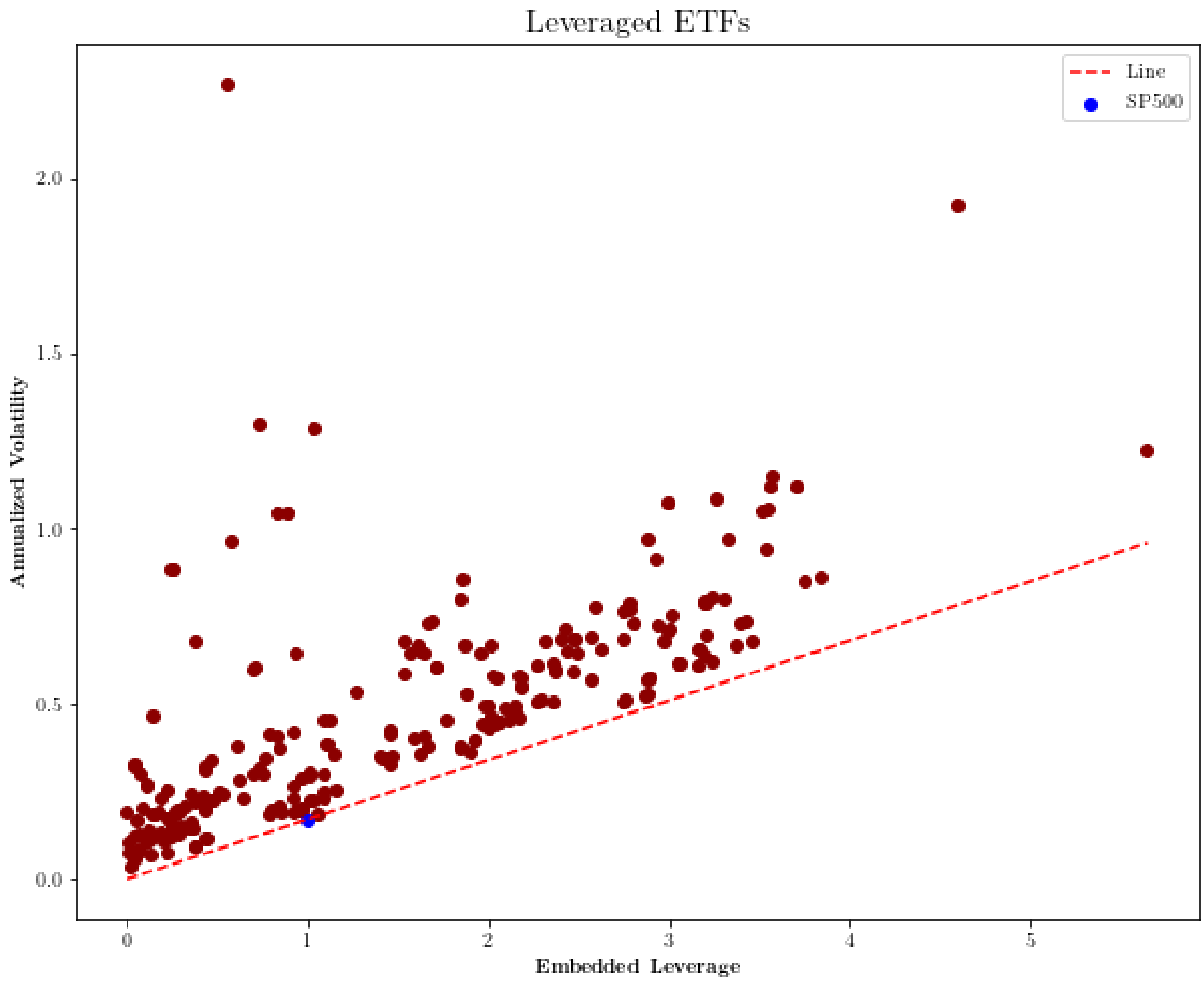

Figure 4: This figure shows how embedded leverage in this data set magnifies annualized volatility. For reference, the S&P500 is included alongside a dashed line that runs through it from the origin.

