From Index Trackers to Risk Managers: The Expanding Role of Derivatives in ETFs

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Abstract

Using regulatory data from the SEC's N-PORT filings, we provide the first systematic study of derivative use by exchange-traded funds (ETFs). Nearly 60% of ETFs use derivatives, with greater derivative weight and exposure than mutual funds. Derivative use varies across ETF types: passive ETFs primarily use futures and forwards to reduce costs, while active ETFs rely on options strategies to improve risk profiles. Despite charging higher fees, active derivative-using ETFs attract more flows and exhibit reduced fee sensitivity. We show that these flows appear to be driven by superior downside protection, suggesting that investors value this benefit. Moreover, the extent of derivative reliance predicts both improved risk profiles and higher fees. Overall, our study highlights the strategic role of derivatives in ETF market competition.

JEL codes: G13, G20, G23

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1 Introduction

Exchange-traded funds (ETFs) were initially developed as passive index-tracking fund management vehicles. However, as more money has flowed into these products, significant innovations are emerging in the industry to meet dynamic market demands and investor preferences. According to the SEC N-PORT filings, the number of U.S.-domiciled equity ETFs holding derivatives (hereafter, derivative ETFs) has grown from approximately 800 in 2020 to over 1,400 in 2024. Over the same period, their total assets under management have increased from \$3.5 trillion to \$6.5 trillion, as shown in Figure 1. By 2024, out of a total of 2,476 equity ETFs, 60% used derivatives, and these derivative ETFs collectively managed 82% of the total net assets in the equity ETF market.

In September 2019, the SEC adopted Rule 6c-11 to facilitate greater competition and innovation among ETFs.[1] That same year, it also adopted Rule 19b-4 and approved the new Cboe rule allowing the in-kind transfer of options in ETF.[2] In October 2020, the SEC introduced Rule 18f-4, which streamlined the risk management procedure for ETF issuers to use derivatives in their portfolios.[3] These regulatory changes have played a key role in both expanding the ETF industry and increasing derivative usage in their portfolios, not simply for index tracking purposes but to add an active element to their portfolio return (Easley, Michayluk, O'Hara and Putniņš, 2021).

There is an extensive literature on the costs and benefits of derivative use by mutual funds and hedge funds (e.g., Koski and Pontiff (1999), Frino, Lepone and Wong (2009), Chen (2011), Aragon and Martin (2012), Cici and Palacios (2015), and Kaniel and Wang (2024)). However, despite the growing use of derivatives by ETFs in the market, how ETFs use derivatives and why investors are drawn to these more complex products have not been studied. To the best of our knowledge, our paper is the first contribution in this area.

Our study relies on recently available SEC N-PORT fund filings, which contain more detailed data on fund derivative use than was previously available. Importantly, previous studies without N-PORT data did not have the information to calculate the contribution

[1] https://www.sec.gov/files/rules/final/2019/33-10695.pdf
[2] https://www.sec.gov/files/rules/sro/cboe/2019/34-87340.pdf
[3] https://www.citigroup.com/global/insights/securities-services/us-derivatives-rule-three-things-to-know

of the derivative part of fund portfolios to the overall fund return. The granularity of this dataset allows us to directly assess whether and how derivative use enhances or detracts from fund performance.

Using N-PORT filing data, we address the following questions in this study. First, to what extent do ETFs use derivatives and how much do these derivative holdings contribute to ETF performance? Second, what derivatives do different types of ETF hold and what derivative strategies do they employ? Do they use these strategies to speculate, hedge, or for other purposes? Third, how does derivative use affect investor flows and fund fees? Lastly, what drives the flows into those ETFs: is it cost savings, enhanced risk-adjusted performance, or superior downside protection?

We first examine the extent of derivative use in the U.S. domiciled equity ETFs. Our results show that derivatives are used more by ETFs than by mutual funds. Among 2,476 equity ETFs in our sample, 60% of them use derivatives, managing 82% of total net assets. In contrast, 34.7% of equity mutual funds use derivatives and manage 36% of total assets (Kaniel and Wang, 2024). We also find that derivatives have a higher portfolio weight in ETFs than in mutual funds. The derivative positions in ETFs have an average absolute portfolio weight of 21.60% and gross notional exposure of 100.28%, whereas the two measures are 2.48% and 23.52% for equity mutual funds.

Given the distinct investment objectives of different types of ETFs, we categorize derivative-using ETFs as passive, active, and leveraged ETFs. For these types of ETF, we investigate how derivative holdings contribute to fund performance. To answer this question, we decompose fund returns into the contribution from derivative holdings and non-derivative holdings. We find that derivatives contribute positively to the performance of passive and active ETFs and negatively to leveraged ETFs. Passive and active ETFs have monthly Sharpe ratios of 0.14 and 0.18, respectively; however, their Sharpe ratios drop to 0.07 and 0.09 when the derivative part of fund portfolios is excluded. For leveraged ETFs, the Sharpe ratio increases from -0.05 to 0.2 when excluding the derivatives part, indicating that derivatives contribute negatively to the ETF returns.

We then analyze derivative allocations across different ETF types. For derivative-using active ETFs, nearly 80% of gross notional exposure comes from options, typically used for creating certain payoff structure such as buffer or downside protection, and to generate income by writing call and put options. Passive ETFs primarily use futures to gain market exposure for illiquid or foreign assets and manage foreign exchange risk through forward contracts. Leveraged ETFs, in contrast, are major swap users for amplifying or inversing returns.

To understand the derivative strategies implemented by ETFs, we employ a machine learning technique named K-Means clustering analysis to categorize derivative users based on their derivative holdings. Using this tool, we identify five distinct derivative strategies: foreign exchange (FX) hedge, long non-option derivative equity (speculation), short non-option derivative equity (hedging motives), covered call and put protection (hedging motives), and complex options. By examining the usage of different derivative strategies across ETF types, we find that passive derivative users mainly use three strategies: long non-option derivative equity (49.12%), foreign exchange hedge (23.68%), and covered call and put protection (21.05%). Over half of the active users (58.26%) use covered call and put protection, while 31.53% of them use complex options strategies. Leveraged ETFs focus on the use of long non-option derivative equity and short non-option derivative equity strategies for amplifying index returns.

Next, we examine the investor demand for derivative-based ETFs. On the one hand, we find that passive derivative users charge lower fees, exhibit similar tracking errors, and attract similar levels of investor flows, compared to passive nonusers. Passive derivative users also show a similar level of investor flow sensitivity to ETF fees and past performance. On the other hand, we find that active derivative users charge higher fees but do not show better performance in terms of their returns and alpha. However, they attract significantly more investor flows and exhibit reduced fee sensitivity compared to active nonusers.

To better understand the investor demand for these derivative-based ETFs, we examine whether derivative use enables ETFs to compete in cost, quality, or both. Ben-David, Franzoni, Kim and Moussawi (2023) document that ETFs can compete along the price and quality dimensions to attract investor flows. In this context, price reflects cost (e.g., fees), while quality captures non-price attributes valued by investors. Our results indicate that passive ETFs with derivatives compete primarily on price by offering similar return performance at lower costs. This highlights the role of derivatives in passive ETFs as a cost-saving tool. In contrast, ETFs in the active segment are significant derivative users and charge higher fees. We find that active ETFs with greater derivative return contributions are also more expensive, suggesting that they use derivatives to compete on quality rather than cost. While these funds do not deliver higher raw returns or alpha (net-of-fee 12-month returns or Fama-French five-factor alpha), they provide superior risk-adjusted performance (Sharpe ratio) and exhibit stronger risk profiles across multiple dimensions, including total volatility, market beta, downside risk, and tail risk. These superior risk-based performances are positively associated with the level of derivative return contribution.

Importantly, we find that the superior downside protection, as measured by maximum drawdown, helps explain the higher investor flows into these funds. This reveals that investors value the risk management benefits delivered by derivative strategies and are willing to pay more for products that offer better downside protection.

Our paper is related to the literature on why and how derivatives are used by the fund industry. In one of the first studies in this area, Koski and Pontiff (1999) use phone survey data to show that derivatives are mainly used by mutual funds for hedging purposes and that there is no significant difference between the risk and performance of funds that use derivatives and those that do not. Using SEC N-SAR filings which contain data on mutual funds' derivatives positions, Deli and Varma (2002) show that derivatives provide a cheaper way for the funds to maintain a target level of exposure in the face of investors inflows and outflows. A related study, Frino, Lepone and Wong (2009) using Morningstar Direct data, find similar results when examining why fund managers use index futures.

Natter, Rohleder, Schulte and Wilkens (2016) use SEC N-SAR filings and find that mutual fund investors benefit from the use of options as a hedging strategy. This aligns with research on derivative usage in hedge funds by Chen (2011) and Aragon and Martin (2012), who demonstrate the hedging motive for fund derivative use. Using CRSP data, Cici and Palacios (2015) find that mutual funds hold options for income generation by writing call options and for portfolio insurance by purchasing put options. Agarwal, Ruenzi and Weigert (2017) and Agarwal, Ruenzi and Weigert (2024) show that hedge funds take long positions in put options to mitigate tail risk and contribute to their unobserved performance.

More recent studies use N-PORT data to study derivatives holdings by mutual funds.

Focusing on equity funds, Kaniel and Wang (2024) show that derivative use materially contributes to fund returns, and most funds use derivatives to amplify fund returns. Choi, Kim and Randall (2023) study interest rate derivative use in fixed-income funds and find that interest rate derivatives increase duration risk and that these derivatives are employed for both hedging and speculative purposes. Barth, Kahn, Monin and Sokolinskiy (2024) also study the use of derivatives by fixed-income mutual funds and show that mutual funds use treasury futures to match the duration of the benchmarks that they track.

Our paper also contributes to the literature on innovations in the ETF industry. Various papers examine new types of ETF products and their impact on the underlying markets they trade in. For example Huang, Song and Xiang (2020) study the performance of smart beta ETFs, while Huang, O'Hara and Zhong (2021) examine the impact of industry ETFs on informed trading and market efficiency. Ben-David, Franzoni, Kim and Moussawi (2023) shows that specialised ETFS on the latest hot themes tend to hold attention-grabbing and overvalued stocks and do not create value for investors on average. Khomyn, Putniņs and Zoican (2024) show that more liquid ETFs for a given index charge higher fees and attract short-horizon investors who are more sensitive to liquidity than to fees. Our paper contributes to this literature on innovation in the ETF space by studying ETF innovation with derivative holdings.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 discusses the extent of derivative use in ETFs. Section 4 studies the derivatives allocation by ETFs. Section 5 examines the impact of derivative use on investor flows. Section 6 documents the impact of derivative use on ETF competitiveness in terms of fees and performance.

2 Data

In this section, we discuss the main data source and then describe our data collection process.

2.1 The Form N-PORT Filing from SEC

Our main dataset relies on the SEC's Form N-PORT filings, which are monthly portfolio investment reports used by registered management investment companies, exchange-traded funds organised as unit investment trusts, or series other than money market funds.[4] Since the filings are only publicly available from September 30, 2019, our sample period spans from September 30, 2019, to January 31, 2024.