The costs to retail investors can also be explored through more risk-adjusted models and different types of ETFs. Using previous day's AUM as the determinant for investment weight, two portfolios were constructed in order to view alphas for the 3 and 4 factor models as well. The first portfolio consists of long only ETFs and the second portfolio consists of only short ETFs. For both Portfolios, the ETF positions are rebalanced every trading day. The AUM is calculated as the shares outstanding, multiplied by the closing price.

Table 3, which holds the results, shows negative annualized alphas, with Long ETFs having slightly more negative alphas compared to the Short ETFs.

Table 3: AUM Weighted Portfolio Alphas

Portfolio	Model	Alpha Annualized
Long ETFs	CAPM	-0.148
	3-factor Model	-0.144
	4-factor Model	-0.144
Short ETFs	CAPM	-0.145
	3-factor Model	-0.138
	4-factor Model	-0.137

Table 4 uses the same models (CAPM, 3-Factor, and 4-Factor) to measure risk adjusted returns, but this time the portfolio was constructed using equal weighting. The portfolio rebalances daily based on the number of unique tickers that traded on the day.

Table 4: Equal Weighted Portfolio Alphas

Portfolio	Model	Alpha Annualized
Long ETFs	CAPM	-0.062
	3-factor Model	-0.051
	4-factor Model	-0.052
Short ETFs	CAPM	-0.005
	3-factor Model	-0.005
	4-factor Model	-0.005

Using equal weights results in negative alphas across all categories and models. A consistent trend across all tables and analysis is that Short ETFs, despite leverage level, tend to have higher alphas than their Long ETF counterparts.

3 Complication

The growth of Structured Payout ETFs that embed options has now allowed retail investors to easily access options payout structures. While previously, retail investors would have to previously required them to identify type of options, position direction, and strike prices, these new ETFs relinquish this responsibility on the Asset Managers.

As explored in the introduction, the level of complexity between different Options-Embedded ETFs differs depending on its purpose. There is potential for complexity to have an impact on risk-adjusted returns, in particular increased complexity could lower risk-adjusted returns. More complexity increases transaction costs which in this case are incurred by the Asset Managers. Retail investors would pay for the price of this complexity through increased Expense Ratios, which in the sample, average around 77 basis points. Additionally, complicated strategies can rely on very specific market conditions to generate profits. If the market behaves unexpectedly, then the strategy could under perform or result in losses.

In order to understand the relationship between alpha and complication, I develop a proxy for complication by counting the number of "kinks" or "vertices" in the payout structure of the ETF. For example, a covered-call or yield-enhancing ETF would be considered the least complicated with a vertex value of "1".

Table 5 and Table 6 contain the results of two regressions. The first measures the relationship between vertices and alpha. The second control adds additional controls for leverage level's effect on alpha by creating dummy variables for the five Beta categories used in Table 2.

Table 5: Vertex Alpha Regression

	β	**t**	**p($\lvert t\rvert$)**	**[0.025 , 0.975]**
Constant	0.0191	0.727	0.469	[-0.033, 0.071]
Vertices	-0.0088	-0.950	0.344	[-0.027, 0.010]

Table 6: Vertex Alpha Regression, with Beta Controls

Variable	β	**t**	**p($\lvert t\rvert$)**	**[0.025 , 0.975]**
Vertices	-0.0168	-1.766	0.081	[-0.036, 0.002]
Beta Quintile 1	0.0390	3.392	0.001	[0.016, 0.062]
Beta Quintile 2	0.0171	1.391	0.167	[-0.007, 0.041]
Beta Quintile 3	0.0041	0.332	0.740	[-0.020, 0.028]
Beta Quintile 4	-0.0003	-0.028	0.978	[-0.024, 0.023]
Beta Quintile 5	-0.0255	-2.394	0.019	[-0.047, -0.004]

The regression results above show a negative relation between vertices and alpha, implying that an increase in complication leads to a lower risk-adjusted return, which confirms the hypothesis above. However, the results are slightly marred with neither t-statistic being significant for the "Vertices" variable. However, controlling for leverage, or beta as seen in Table establishes a stronger, more significant relationship between the vertices and alpha. Increasing the ”complication level” by 1, meaning adding a vertex in the payout structure, results in sacrificing around 2 basis points of alpha.

4 Retail Flow

This last section aims to understand the trading patterns of retail investors, specifically whether they are contrarian or trend following, chasing returns from the Leveraged ETFs. If acting in a contrarian manner, retail investors could potentially be providing liquidity to the market and institutional investors. The behavior currently differs across asset classes. Retail investors act in a contrarian manner for the general stock market as well as commodities. However, for cryptocurrency, investors trend chase as mentioned in the introduction. Given that ETFs hold underlyings that cross all of the forementioned asset classes, the trading direction could be either be contrarian or trend-following.

In order to develop a measure to compute and analyze the retail flow and direction per day, I use two proxies of retail order imbalance:

$$\frac{R_{buy} - R_{sell}}{R_{buy} + R_{sell} + I_{orders}} \tag{4}$$

$$\frac{R_{buy} - R_{sell}}{R_{buy} + R_{sell}} \tag{5}$$

In the above equations, R_{buy} indicates the number shares in retail initiated buy orders, R_{sell} shows the number of shares in retail initiated sell orders, and I_{orders} represents the number of shares traded by non-Retail or Institutional investors. Equation 4 measures the direction in which over all the trades that occur in proportion to the total number of shares traded on the same day and Equation 5 limits it to only the retail trades on that day.

These variables are then compared against past, contemporaneous, and future returns. Measuring this variable against past returns s allows me to see how investors are reacting to market movements, and what direction they go in. The relationship between future returns and retail trading is also important because if retail trades predict future returns, it could be evidence of liquidity provision and/or access to private information.

4.1 Non-Parametric Estimation

In order to perform a non-parametric analysis, the data had to be arranged into wide format. Taking a table that contained 4 columns: week number, tickers, the weekly return, and the retail flow measure (calculated either as equation 4 or 5), it was transformed into the following:

Table 7: Sample Table

Ticker	**Week**	**Over Retail**	**Over Total**	**Return**	**Return-1**	**Return-2**	**Return-3**	**...**
SPY	1	-0.40	-0.15	0.02	–	–	–	...
SPY	2	-0.10	-0.05	0.04	0.02	–	...	–
SPY	3	0.12	0.08	-0.01	0.04	0.02	–	...
SPY	4	0.1	0.08	-0.02	-0.01	0.04	0.02	...

This table contains fictional numbers for the sake of demonstration. The table is as wide as weeks in the data set and as long as the number of weeks where trading occurred multiplied by the number of tickers.

Once the table was made, weekly returns were categorized into quintiles, ranging from ”Heavy Sell” containing the weeks with the most retail outflow, to ”Heavy Buy” that contained the weeks with the most retail inflow.

The data was then categorized into analyzing the returns from the week before, contemporaneously, and future returns. This was chosen because The results in Table 8, 9, and 10 show the returns when retail flow is sorted according to Equation 4. The results in Table 11, 12, and 13 show the returns when retail flow is sorted according to Equation 5.

Table 8: Contemporaneous Returns (t), Eq. 4

	Heavy Sell	Sell	Neutral	Buy	Heavy Buy
Mean	-0.08%	0.07%	0.07%	-0.12%	0.02%
Std	1.11%	1.63%	1.67%	-1.54%	1.12%
Min	-14.41%	-25.25%	-35.88%	-19.64%	-13.75%
25%	-0.48%	0.52%	-0.59%	-0.71%	-0.34%
50%	-0.06%	0.02%	0.03%	-0.04%	0.04%
75%	0.32%	0.64%	0.69%	0.52%	0.45%
Max	15.64%	43.72%	31.26%	27.66%	11.07%
Avg Retail Flow	-7.27%	-0.99%	2.30%	12.48%	37.81%