We take advantage of the rich information about derivative positions disclosed in the N-PORT dataset, which offers two advantages over previously used fund datasets. First, it provides fund-level (un) realised Profit-and-loss (PnL) and the attribution of (un) realised PnL to derivative investments and non-derivative assets, which enables us to examine how derivatives contribute to fund returns more directly. Second, it contains a comprehensive categorisation of derivatives used into forward, future, option, swaption, swap, warrant, and other. Previous studies have used datasets where certain derivative uses are bundled together and where swap use is not identified

Moreover, N-PORT filings report derivative holdings with distinct information according to the category of the derivative. For each derivative contract, they not only report portfolio weight and notional amounts but also specify the reference asset category for each derivative, including commodity, credit, equity, foreign exchange, interest rate, and others. More specifically, the information for options covers type (put/call), payoff profile (write/purchase), exercise price, expiration date, and unrealised PnL. For swaps, the dataset provides detailed information on both the payers and receivers, including the underlying assets for both legs and specifies whether payments are made or received on a fixed or floating basis. This detailed data on derivative positions allows us to investigate the extent of derivative use by funds and understand their derivative strategies.

2.2 Data Collection

We download the universe of N-PORT filings from 2019 to 2024 from the SEC's website by using the EDGAR Application Programming Interfaces.[5] In total, there are 230,758 filings in the sample period. Each N-PORT filing contains data at both monthly and quarterly frequencies and is identified by the EDGAR series identifier (series ID) and reporting date.

[4] https://www.sec.gov/files/formn-port.pdf

[5] The website is: https://www.sec.gov/search-filings/edgar-application-programming-interfaces. However, the Form N-PORT Data Sets have been available for download since the 29th of July, 2024, which is readily available data sorted by SEC, sourced from https://www.sec.gov/newsroom/whats-new/2407-form-nport-data-sets.

The N-PORT dataset contains monthly fund-level performance information. We extract the monthly total return for each share class in each series ID and monthly PnL attributable to derivatives and other non-derivative investments. Additionally, this filing also provides detailed flow information, which includes the aggregate dollar amounts for sales and redemptions/repurchases of fund shares. We use them to calculate fund flows by scaling their total net assets.

The N-PORT dataset contains quarterly portfolio holdings including derivatives. We extract the identification of investment, the amount of each investment(balance, units, portfolio weight)[6], type of derivative instrument, underlying asset type, payoff profile(long/short), notional amount, exercise price for option contract, information of receiver and payer for swap contract, and currency code for each derivative contract.

The ETF sample used in our study contains all equity ETFs that have been listed and traded on the stock exchanges in the US from September 2019 to January 2024. To construct our ETF sample data, we obtain the data on fund characteristics from the CRSP Survivor-Bias-Free US Mutual Fund and MorningStar Direct, which includes mutual fund returns, fund size, Lipper classifications, ETF flag, expense ratios, Morningstar category, active management, and primary prospectus benchmark. We define the equity ETF as one with a Lipper asset code of "EQ" and an ETF Flag of "F" based on the CRSP dataset. Finally, we merge the N-PORT data with CRSP and MorningStar data following Barth, Kahn, Monin and Sokolinskiy (2024) by first using fund tickers and then using fund names where tickers are not available. In the case that there are multiple matches in the merge procedure, we manually check the ETFs and hand-match them. The final sample contains 2,476 U.S. equity ETFs for the period 2019 through 2024 based on the unique identifier "crsp_fundno" from the CRSP dataset.

[6] According to the explanation in N-PORT form, Balance indicates whether the amount is expressed in the number of shares, principal amount, or other units. For derivatives contracts, as applicable, provide the number of contracts.

3 Overall Derivative Usage in ETFs

To examine the extent of derivatives used by ETFs, following Kaniel and Wang (2024), we calculate gross notional exposure of derivative holdings as the sum of the absolute notional amounts of derivative positions scaled by fund size. Although the N-PORT dataset provides the notional amounts for derivatives, there is no notional amount value reported for options. Therefore, we calculate it as the number of contracted shares multiplied by the exercise price following Merton (1998). In addition, for option contracts denominated in currencies other than USD, we convert the notional amounts to USD by multiplying them with the exchange rate on the reporting date.

As portfolio weights are displayed as negative for short positions and positive for long positions in N-PORT filings, we calculate the portfolio weight of derivatives by summing the absolute derivative weight for each ETF's portfolio on each reporting date.

Panel A in Table 1 reports the number of derivative-using ETFs and the breakdown of derivative usage by category. We define derivative-using ETFs as those that use derivatives at least once during the sample period. By January 2024, there are 1,481 derivative-based U.S. domiciled equity ETFs with total net assets of \$6.6 trillion, out of a total of 2,476 U.S. domiciled equity ETFs with \$8 trillion in net assets. In contrast, there are 3,106 U.S. domestic equity active mutual funds reported in Kaniel and Wang (2024), 1,079 (34.7%) of which use derivatives and manage 36% of total assets. It shows that a higher proportion of ETFs use derivatives than mutual funds. Among derivative users, 644 ETFs use futures, 160 forwards, 338 options, 244 swaps, and 201 warrants.

Derivatives also play a more important role in ETFs compared to mutual funds. The average absolute portfolio weight and gross notional exposure of derivative positions are 21.69% and 100.28%, respectively for ETFs, while the two measures are 2.48% and 23.52% according to Kaniel and Wang (2024) for equity mutual funds. After breaking down the types of derivatives, we observe that options and swaps have higher portfolio weight and notional exposure than other derivatives in ETF portfolios. Even though the number of ETFs that use futures (644) is greater than those that use any other derivatives, on average, option contracts account for the most in both portfolio weight (15.92%) and gross notional exposure

(56.24%). Swaps are behind with 4.28% in absolute weight and 29.61% in gross notional exposure. This is in contrast to the mutual fund industry, where options provide merely 0.55% gross notional exposure according to Kaniel and Wang (2024). Other derivatives have much lower weights and notional exposure than options and swaps. The portfolio weights for futures, forward, and warrant are 1.42%, 0.07%, and 0.01%, respectively, with gross notional exposure of 10.22%, 4.33%, and 0.05%.

A plausible reason why derivatives are used more in ETFs than mutual funds is the ETFs' structural cost advantage. Mutual funds must meet redemptions by liquidating underlying assets, thereby realising capital gains and incurring trading costs. In contrast, ETFs creat and redeem in-kind shares with authorised participants (APs), which allows portfolio adjustments without triggering taxable events and avoids the transaction costs associated with frequent asset sales. Agarwal et al. (2023) provide evidence that in-kind transactions offer structural advantages in managing redemptions and trading costs. Furthermore, since 2019, the SEC has expressly approved the in-kind transfer of option contracts for ETFs, enhancing the efficiency of their options strategies. Together, these features reduce both tax and implementation costs for ETF sponsors, making derivative use more attractive in the ETF wrapper than in the mutual fund.

To evaluate how derivatives contribute to ETF returns, we calculate derivative-induced returns (DR), non-derivative-induced returns (non-DR), and derivative relative contribution (DC).

$$DR_t = \frac{PnL_t^{Realized} + PnL_t^{Unrealized} - PnL_{t-1}^{Unrealized}}{TNA_{t-1}} \quad (1)$$

where the $PnL_t^{Realized}$ is the net realized gain (loss) attributable to derivatives at month t, $PnL_t^{Unrealized} - PnL_{t-1}^{Unrealized}$ is the net change in unrealized appreciation (or depreciation) attributable to derivatives at month t, both of them are directly extracted from N-PORT filings. TNA_{t-1} is the total net asset at month t-1 from CRSP data.

Similarly, *non-DR* denotes the return generated by non-derivative holdings and is calculated as:

$$non\text{-}DR_t = Ret_t - DR_t \quad (2)$$

where non-DR$_t$ is the return generated by non-derivative holdings at month t, Ret_t is the fund return in month t. The contribution of derivative positions to total fund returns (DC) is measured as:

$$DC_t = \frac{|DR_t|}{|DR_t| + |non\text{-}DR_t|} \tag{3}$$

Panel B in Table 1 presents statistics on the distribution of derivative weights, exposures, and derivative return contributions across ETFs. It shows that there is substantial cross-sectional variation in the extent of derivative use. While the fund at the 50th percentile has a derivative weight of 0.11 % and gross notional exposure of 3.31 %, the fund at the 90th percentile has a derivative weight of 109.2 % with gross notional exposure of 304.6%.

The last three columns in Panel B of Table 1 present summary statistics for the derivative return (DR), the non-derivative return (non-DR), and the derivative contribution (DC)which represents the average contribution of derivatives to total ETF returns. The average monthly DR (non-DR) is 1.18bps (47.69bps), showing that derivatives on average contribute positively to ETF returns. Moreover, the average contribution of derivatives to monthly total returns is 23.87%, where 30% of observations have a derivative return over 9.06%.

4 How Do ETFs Use Derivatives?

To explore the motives behind the use of derivatives by different types of ETFs, we further categorize these derivative-using ETFs in this section. We calculate a series of variables representing fund characteristics for each ETF type, allowing for a comprehensive comparison. Through this comparison, we examine the extent of derivative use across different ETF types, their intention in using derivatives, and the impact of derivative use on fund returns. In the next two subsections, we examine their derivative allocations based on derivative categories and underlying asset categories to explain the distinct strategies that different ETFs use in their derivative use.

4.1 Fund Characteristics

As ETFs may use derivatives for different reasons according to their types, we split our sample by ETF type. We begin this section by explaining our classification method, followed by an analysis of our findings for each fund type.

We first split derivative-based ETFs into token and non-token users using the median of gross notional exposure according to Panel B in Table 1, where we define token (non-token) users as having gross notional exposure lower (higher) than 3.31%. We then categorise the non-token derivative users into three groups: active, passive, and leveraged based on their distinct investment objectives.

The investment objective of leveraged ETFs is to amplify the daily return of their underlying index according to a certain leverage ratio (e.g., 2X, 3X) [7]. They are viewed as trading tools since they are not supposed to be suggested as long-term investments according to SEC regulations. For this reason, we classify non-token derivative-using ETFs as leveraged ETFs if their corresponding Morningstar global category classification is "trading tools".[8]

The remaining sub-sample of non-token derivative users is then classified into active and passive ETFs based on whether the variable "active management" field for the fund is marked 'Yes' or 'No' in the Morningstar Direct database. The classification yields five groups for our ETF sample namely: non-users, token users, passive, active, and leveraged, where non-users are those who never held any derivative positions over our sample period. Table A2 shows some examples of the principle investment strategies in the fund prospectus for passive, active, and leveraged ETFs. We show two examples of passive derivative users: Global X S&P 500 Covered Call ETF and iShares MSCI EAFE ETF. The first one replicates an option-based index: CBOE S&P 500 BuyWrite Index, which is designed to track the performance of a covered call strategy. The second one uses derivatives such as stock index futures to replicate the iShares MSCI EAFE index. We also show four examples of active derivative users. These ETFs mainly use options to achieve investment objectives by selling options, buying put options, or employing pre-defined option-based strategies. Lastly, two leveraged ETF examples show that these ETFs use swaps and futures to replicate (2x or -3x)

[7]Their target returns are mainly achieved by using derivative contracts like options and swaps (Gilstrap, Petkevich, Teterin and Wang (2024)).