Table 9: Lagged Returns (t-1), Eq. 4

	Heavy Sell	Sell	Neutral	Buy	Heavy Buy
Mean	-0.01%	0.02%	0.02%	-0.04%	-0.03%
Std	1.13%	1.58%	1.75%	1.55%	1.03%
Min	-13.75%	-25.25%	-35.88%	-19.64%	-13.78%
25%	-0.41%	-0.56%	-0.66%	-0.62%	-0.40%
50%	-0.01%	0.00%	0.01%	-0.01%	0.00%
75%	0.38%	0.59%	0.70%	0.58%	0.38%
Max	27.66%	31.26%	47.32%	17.71%	11.86%
Avg Retail Flow	-7.27%	-0.99%	2.30%	12.48%	37.81%

Table 10: Future Returns (t+1), Eq. 4

	Heavy Sell	Sell	Neutral	Buy	Heavy Buy
Mean	0.02%	0.00%	-0.02%	-0.02%	-0.02%
Std	1.16%	1.59%	1.69%	1.58%	1.12%
Min	-18.17%	-35.88%	-24.63%	-25.25%	-14.41%
25%	-0.40%	-0.58%	-0.69%	-0.63%	-0.42%
50%	0.00%	0.00%	-0.01%	-0.01%	-0.01%
75%	0.43%	0.59%	0.68%	0.58%	0.38%
Max	27.66%	24.48%	18.42%	31.26%	43.72%
Avg Retail Flow	-7.27%	-0.99%	2.30%	12.48%	37.81%

Table 11: Contemporaneous Returns (t), Eq. 5

	Heavy Sell	Sell	Neutral	Buy	Heavy Buy
Mean	-0.08%	0.07%	0.06%	-0.12%	0.04%
Std	1.07%	1.62%	1.74%	1.55%	1.05%
Min	-14.87%	-25.25%	-35.88%	-19.64%	-13.75%
25%	-0.47%	-0.52%	-0.65%	-0.70%	-0.32%
50%	-0.06%	0.00%	0.01%	-0.01%	0.01%
75%	0.36%	0.62%	0.73%	0.59%	0.37%
Max	43.72%	24.48%	31.26%	27.66%	14.01%
Avg Retail Flow	-47.10%	-7.81%	1.31%	9.81%	42.48%

Table 12: Lagged Returns (t-1), Eq. 5

	Heavy Sell	Sell	Neutral	Buy	Heavy Buy
Mean	-0.01%	0.03%	-0.01%	-0.03%	-0.01%
Std	1.05%	1.62%	1.82%	1.52%	0.97%
Min	-12.27%	-25.25%	-35.88%	-19.64%	-11.42%
25%	-0.40%	-0.56%	-0.72%	-0.62%	-0.37%
50%	-0.02%	0.01%	0.00%	-0.01%	0.01%
75%	0.36%	0.62%	0.73%	0.59%	0.37%
Max	43.72%	31.26%	18.19%	15.16%	11.86%
Avg Retail Flow	-47.10%	-7.81%	1.31%	9.81%	42.48%

Table 13: Future Returns (t+1), Eq. 5

	Heavy Sell	Sell	Neutral	Buy	Heavy Buy
Mean	0.02%	0.00%	-0.02%	-0.03%	-0.01%
Std	1.07%	1.60%	1.79%	1.54%	1.08%
Min	-11.93%	-35.88%	-25.25%	-14.87%	-12.27%
25%	-0.39%	-0.58%	-0.73%	-0.63%	-0.40%
50%	0.00%	0.00%	-0.01%	-0.02%	-0.01%
75%	0.41%	0.61%	0.73%	0.57%	0.38%
Max	27.66%	20.59%	31.26%	18.03%	43.72%
Avg Retail Flow	-47.10%	-7.81%	1.31%	9.81%	42.48%

In order to see contrarian behavior, one would need to see positive returns in the "Heavy Sell" and "Sell Columns" alongside negative returns in the "Buy" and "Heavy Buy" columns. However that is not the case with both median and mean returns in each bucket nearing 0.

A more interesting trend is the asymmetry of retail flow seen in Tables 8, 9 and 10. when using Equation 4 to characterize the flows. When looking at Tables 11, 12 and 13, the average retail flow is more balanced with the Heavy Sell bucket having an average retail flow of -47.10% and the Heavy Buy bucket having an average retail flow of 42.87%. However, this is not the case when using Equation 5. What this seems to imply is that retail traders will sell leveraged ETFs when activity in the market is elevated, i.e. the denominator is larger from adding in institutional orders.

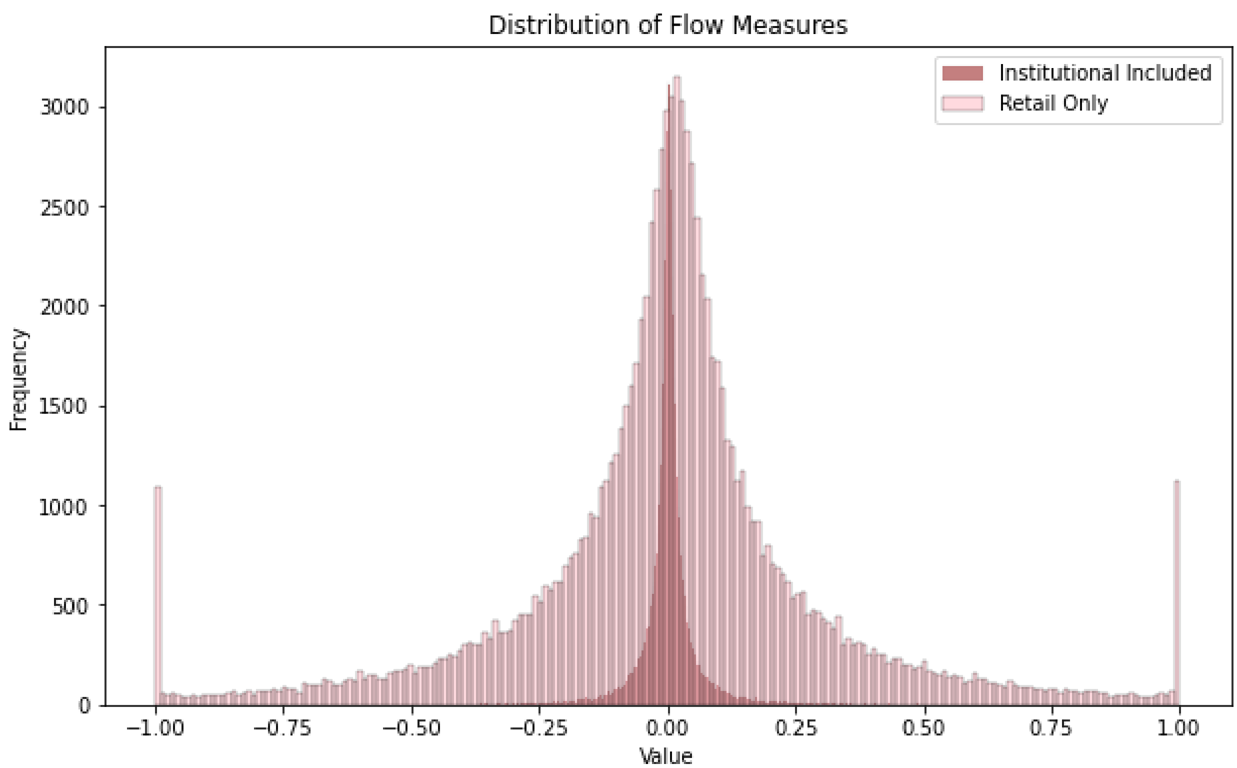

Figure 5: This figure displays the distribution of retail flows under both calculations methods.