[8]The Global Category Classification Report in Morningstar defines trading tools as portfolios that replicate a multiple or inverse multiple of the returns of a reference index over a short period. While the replication is efficient over the identified period, the compounding features generate returns that often do not match the long-term performance of the index. More information can be found at: https://www.morningstar.com/content/dam/marketing/shared/research/methodology/860250-GlobalCategoryClassifications.pdf

daily performance of S&P500 index.

Table 2 presents the number and the characteristics of funds in these different groups, where fund sizes and expense ratios are obtained from the CRSP dataset. It shows that out of our sample of 2,476 ETFs, 995 ETFs never use derivatives and 657 of them are token users. Among the 824 non-token derivative ETFs (33% of the total number of funds), the number of active ETFs (416) is greater than the number of passive ETFs (247) and leveraged ETFs (161).

There are distinct differences among the five groups of ETFs. Regarding the extent of derivative use, active and leveraged ETFs use derivatives more heavily than passive ETFs. Active ETFs have the highest portfolio weight in derivatives among ETF types, with gross notional exposure of 264.70% and derivative portfolio weight of 68.21%. Leveraged ETFs have gross notional exposure of 170.29% and derivative weight of 22.12% while passive ETFs have a lower average exposure of 66.26% and portfolio weight of 5.79%. Although active ETFs have a higher weight to derivatives, their derivative relative contribution (DC) of 67.21% is smaller than the DC for leveraged ETFs which is 79.42%.

Panels (a) and (b) in Figure 2 show the average gross notional exposure across ETF types and over time. Leveraged ETFs and active ETFs maintain a higher exposure to derivatives both cross-sectionally and in time series. Panel (a) shows that active ETFs exhibit more cross-sectional variation in derivatives notional exposure than other types. Panel (b) shows the median notional exposure of derivatives for token users, passive ETFs, and leveraged ETFs remains relatively stable over the sample period, while active ETFs increase their notional exposure drastically from 2020 to 2021. Their median notional exposure first increases from lower than 100% to 700%, then drops to about 300%, which remains higher in the rest of the sample period than leveraged and passive ETFs. The change is likely driven by the interaction among three forces: the implementation of SEC's "derivatives rule" in 2020, investors' demand, and the COVID-19 period.

In addition to derivative holdings, we also examine other asset holdings to assess the diversity of assets held by ETFs. We obtain portfolio weights of both cash holdings and equity holdings for each ETF from CRSP and calculate their average absolute values in Table 2. We observe that all non-token derivative users hold less equity and more cash than non-derivative users. For example, passive, active, and leveraged ETFs hold 85.11%, 29.18%, and 28.89% of equity, respectively, while non-users hold 89.2% of equity. Passive, active, and leveraged ETFs hold 3.92%, 8.85%, and 52.88% of cash, while non-users hold 1.64% of cash. This can be attributed to the fact that cash holding is needed for margin calls and collateral requirements. Compared with active ETFs, which have 8.85% of cash and 11.63% of cash holding volatility, leveraged ETFs hold a much higher level of cash holding (52.88%) but lower cash volatility (5.84%).

To offer additional insights into cash holdings, Figure 2 also shows average cash holdings for each ETF type, by decile in Panel (c) and over time in Panel (d). Panel (c) shows that active ETFs have greater cross-sectional variation in cash holding than other types of ETFs. Panel (d) shows that leveraged ETFs maintain much higher cash holdings than other types, which also shows time variation in the sample period. Cash holdings of active ETFs are in general stable except for the period between 2020 and 2021. The plausible explanation for the significant cash holdings in leveraged ETFs might be associated with their use of derivatives and borrowed money. Since they are designed as trading tools to both positively and negatively amplify underlying assets' returns, they would borrow from the margin loan provider to achieve their negative leveraged ratios in addition to using derivatives.[9]

As the N-PORT dataset allows us to decompose fund returns to understand the impact of derivative positions on overall fund performance, we calculate fund return, return volatility, fund Sharpe ratio, non-derivative return (non-DR), volatility of the non-derivative return, and the Sharpe ratio of returns induced by non-derivative assets (non-DR Sharpe ratio) for each ETF over our sample period. The fund return is an average monthly net (after-fee) return from CRSP. The Sharpe ratio is calculated as the monthly fund return divided by fund return volatility.

Table 2 shows that derivative users exhibit lower fund returns and lower return volatility compared to non-users, who have an average fund return (return volatility) of 78.41 (575.54) bps. Passive, active, and leveraged ETFs have average returns of 69.87, 60.47, and -17.33 bps. They also have lower return volatilities than non-users: 499.91, 345.09, and 363.81 bps,

[9]More information can be found in: https://leverageshares.com/documents/prospectus/Leverage-Shares-Base-Prospectus-(CBI)-Final-17-July-2024.pdf

respectively. Leveraged ETFs stand out with a negative average fund return, which might help explain why the SEC prohibits leveraged ETF producers from marketing their products as suitable for long-term investments to investors. Considering the tradeoff between risk and return, active ETFs achieve the highest Sharpe ratio of 0.18, whereas non-users, token users, and passive ETFs have the same level of Sharpe ratio of 0.14. This outperformance may suggest the value-added of active management in active ETFs compared with passive and leveraged ETFs.

To further show the impact of derivative holdings on fund performance compared to non-derivative holdings, we calculate derivatives-induced return, volatility, and Sharpe ratio, with portfolio return, volatility, and Sharpe ratio excluding the contribution of derivative holdings. We observe that derivative usage has enhanced the fund returns of all derivative users, except for leveraged ETFs. Fund returns excluding derivatives-induced returns for passive and active ETFs are 36.52 and 18.22 bps, while the total fund returns increase to 69.87 and 60.47 bps, respectively. Notably, the Sharpe ratios for passive (0.14) and active (0.18) ETFs are double those of their non-derivative Sharpe ratios, which are 0.07 for passive ETFs and 0.09 for active ETFs.

To examine how many ETFs in which fund returns are enhanced by using derivatives in our sample, we show the distributions of the difference between the Sharpe ratio and the non-DR Sharpe ratio in Figure 3. The difference between the Sharpe ratio and the non-DR Sharpe ratio is calculated by subtracting the non-DR Sharpe ratio from the Sharpe ratio. Derivative positions enhance fund performance if this value is positive. Panel (a) shows that the distribution of the difference between these two Sharpe ratios for active ETFs is distinctly right-skewed, indicating that the use of derivatives positively contributes to the performance of most of these ETFs. A similar pattern is shown in Panel (b) for passive ETFs and Panel (d) for token users, suggesting most of them might also use derivatives for enhancing returns. Panel (c) shows that derivatives contribute negatively to the return of most leveraged ETFs.

We also calculate the average CAPM beta and the correlation between derivative-using (DR) and non-derivative (non-DR) ETFs over our sample period for each ETF, which provides insights into the purposes behind using derivatives within different ETF categories. CAPM beta is the coefficient estimate from regressing an ETF's excess return on the market excess return. As shown in Table 2, non-users have the largest CAPM Beta of 0.99 and token users are closely behind with 0.95 while the average betas of passive, active, and leveraged ETFs are 0.83, 0.6, and 0.5, respectively. The value of CAPM beta positively correlates to equity allocation in a portfolio. Non-users, token users, and passive ETFs all allocate over 80% to equity while active and leveraged ETFs allocate less than 30%. The smallest CAPM Beta of leveraged ETFs can be attributed to their substantial cash holdings of 52.88% and relatively smaller equity holdings of 28.89%. Leveraged ETFs provide multiple times of positive or negative market exposure to the investors, while their average CAPM is only 0.5, suggesting that they may only provide multiple times of exposure over a daily instead of a monthly horizon.

The time series DR and non-DR data allow us to calculate their correlations and see the intention behind derivative use. Table 2 shows that token users have an average correlation of 0.54. The strong positive correlation suggests that they tend to use derivatives for gaining exposure instead of hedging. Active ETFs exhibit an average negative correlation of -0.05 while passive and leveraged ETFs both have this correlation close to 0, with 0.01 and 0.09, respectively. This observation suggests that active ETFs are more likely to use derivatives for hedging. However, there is no clear evidence to show whether passive ETFs use derivatives for hedging like active ETFs.

Next, we compare the fees charged by different ETF types. We use expense ratios and total net assets from CRSP as ETF fees and ETF sizes. Table 2 shows that active ETFs and leveraged ETFs, which have smaller sizes and greater derivative weight, charge higher fees than other types of ETFs, with average annual fees of 0.61% and 0.77%, respectively. Interestingly, passive derivative users have the lowest fee. Expense ratios of non-users are 0.44%, token users 0.29%, and passive ETFs 0.33%.

After discussing the fees charged by these ETFs, we examine the fund flows they receive. We calculate fund flows, flow volatility, flow sales, flow redemption, and flow reinvestment for each ETF category on average. The fund flow is computed as $(TNA_{t+1} - TNA_t * Return_{t+1})/TNA_t$, where t is last month, t+1 is current month, TNA is total net assets, and return is fund return from CRSP. Flow volatility is the standard deviation of monthly fund flows over the sample period. Flow redemption, flow reinvestment, and flow sales are calculated as the aggregate dollar amounts for redemptions, repurchases, and sales of fund shares in each month, extracted from the N-PORT filings and scaled by the fund size of the previous month.

Table 2 indicates that investors are attracted to active ETFs, as these ETFs exhibit the highest fund flows (9.91%) among all categories. They also have the highest flow volatility (28.16%), which may suggest that investors' demand for active ETFs is not stable over time. They also have the lowest flow redemptions (-5.29%) and the second-highest flow sales (17.34%), with average flow sales more than twice those of passive funds (7.01%). Leveraged ETFs exhibit lower flow volatility (5.8%) than active ETFs (28.16%), and experience the highest flow sales (20.41%), negative flow redemptions (-1.36%), and near-zero flow reinvestment.

In summary, both active ETFs and leveraged ETFs are significant users of derivatives. Derivative use in leveraged ETFs appears to be more persistent and is unlikely to be associated with the market condition. These ETFs primarily use derivatives to achieve their targeted leverage ratios on the returns of underlying assets. Active ETFs, on the other hand, are more likely to use derivatives for managing market risk and enhancing fund performance, which might help attract investor flows. Passive ETFs may also use derivatives for enhancing returns, while there is no conclusive evidence on whether their derivative holdings are used for hedging or speculation. Token users seem to use derivatives mainly for amplification rather than hedging. These findings motivate us to further explore the difference in allocating derivative categories among different ETFs in Section 4.2.

4.2 Derivative Allocations

In this section, we investigate different types of derivatives used by each ETF type. Table 3 presents the notional exposure by derivative types for each ETF category. The table further breaks down this derivative instrument exposure into long and short positions based on the payoff profile. Appendix A.1 contains details of how we classify the payoff profile of different derivatives used by ETFs.