4.2 Regression Results

In addition to the non-parametric estimation done above, 6 regressions were run in order to estimate the relationship between contemporaneous, lagged and future returns against both measures of retail flow. Table 14 contains the results of regressions when retail flow is measured with Institutional Flow included (Equation 4). Table 15 contains the results when retail flow does not include institutional trading (Equation 5).

Table 14: Institutional Included Regression Results

Time Period	β	**t**	**p($\|t\|$)**	**[0.025 , 0.975]**
Lagged	0.0140	-0.918	0.358	[-0.044, 0.016]
Contemporaneous	0.0562	3.703	0.000	[0.026, 0.086]
Future	-0.0212	-1.389	0.165	[-0.051, 0.009]

Table 15: Retail Regression Results

Time Period	β	**t**	**p($\|t\|$)**	**[0.025 , 0.975]**
Lagged	-0.0684	-1.020	0.308	[-0.200, 0.063]
Contemporaneous	0.3107	4.641	0.000	[0.179, 0.442]
Future	-0.1535	-2.286	0.022	[-0.285, -0.022]

Both the regressions had low R^2 but implied a positive relationship beta between Contemporaneous returns and retail flow, which could possibly imply trend following, but in order to draw that conclusively, the coefficient for the Lagged returns would also need to be positive and significant- which is not the case in either regression. The negative Beta for Future returns in both regressions implies that there is no evidence of a liquidity provision from Retail traders nor trading on insider information.

5 Conclusion

5.1 Summary of Findings

Leveraged ETFs provide an opportunity for investors that was previously not possible. Both access to leverage and complicated options payout structures are increased due to these innovative ETFs. Investors are able to speculate on indices, sectors, asset classes, countries and single stocks.

The increased retail adoption of these securities raises important questions about the implicit and explicit costs of trading these ETFs: what did retail investors have to sacrifice, besides basis points for expense ratios, in order to access both leverage and different payout structures?

The first is lower risk adjusted returns. Consistent with previous findings, I find that embedded leverage leads to lower risk adjusted returns and mostly negative alphas. This trend is present when both using an AUM weighted portfolio of the sample as well as an equal weighted portfolio. Additionally, an increase in embedded leverage also causes an increase in annualized volatility in an almost linear relationship. This represents one of the costs that investors have to pay for investing in leveraged ETFs in addition to the explicit costs associated with Expense Ratios.

However, investors are not only paying for access to leverage, but also access to complication. After running a regression that uses the ticker's vertices in the payout structure as a proxy for complication, against the ticker's alpha, the results show that there is a negative relationship between the number of kinks and alpha. Investors give up risk adjusted return in exchange for a more complicated payout structure. This could be due to the increased transaction costs associated with complexity, or the sensitivity to specific market conditions needed for the ETF to payout.

In addition to explicit costs that appear in the returns, there are behavioral costs associated with the trading patterns of retail investors. Across asset classes, retail investors differ with regards to whether they trend follow or act in a contrarian manner to the market. An analysis of the data set shows that investors do not act in a contrarian manner. Additionally, a negative beta when regressing future returns against retail flow implies that there is no evidence of retail investors acting as a liquidity provision. Additionally, there is no evidence of retail investors trading on inside information, which would have been unlikely to begin with since they are trading marketable portfolios.

5.2 Limitations and Going Forward

Time permitting, there should be a stricter filter applied to the funds when completing the analysis on retail flows. A very basic filter that limited the analysis to tickers that averaged at least 15%

of their volume from retail traders. However, a more effective filter would be a dynamic filter that throws out and includes funds based on their retail trading volume in the month before. This would allow for clearer results in both the non-parametric and regression.

Additionally, further research should develop a more robust way of determining which ETFs fit the criteria for analysis. Combining the derivatives filter onto the previous "Leveraged" filter and then hand-removing commodity based ETFs leads to human error and possibly including tickers that could be outliers and obscure the results.

Lastly, adoption of leveraged and defined payout structures is increasing rapidly. Repeating this analysis with additional trading and retail flow data in 2023 could lead to a more robust analysis, potentially with stronger results.

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