According to our classification, futures have two positions: long and short. Forwards are categorised as long USD and short USD. Options are divided into four positions: long call, short call, long put, and short put. Swaps are classified into long, short, and longshort positions, with the longshort representing exposure to both receivers and payers. Warrants only have long positions. Table 3 presents the fraction of gross notional amounts by derivative categories (DerivCat) for each ETF group. For each derivative category within each ETF group, we report the fraction of gross notional amounts by their payoff profile. This table shows significant heterogeneity in derivative use across different ETF types. Based on the fraction of gross notional amounts, active ETFs have the most exposure from options, while passive ETFs are mainly exposed to futures and forwards. Leveraged ETFs focus on the use of swaps.

Active ETFs generate most of their gross notional exposure from options (79.70%) followed by futures (13.17%) and then swaps (6.92%). Within the option allocation, they have more exposure generated by put options than call options with their exposure distributed across long calls (5.20%), short calls (32.80%), long puts (34.43%), and short puts (27.58%). Their higher exposure in short call options and long is consistent with the investment strategy of premium income ETFs (e.g. JPMorgan Equity Premium Income ETF). The breakdown of option exposure observed for active ETFs therefore suggests that active ETFs use options for both generating income and hedging purposes.

Passive ETFs get most of their gross notional exposure from futures (77.14%) followed by forwards (19.23%). They use futures mainly for long positions as 99.73% of their futures' exposures are in long positions. This is probably because futures can offer them a cheaper and easier way to gain asset exposure, especially for illiquid assets and those traded in foreign markets. Additionally, they have a higher fraction of forward exposure than active and leveraged ETFs, with 74.14% of this exposure due to long USD forward positions, which are used to secure their USD returns through long hedging strategies.

Compared to active and passive ETFs, swaps are most heavily used by leveraged ETFs (97.67%), primarily in long positions (75.99%). This suggests that the derivatives used by leveraged ETFs to amplify underlying indices' returns rely on swap agreements. This may partially explain why leveraged ETFs hold a larger fraction of cash holdings observed in Table 2, as well as the increased counterparty risk associated with these positions.

In addition, we show that the actual derivative use aligns with the descriptions provided in their prospectus, where the detailed analysis is provided in Appendix A.3. Taken together, our results show that derivative use varies across ETF types: passive ETFs primarily use futures and forwards, active ETFs focus on options, and leveraged ETFs rely on swaps.

4.3 Derivative Strategies

To understand how ETFs use derivatives, we first explore what derivative strategies are used for these products. To classify their derivative strategies, we employ an unsupervised machine-learning technique, the "K-Means++ algorithm", to categorise these ETFs based on the notional amounts of their derivative holdings. This method can help identify a potentially broad set of derivative strategies and allow us to be agnostic about the set of strategies ex-ante, as used by Kaniel and Wang (2024) to classify derivative strategies for mutual funds. Then, based on the correlation between derivative return and non-derivative return, we analyse whether each of these strategies involves speculation, amplification, or hedging.

4.3.1 K-Means Clustering

The goal of applying K-means clustering here is to identify patterns among ETFs by grouping them based on similar derivative characteristics. To generate the input data for this clustering process, we begin by calculating the total notional amount for each type of derivative position, categorised across underlying assets for ETFs in each quarter. The N-PORT filings provide data on both the derivative type used and their underlying asset categories. Derivatives are classified as futures, forwards, options, swaps, and warrants, while underlying asset categories provided include equity, interest rate, foreign exchange, commodity, and other assets.

We then aggregate notional amounts by derivative instrument and payoff profile. For example, for options, we aggregate each option's notional amounts by payoff profile, segmented into long call, short call, long put, and short put positions and for forwards, we aggregate notional amounts by long and short USD positions. We do likewise for the remaining derivatives, yielding groups like long call equity or short forward USD. For each ETF and reporting period, we then calculate the fraction of notional amounts for each derivative group and use the average fraction and standard deviation over the sample period as key K-Means inputs. With the calculated inputs, K-means clustering groups ETFs into distinct clusters with similar derivative holdings and ensures that each cluster exhibits unique characteristics.

K-means is a distance-based algorithm relying on an optimisation process that minimises intra-cluster distances while maximising inter-cluster distances. For evaluating the K-means model, the inertia value measures the sum of distances of all the points within a cluster from the centroid of that cluster. The change in inertia values of one cluster to another cluster measures the inter-cluster distances. To determine the optimal number of clusters, we plot an elbow curve with K (the number of clusters) on the x-axis and inertia on the y-axis. The optimal K is identified at the point where a further increase in K yields minimal reductions in inertia, indicating a balance between minimising inertia and maximising the distinctiveness of each cluster. This approach ensures the chosen clusters reflect meaningful segmentation in ETFs' derivative strategies.

Our elbow curve, shown in Figure A1 drops steeply initially, indicating substantial improvement in clustering quality as the number of clusters first increases. However, the rate of decrease in inertia slows around five clusters, highlighted by the red box. Based on this, we manually check ETF prospectuses relating to each cluster and determine the strategy used by each cluster.

We name the five strategies by looking at the derivative holdings in these clusters. Strategy (1): Foreign exchange (FX) hedge. The primary derivative used in this strategy cluster is forward contracts on USD, which are employed to hedge foreign currency risk associated with foreign investments. Strategy (2): Long non-option equity derivative. Derivative holdings in this strategy are mainly long derivative non-option positions where the underlying assets are equity. Strategy (3): Short non-option equity derivative. Derivative holdings in this strategy are mainly short derivative non-option positions where the underlying assets are equity. Strategy (4): Covered call and put protection. Derivative holdings in this cluster are mainly short-call or long-put option holdings. Strategy (5): Complex option. The strategy in this cluster primarily involves complex option strategies that alter the ETF payoff profile in more complex ways than strategy (4). For example, the strategy includes accelerating upside payoffs (accelerated strategy), putting a collar on ETF payoffs that limit both upside and downside payoffs (collar strategy) and absorbing downside losses in a limited range in return for foregoing some upside (buffer strategy).

4.3.2 Hedge, Speculation, or Amplification

To examine whether these five derivative strategies are used for hedging, speculation, or amplification, we calculate the correlation between the derivative return and non-derivative return for ETFs that use these particular strategies and plot their distribution by derivative strategy category and the results of doing so are shown in Figure 4. Our results show that ETFs that use the FX hedge strategy have correlations between derivative return and non-derivative return components that are concentrated around zero and in the left tail, indicating that this strategy is primarily for hedging, which is exactly what we would expect. ETFs using the long non-option derivative equity strategy show correlations in the right tail, suggesting that they use derivatives for speculation. Conversely, the correlations for both the short non-option derivative equity strategy and the covered call and put protection strategy are both concentrated in the negative range which tells us that the main purpose for these two strategies is hedging.

For complex options strategies, the correlation distribution is more balanced, and there is no clear evidence that this strategy involves hedging or speculation. This may be due to the fact that some of the strategies involve speculation (e.g. Accelerated strategy), and some of the strategies involve hedging (e.g. Buffer strategy).

We then present the fraction of ETF types that use these five derivatives strategies in Table 4. Most token derivative users use the long non-option derivatives on the equities strategy (91.1%), indicating that token users mainly use derivatives for speculation. Passive ETFs mainly employ three different strategies: long non-option derivative equity (49.12%), FX hedge (23.68%), and covered call and put protection(21.05%). This suggests that passive ETFs use derivatives for different purposes, including gaining exposure to assets traded in foreign markets or illiquid assets, hedging foreign currency risk, and tracking benchmarks embedded with derivative strategies (e.g., covered call and put protection). For example, Global X NASDAQ 100 Covered Call ETF follows a benchmark of the CBOE NASDAQ 100 BuyWrite index. WisdomTree PutWrite strategy ETF follows a benchmark of CBOE S&P 500 PutWrite Index.

For active derivative users, over half of them (58.26%) use covered call and put protection, while 31.53% use complex options strategies. This suggests that many active users employ derivatives primarily for hedging. Leveraged ETFs focus on long non-option derivative equity and short non-option derivative equity strategies, indicating that leveraged ETFs use derivatives mainly to amplify index returns in both positive and negative directions, which aligns with their investment objectives.

5 Investor Demand for Derivative ETFs

Given the rapid growth of derivative-based ETFs over the past five years, this section examines whether these ETFs attract more investor flows than nonusers, and whether derivative use influences flow sensitivity to fees and performance. Prior studies have documented that new types of ETF products are created to compete for investor demand (see, e.g. Huang, Song and Xiang (2020), Ben-David, Franzoni, Kim and Moussawi (2023), and Atilgan, Demirtas, Gunaydin and Oztekin (2024)). Accordingly, we expect that derivatives might be used by ETFs to cater for investors' needs. For example, Buffer ETF is a new type of ETF product that uses derivatives to offer downside protection and caters to the preferences of risk-averse investors. In this section, we examine two questions: 1) whether ETFs using derivatives exhibit more fund flows, and 2) whether investors' demand for derivative-using ETFs affects their sensitivity to past performance and fees, when making their investment decisions.

To answer these questions, we conduct panel regressions of ETF flows on a derivative dummy, past performance and fund fees (proxied using the expense ratio following Ben-David, Franzoni, Kim and Moussawi (2023)). In each regression, the derivative dummy equals one if the ETF uses derivatives during the sample period and the gross notional exposure of derivatives is higher than the median level (3.31%), and zero otherwise. To test whether derivative use affects investor sensitivity to performance and fee, we interact the derivative dummy with past performance and fee. We also include *Size*, *Turnover ratio*, and *past-year return volatility* as control variables. Calendar-month fixed effects is included in the regression. Standard errors are clustered at both the ETF and calendar-month levels.

Panel A in Table 5 documents the results for passive ETFs. The results show that performance (fee) and future flow have a significantly positive (negative) relationship, consistent with findings in the literature. The coefficient of the interaction term of the derivative dummy and performance is insignificant in four out of five regressions, and the one of the derivative dummy and expense ratio is insignificant in all regressions. It suggests that derivative use does not reduce flow sensitivity to performance in most cases and does not reduce flow sensitivity to fees. After accounting for ETF fees and performance, passive derivative users do not exhibit more fund flows than nonusers as the coefficient of *Derivative* is insignificant in all regressions. One possible explanation is that passive ETFs may use derivatives to compete for investor flows through improving fund performance or lower fees rather than directly attracting investor flows.

Panel B documents the results for active ETFs. Interestingly, derivative use in these funds significantly increases fund flows as the derivative dummy is significantly positive across five regressions. The interaction coefficient between performance and the derivative dummy is insignificant in four out of five regressions. In contrast, the interaction between the expense ratio and the derivative dummy is significantly positive across all regressions, suggesting that derivative use reduces investors' sensitivity to fees. This finding implies that investors value more than just performance and fees when investing in active ETFs that use derivatives. This also suggests that investors potentially appreciate other attributes such as risk management, strategy complexity, or portfolio flexibility.

Gennaioli et al. (2015) and Hitzemann, Sokolinski and Tai (2022) document that managers can charge fees for providing access to financial markets even in the absence of superior performance. Based on this idea, one potential value to investors from these products is that these ETFs give investors access to derivative strategies that they would otherwise struggle to access due to the complexity and requirements of trading derivatives systematically.

Overall, the results of flow sensitivity to past performance and fees show that derivatives use does not affect flows or flow sensitivity in passive ETFs, whereas derivative use increases flow and reduces flow sensitivity to fees in active ETFs. The evidence suggests that passive derivative users and active derivative users may compete in different segments of the ETF industry. In the following section, we show that derivative use in passive ETFs allows them to charge lower fees, positioning them competitively in the price-driven market. This may explain the rationale behind the use of derivatives in passive ETFs. For active ETFs, derivative users charge higher fees, indicating a strategy of competing on quality by enhancing performance to attract flows and reduce investor sensitivity to fees. In the next section, we assess the potential value that active derivative-based ETFs may offer to investors.

6 Derivative Use and ETF Competition

Competition in markets can occur along price and quality dimensions, as described by the framework in Bordalo et al. (2016). In the ETF industry, Ben-David et al. (2023) find that both types of competition exist. In this framework, price competition means that ETF issuers offer cheaper ETF products to attract investor flows, while quality competition indicates that issuers focus on superior fund performance and/or risk. In the context of derivatives-based ETFs, we conjecture that the use of derivatives can help ETF issuers compete on both price and quality dimensions. From Table 3, we observe that passive ETFs mainly hold futures and forwards contracts. These instruments may facilitate cheaper and more efficient tracking of their target indices, as mentioned in their fund prospectus[10]. In contrast, active ETFs, which mainly hold options that can be constructed as complex strategies, may creat value in the quality competition.

6.1 Price Competition

To test the conjecture that derivatives are used by ETFs for competing on price, we use the ETF expense ratio as its price and compare the price difference between derivative users and nonusers. Figure 5 displays the average fund fees charged by derivative users and nonusers across time for passive ETFs and active ETFs. It shows that derivative users charge lower fees than nonusers in passive ETFs over the sample period, whereas derivative users charge higher fees than nonusers in active ETFs.

We next estimate panel regressions of ETF fees in month t+1 on a derivative dummy and control variables to further compare the difference in fees charged by derivative users and nonusers. Our control variables in these regressions include *Size*, *Fund age*,*Turnover ratio*, *Expense ratio*, and *Illiquidity*. Time-fixed effects at the calendar-month level and index fixed

[10]https://www.invesco.com/uk/en/financial-products/etfs/invesco-nasdaq-100-swap-ucits-etf-acc.html

effects are included in the regressions. Standard errors are clustered at both the ETF and calendar-month levels.

Panel A in Table 6 shows results for active ETFs and passive ETFs. For passive ETFs, the coefficient on the derivative dummy is negative and significant at the 1% level across all regressions, indicating that, after controlling for fund characteristics, derivative-using passive ETFs charge lower fees than non-derivative-using ETFs. In contrast, active ETFs that use derivatives tend to charge higher fees, as the derivative dummy is significantly positive in all regressions. Our regression results are consistent with Figure 5, which supports the conjecture that passive ETF issuers use derivatives to enhance price competition and active ETFs are likely to compete on performance dimension other than price.

To further examine whether derivative usage helps explain ETF fees, we regress fees in month t+1 on the derivative relative contribution (DC), as defined in Equation (3). It measures the contribution of derivative positions to total fund returns. The results, presented in Panel B of Table 6, show that the coefficient on DC is insignificant for passive ETFs. This suggests that while derivative use is associated with lower fees among passive ETFs (as shown in Panel A), the extent of derivative usage does not further explain fee variation. This is consistent with the idea that passive ETFs use derivatives as a cost-saving tool, for example, to improve index tracking or manage exposures efficiently. In contrast, the positive coefficient of DC for active ETFs shows that DC is significantly positively associated with fees among active ETFs, indicating that active ETFs whose returns rely more heavily on derivatives tend to charge higher fees. This suggests that active ETFs may use derivatives to deliver performance or risk management features that justify their higher pricing.

6.2 Quality Competition

6.2.1 Passive ETFs: Index Tracking Performance

Following the idea that passive ETFs may use derivatives to improve index tracking, we examine whether derivative use enhances the quality of passive ETFs by helping them more effectively replicate their target indices. Derivatives, such as index futures, enable fund managers to track benchmarks more directly than through traditional sampling or full replication strategies. In this section, we use index tracking performance as a proxy for fund quality to assess whether derivative use facilitates quality-based competition among passive ETFs.

To test this conjecture, we calculate three tracking errors as used by Bae and Kim (2020) to measure index tracking performance. The first measure is $|ETF - Index|$, the absolute value of daily return differences between the ETF and its index averaged over the month. The second measure is $|NAV - Index|$, the absolute value of the daily return differences between an ETF's net asset value (NAV) and its index, averaged over each month. The third is $|ETF - NAV|$, which represents the difference between $|ETF - Index|$ and $|NAV - Index|$. This difference may arise if an ETF is trading at a premium or discount relative to its NAV. We regress these three passive ETF tracking errors in month t+1 on the derivative dummy and control variables as used in the previous section. Regressions include calendar-month and index fixed effects. Standard errors are clustered by month and ETF levels.

Table 7 presents the results for derivative use and tracking errors in passive ETFs. The derivative dummy is insignificant across three regressions with different tracking error measures, implying that derivative users do not have lower tracking errors than nonusers. It contradicts our conjecture that passive ETFs are using derivatives to compete on quality by achieving more accurate index tracking. The plausible explanation is that the target index for passive derivative-using ETFs is more difficult to track. When their indices include emerging market stocks, derivatives, or other illiquid assets, they prefer to use derivatives (Antoniewicz and Heinrichs (2014)). Also, some target indices are originally embedded with derivative strategies as documented in Section 4.3.2. Therefore, using derivatives in passive ETFs does not help enhance their quality competition.

6.2.2 Active ETFs: Better Return or Risk Performance

In this section, we test the conjecture that active derivative users compete on quality by delivering better return or risk profiles to attract investor flows. This is motivated by the observation that derivative users in active ETFs charge higher fees than nonusers, as shown in Figure 5 and Table 6. First, we test whether active derivative users deliver superior return or risk performance compared to nonusers. Second, we examine whether their superior performance is associated with the extent of derivative usage.

To test whether derivative users perform better than non-users, we estimate panel regressions of ETF performance on a derivative dummy and control variables. In each regression, the derivative dummy is one if the ETF uses derivatives, and zero otherwise. The dependent variable in each regression is a fund performance metric, where we use three return-based and five risk-based measures as proxies across different model specifications. Regressions include calendar-month and index fixed effects. Standard errors are clustered by month and ETF levels.

The three return-based measures are: 1) *Cret*: calculated as the past 12-month cumulative return (Cumulative Return); 2) *FF5 Alpha*: the intercept from a regression of the ETF excess return on the Fama-French five factors, and 3) *Sharpe*, Sharpe ratio. All return measures are calculated net of fees and estimated over a 12-month window using monthly data. The five risk-based measures include: 1) *Total*, refers to total risk, the annualised return volatility, calculated as the standard deviation of monthly net-of-fee returns over the past 12 months; 2) *Downside* refers to downside risk, which is the annualised volatility of negative monthly returns, based on the standard deviation of the respective net-of-fee returns over the past 12 months; 3) *Market*, refers to market risk, defined as the fund beta; 4) *Max DD*, refers to the maximum drawdown, defined as the largest observed percentage decline from a peak in cumulative net value over the past 12 months; 5) *VaR_95%* is the 95% Value at Risk, defined as the 5th percentile of the return distribution, capturing the losses in extreme scenarios.

Panel A in Table 8 presents the results. The coefficient of *Derivative* on return measures shows that derivative users do not generate superior performance than nonusers in active ETFs in terms of the cumulative returns and Fama-French five-factor alpha. However, the coefficient of *Derivative* on the Sharpe ratio is significantly positive, suggesting that derivative users achieve higher risk-adjusted returns than nonusers.

For risk-taking performance, the coefficient on *Derivative* is significant at the 1% level across all five regressions using risk measures. This indicates that active ETFs using derivatives are associated with lower overall risk, including total risk, downside risk, market risk, maximum drawdown, and 95% probability of the past 12-month loss. Specifically, the significantly positive coefficient of *Derivative* on *Max DD* indicate that derivative users experience significantly smaller maximum drawdowns over rolling 12-month periods than nonusers. Regarding tail risk, the positive coefficient of *Derivative* on *VaR_95%* implies that derivative-using active ETFs have higher 5th percentile returns over rolling 12-month periods, meaning they deliver better performance in worst-case scenarios and offer greater downside protection than nonusers.

To illustrate how derivative users provide downside protection compared to nonusers over time, especially when benchmarked against the same index, we focus on ETFs linked to the S&P 500. Among active derivative-using ETFs, we observe that nearly 44% are benchmarked against the S&P 500 and employ buffer protection strategies that use derivatives to limit losses relative to a target percentage decline in the index. We then construct two equally-weighted portfolios for this test: one (Buffer ETFs) consisting of active derivative-using ETFs and another (S&P 500 ETFs) of traditional passive ETFs, both benchmarked against the S&P 500. [11] We visualise the time-series differences in downside risk taking between buffer ETFs and S&P 500 ETFs in Figure 6. As expected, it suggests that buffer ETFs consistently exhibited less maximum drawdown and lower tail risk over the past 12 months [12].

Given these results, a further question we explore is whether the extent of derivative usage can predict their superior performance. Focusing on derivative-based active ETFs, we regress each performance measure in month t+1 on the derivative relative contribution (DC), as defined in Equation (3). Panel B of Table 8 presents the results. Consistent with Panel A, the coefficient on DC is statistically significant for the Sharpe ratio and all five risk measures, indicating that ETFs with greater derivative reliance tend to exhibit stronger risk profiles. For instance, the coefficient on DC in the Sharpe ratio regression is 0.135 (t = 2.66), implying that a higher proportion of derivative-induced returns is associated with higher risk-adjusted performance.

Overall, these findings highlight the role of derivatives in helping active ETFs manage downside risk and enhance return stability. This aligns with the evidence from Chen (2011), who show that hedge funds use derivatives to reduce overall fund risk. Such a hedge fund–like characteristic may be a key attribute that investors value in these ETFs, enabling them to

[11] Since the earliest derivative-using ETF among these 181 active ETFs was launched in January 2014, we extend our sample period from April 2014 through March 2024.

[12] Table A3 also presents the results of difference in risks between two portfolios: Buffer ETFs and S&P 500 ETFs.

overlook the higher fees associated with these products. We explore this hypothesis in the next section.

6.2.3 Active ETFs: the Value of Downside Protection

To understand why investors are willing to pay high fees of active derivative-using ETFs, we investigate whether these ETFs attract investors through their superior risk profiles. By using derivatives, these products offer a broader range of investment solutions tailored to different risk preferences, such as enhanced downside protection. In this section, we investigate whether enhanced downside protection can help explain fund flow among active ETFs.

In Table 9, we regress net flows of active ETFs in month t+1 on a derivative dummy (*Derivative*) and explanatory variables including *Sharpe ratio*, *Expense ratio*, *Max DD* (maximum drawdown), *Size*, *Fund age*, *Turn ratio* (turnover ratio), and *Illiquidity* at month t. Regressions include calendar-month and benchmark index fixed effects. Standard errors are clustered at the month and ETF levels. Consistent with the findings in Section 5, the results in column (1) show that derivative users attract more flows than nonusers, and investors are not sensitive to fund fees but are sensitive to fund performance (the Sharpe ratio).

Next, we include the maximum drawdown (*Max DD*) as an additional explanatory variable in column (2). The coefficient of *Max DD* is -0.088 with a t-statistic of -4.12, indicating that fund flows are significantly and negatively related to the maximum drawdown. Importantly, once *Max DD* is included, the coefficient on *Derivative* falls from 0.072 (t = 2.26) to 0.041 (t = 1.47), while the adjusted R^2 increases. It implies that downside protection (lower drawdowns) can explain the flow advantage for derivative-using ETFs. From columns (2) to (4), *Max DD* remains a significant driver of flows even as we add further controls, underscoring that investors prefer ETFs with smaller maximum drawdowns.

Our analysis reveals the value of downside protection for active ETFs. This helps explain why investors are attracted to derivative-using active ETFs despite their higher fees, which implies that they are paying for the downside protection that these derivative-based products offer. Overall, these results support our conjecture that these active ETFs use derivatives as a tool to enhance their market competition in the quality dimension.

7 Conclusion

In recent years, the ETF industry has experienced significant growth in both the number of ETFs and total assets under management. The ETF universe has also become more complex, more innovative, and more competitive. The evolution of the ETF landscape in the past five years has incorporated more derivative holdings to offer diverse payoff structures tailored to various investors. This paper studies derivative holdings by ETFs using the SEC N-PORT dataset from 2019 to 2024 and sheds light on how ETFs compete for investor flows by using derivatives. While derivative use has been studied in the context of mutual funds and hedge funds, ETF derivative use has to date not been investigated.

Our evidence reveals a new reality in the ETF industry. We show that ETFs use derivatives more prevalently in ETFs than mutual funds, with higher portfolio weights and higher notional exposure. By segmenting the ETF market into three distinct groups, we demonstrate that derivative-induced returns contribute positively to Sharpe ratios for passive and active ETFs, but not for leveraged ETFs, as the N-PORT dataset allows us to decompose fund returns into derivative-induced and non-derivative components.

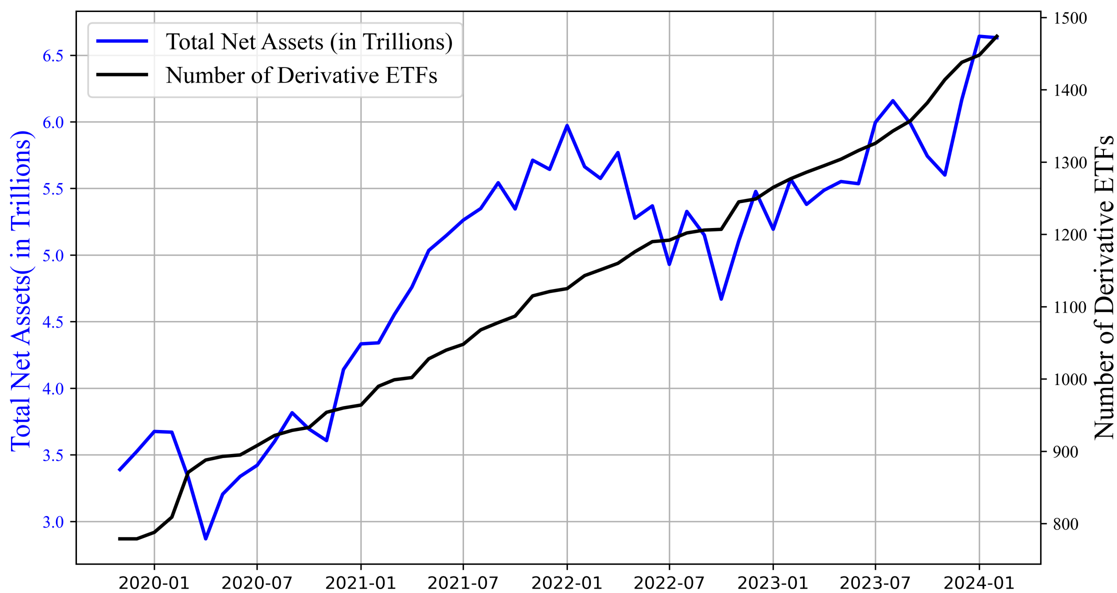
As the ETF industry has become increasingly competitive, we test whether derivative use helps ETFs become more attractive to investors. We find that passive ETF investors prefer products that are either less expensive or offer better return performance. These derivatives-based products do not provide better performance but charge less than non-derivative products. As a result, passive ETFs using derivatives seem to compete primarily on price, leveraging derivatives as a cost-saving mechanism to offer more competitive fee structures.

In contrast, our results show that active derivatives users charge higher fees than others, and those fees tend to increase with the extent to which fund returns rely on derivative holdings. Although they are more expensive, they still attract more flows and exhibit lower sensitivity to fund fees than other ETFs, suggesting that derivative use conveys potential benefits to investors that they value. Our analysis reveals one such benefit: downside protection. We find that active ETFs with derivative use exhibit better downside protection and more stable risk-adjusted returns. In particular, we show that maximum drawdown significantly predicts fund flows, helping to explain why derivative-using ETFs attract more investor capital.

Furthermore, the level of derivative usage, measured by the derivative contribution to returns, is positively associated with improved risk profiles. This suggests that active ETFs with greater use of derivatives tend to deliver better risk performance. As a result, these products may appear to cater to risk-averse investors who are willing to pay higher fees in exchange for greater downside protection. Taken together, these findings indicate that active ETFs can justify their higher fees through stronger risk management, competing on the quality dimension, rather than price, similar to strategies commonly used in the hedge fund industry.

We conclude that the use of derivatives plays an important role in the ETF industry. ETFs can use different derivative contracts to improve their competitiveness by offering different features such as cost efficiency and risk management. ETFs also allow more investors to access sophisticated risk management strategies previously available primarily to institutional investors.

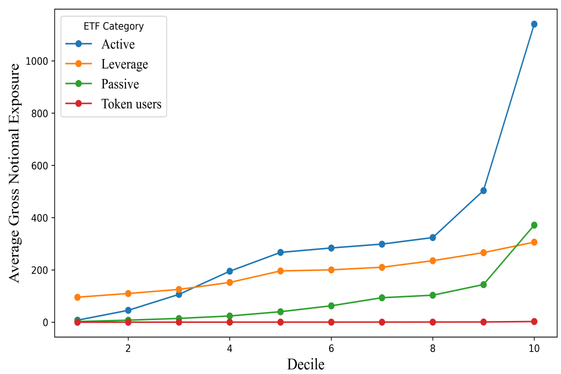
Figure 1: The Growth in Derivatives ETF From 2020 to 2024



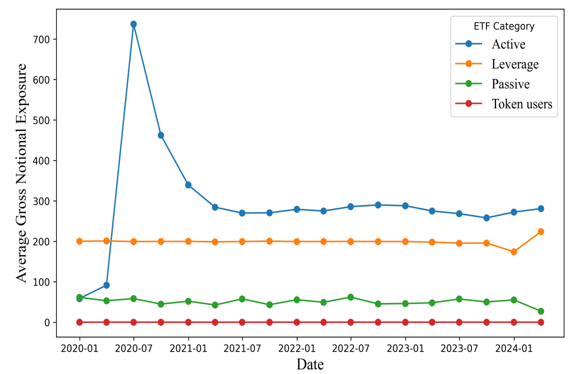
This figure shows the growth of total net assets (in trillions) and numbers in derivatives ETFs from December 2019 to January 2024. The data is compiled from SEC NPORT filings.

Figure 2: Average Gross Notional Exposure and Cash Holdings Across Time

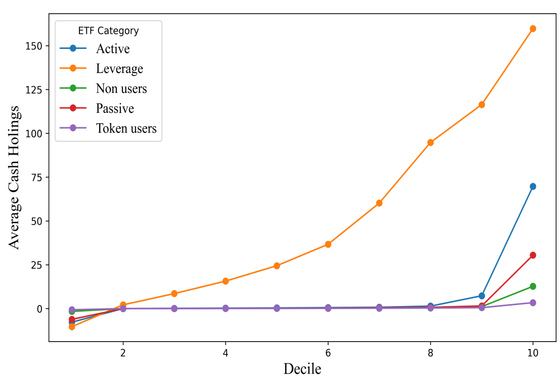
(a) Average Gross Notional Exposure by Decile



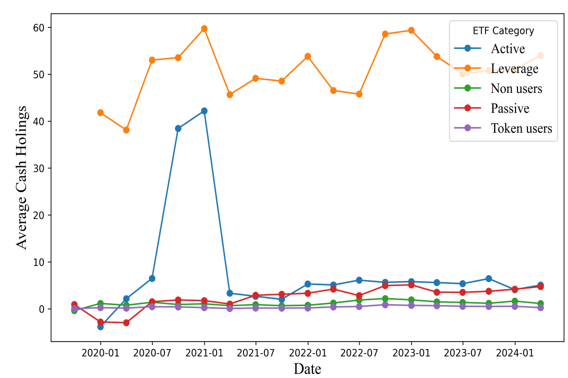
(b) Median Gross Notional Exposure Over Time



(c) Average Cash Holdings by Decile



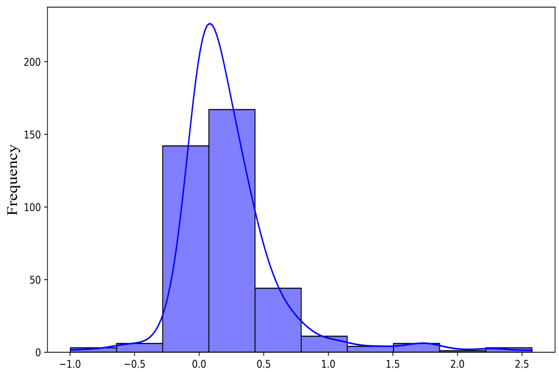
(d) Average Cash Holdings Over Time



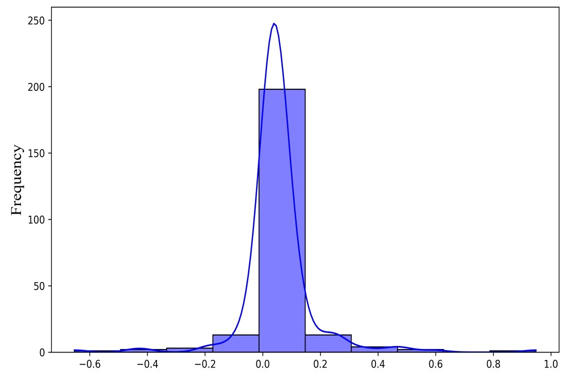
The figure shows average gross notional exposure and cash holdings across different ETF types and time periods. ETFs are grouped into deciles based on their gross notional exposure and cash holdings. Panel (a) presents the average gross notional exposure for each decile, while Panel (c) shows the average cash holdings for each decile. We calculate average gross notional exposure and cash holdings for each quarter, as shown in Panel (b) and Panel (d), respectively.

Figure 3: Distribution of Differences between Sharpe Ratios and non-DR Sharpe Ratios

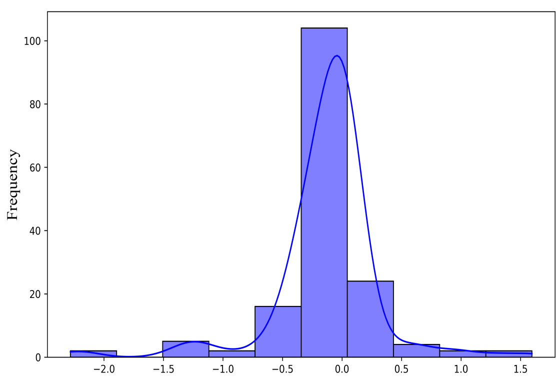
(a) Active Derivative-Based ETFs



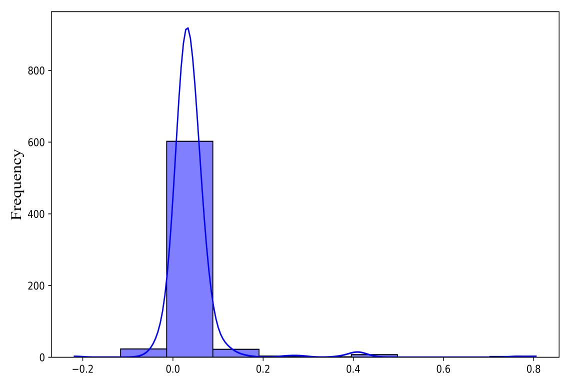
(b) Passive Derivative-Based ETFs



(c) Leveraged ETFs



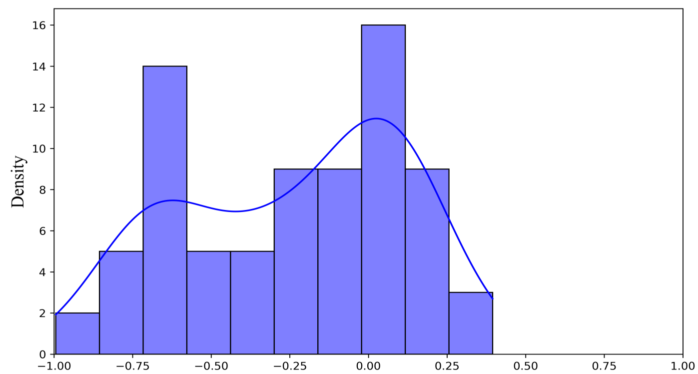
(d) Token Derivetive-Based ETFs



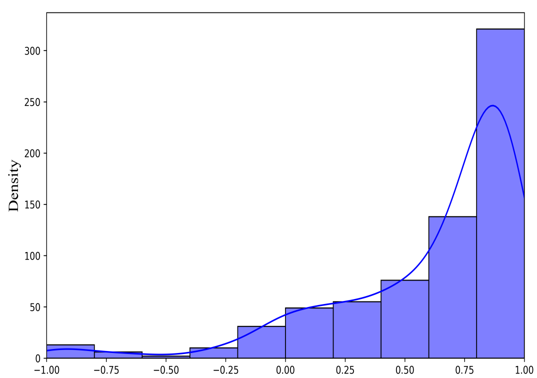
The figure displays the distribution of differences between Sharpe ratios and non-DR Sharpe ratios for each ETF type. We calculate the Sharpe ratio for each ETF by dividing its average fund returns by its volatility of fund returns from September 2019 to January 2024. The non-DR Sharpe ratio is computed by dividing their average non-DR by the volatility of DR from September 2019 to January 2024, where non-DR is the difference between the ETF return and DR and DR is the return induced by derivatives and denotes the sum of monthly realized P&L and the change in unrealized P&L from derivative positions, normalized by the fund size from the previous month. The difference between the Sharpe ratio and the non-DR Sharpe ratio represents the value obtained by subtracting the non-DR Sharpe ratio from the Sharpe ratio.

Figure 4: Distributions of Correlation between DR and non-DR Across Derivative Strategies

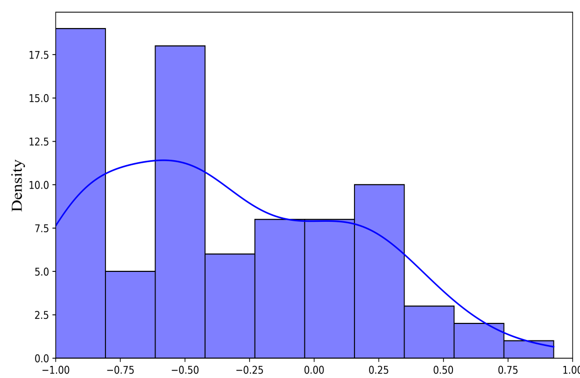
(a) FX Hedge



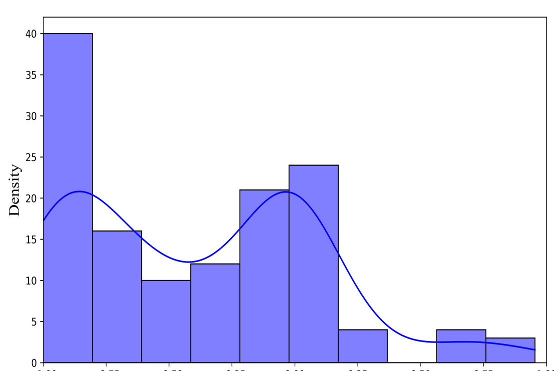
(b) Long Non-option Derivative Equity



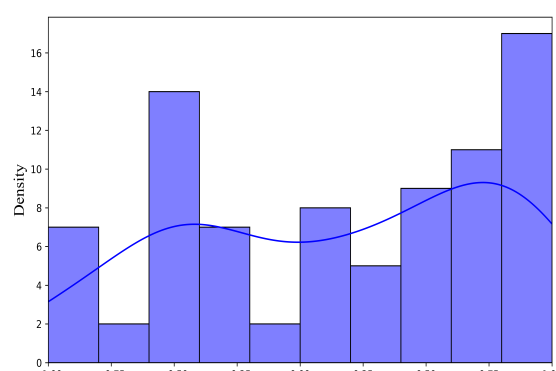
(c) Short Non-option Derivative Equity



(d) Covered Call and Put Protection



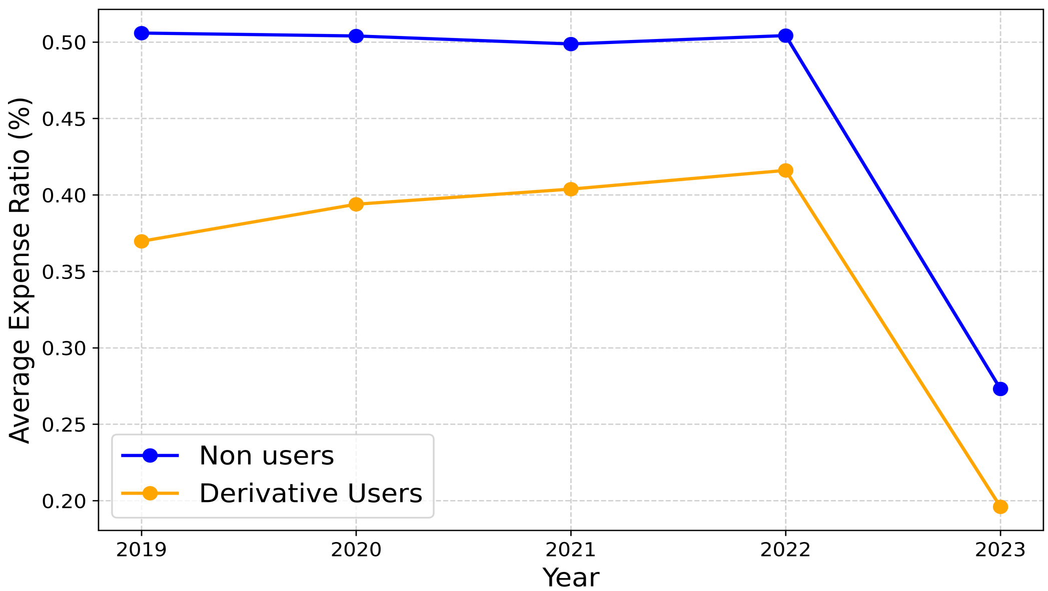
(e) Complex Options Strategies



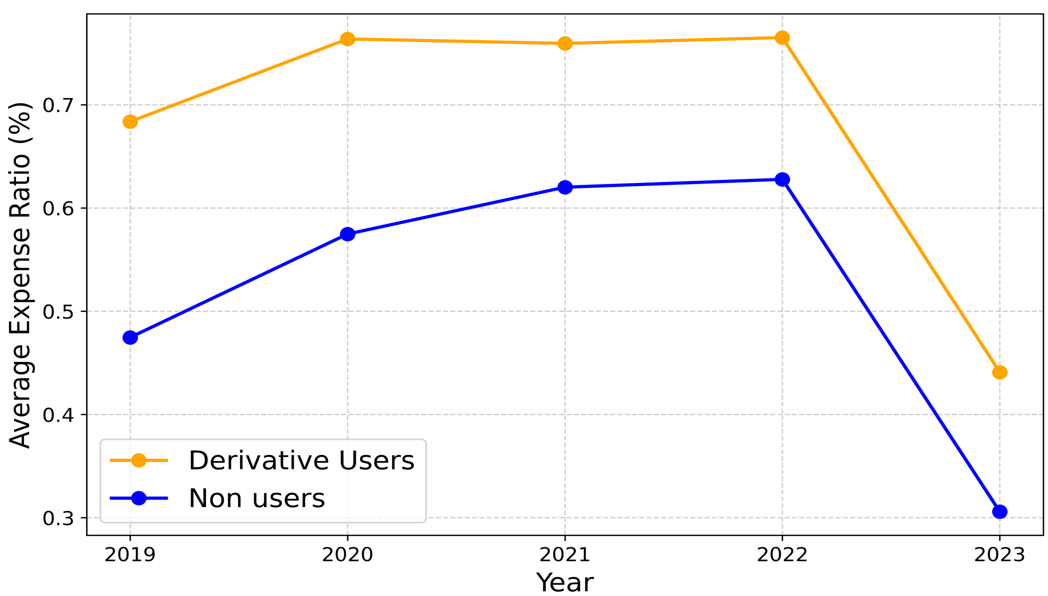
The figure displays the histogram of the correlation between DR and non-DR. DR represents the return generated by derivatives and denotes the sum of monthly realised P&L and the change in unrealised P&L from derivative positions, normalised by the fund size from the previous month and expressed in basis points. non-DR is the difference between the ETF return and DR, as shown in the basis points. The correlation is calculated based on the availability of N-PORT data between September 2019 and January 2024.

Figure 5: Average Annual Fees of ETFs (Derivative Users vs. Nonusers)

(1) Average Annual Fees of Passive ETFs



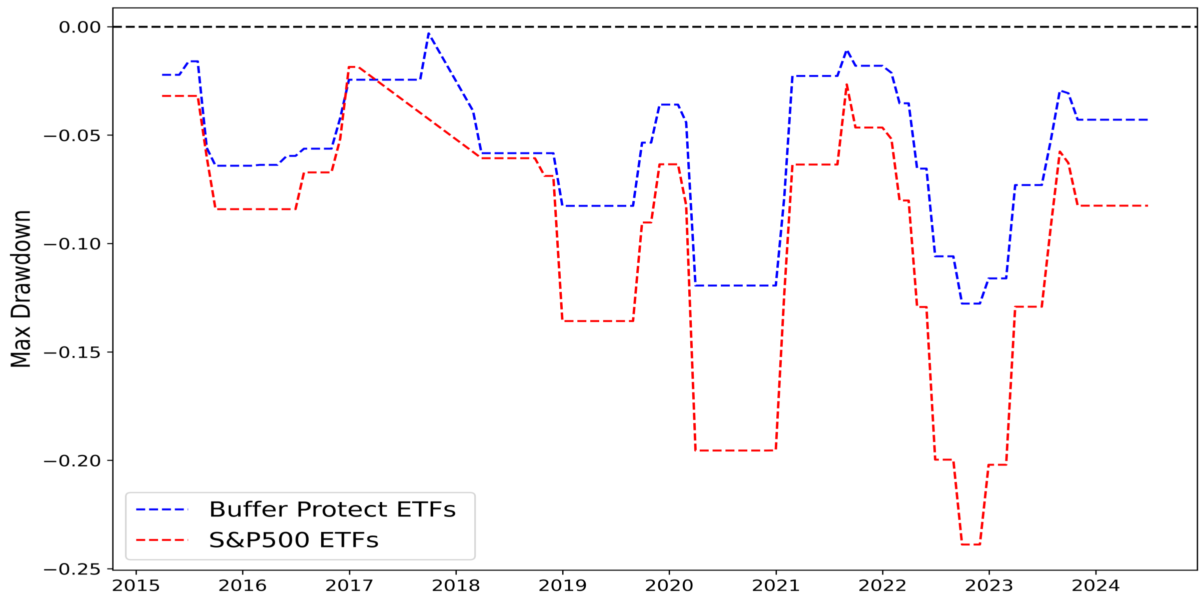
(2) Average Annual fees of Active ETFs



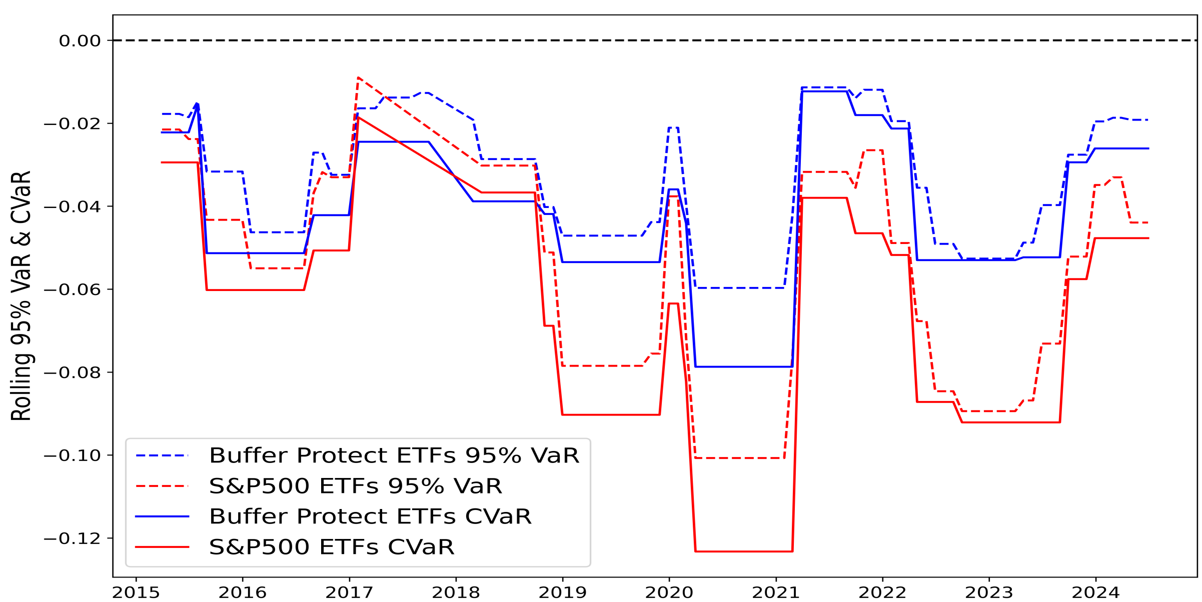
The figure compares the average annual fees charged by ETFs that use derivatives versus those that do not from 2019 to 2023. The annual fee is measured by the expense ratio from CRSP.

Figure 6: Risk Taking in ETFs (Buffer ETFs vs. S&P 500 ETFs)

(1) The Max Drawdown Across Time



(2) The VaR and CVaR Across Time



The figure compares risk measures across time between buffer protect ETFs and passive S&P 500 ETFs. *Max Drawdown* is the largest observed decline from the peak cumulative net value during the past 12 months. *VaR_95%* is calculated as 95% Value at Risk (VaR) by determining the 5th percentile of the returns distribution and *CVaR_95%* is the Conditional VaR, calculated as the average loss beyond this threshold.

Table 1: Overall Derivative Usage in ETFs

The table shows overall derivative usage in derivative-using ETFs. The sample period is from September 2019 to January 2024 and includes all U.S. domestic equity ETFs that use derivatives. Panel A reports the number of derivative-using ETFs and the breakdown of derivative use by category. Panel B presents the summary statistics for key variables. *Absolute Derivative Weight* is the sum of portfolio weights of derivative positions in absolute value, expressed in percentage points. *Gross Notional Exposure* is the sum of the notional amounts of derivative positions, normalized by the fund's total net assets (TNA) and shown in percentage points. *DR* represents the return generated by derivatives and denotes the sum of monthly realized P&L and the change in unrealized P&L from derivative positions, normalized by the fund size from the previous month and expressed in basis points. *non-DR* is the difference between the ETF return and *DR* shown in basis points. *Derivative Relative Contribution (DC)* is the absolute value of the signed derivative relative contribution. It is calculated as the absolute value of *DR* divided by the sum of the absolute value of *DR* and *non-DR*. All variables are winsorized at the 1% level.

Panel A: Breakdown of Derivative Usage

	No. of ETFs	Absolute Portfolio Weight (%)	Gross Notional Exposure (%)
All derivatives	1481	21.69	100.28
Future	644	1.42	10.22
Forward	160	0.07	4.33
Option	338	15.92	56.24
Swap	244	4.28	29.61
Warrant	201	0.01	0.05

Panel B: Summary Statistics of Key Variables

Variable	Absolute Derivative Weight (%)	Gross Notional Exposure (%)	DR (bps)	non-DR (bps)	DC (%)
Mean	21.32	100.28	1.18	47.69	23.87
StdDev	42.62	159.05	380.92	583.15	39.26
Min	0.00	0.00	-1858.74	-1728.38	0.00
10%	0.00	0.10	-115.52	-639.74	0.00
20%	0.01	0.20	-2.52	-356.22	0.00
30%	0.01	0.32	-0.40	-144.35	0.08
40%	0.03	0.57	0.00	0.00	0.22
50%	0.11	3.31	0.00	0.00	0.39
60%	1.89	42.71	0.12	101.84	0.83
70%	9.34	112.23	1.08	271.87	9.06
80%	23.02	205.83	4.17	452.90	76.17
90%	109.22	304.56	157.14	750.90	100.00
Max	267.83	760.62	1769.58	1779.13	100.00

Table 2: ETF Characterisctics

The table reports the characteristics for ETFs. *Cash holdings* is the portfolio weight of cash held by the fund, and *Equity holdings* is the weight of common equity held by the fund, both sourced from CRSP. *TNA* denotes the monthly total net assets from CRSP. *Return* is the monthly return of the fund, also from CRSP. *Return volatility* is the standard deviation of monthly fund returns over the sample period. *Sharpe ratio* is calculated as *Return* divided by *Return volatility*. *Flows* is computed as $(TNA_{t+1} - TNA_t * Return_{t+1})/TNA_t$, where t is last month, t+1 is current month. *Flow volatility* is the standard deviation of monthly fund flows over the sample period. *CAPM Beta* is the coefficient estimate from regressing an ETF's excess return on the market excess return. *Flow redemption*, *Flow_reinvestment*, and *Flow sales* are calculated as the aggregate dollar amounts for redemptions, repurchases, and sales of fund shares in each month, extracted from the N-PORT filings and divided by the *TNA* of the previous month. *Derivative Weight* is the sum of portfolio weights of derivative positions in absolute value. *DR* represents the return generated by derivatives and denotes the sum of monthly realized P&L and the change in unrealized P&L from derivative positions, normalized by the fund size from the previous month. *non-DR* is the difference between the ETF return and DR. *DC* is derivative relative contribution. It is calculated as the absolute value of DR divided by the sum of the absolute value of DR and non-DR.*non-DR vol* is the standard deviation of an ETF's non-DR over the sample period. *non-DR Sharpe ratio* is *non-DR* divided by *non-DR vol*. *Correlation between DR and non-DR* is the correlation between an ETF's DR and non-DR over the sample period.

	Non users	Token users	Passive	Active	Leveraged
Number of ETFs	995	657	247	416	161
Gross notional exposure(%)		0.38	66.26	264.70	170.29
Derivative weight(%)		0.05	5.79	68.21	22.12
Derivative contribution (%)		0.71	13.18	67.06	79.42
Equity holdings (%)	89.20	95.21	85.11	29.18	28.89
Cash holdings (%)	1.64	0.55	3.92	8.85	52.88
Cash holdings volatility(%)	0.37	0.22	1.21	11.63	5.84
Return (bps)	78.41	77.68	69.87	60.47	-17.33
Return volatility (bps)	575.54	562.07	499.91	345.09	363.81
Sharpe ratio	0.14	0.14	0.14	0.18	-0.05
non-DR(bps)		63.32	36.52	18.22	42.35
non-DR vol(bps)		564.01	498.23	201.85	208.26
non-DR Sharpe ratio		0.11	0.07	0.09	0.20
Correlation between DR and non-DR		0.54	0.01	-0.05	0.09
CAPM Beta	0.99	0.95	0.83	0.60	0.50
Expense ratio(%)	0.44	0.29	0.33	0.61	0.77
TNA($trillion)	1.61	5.72	7.51	0.21	0.44
Flows(%)	4.85	2.69	3.39	9.91	4.64
Flow volatility(%)	3.97	2.79	6.05	28.16	5.80
Flow redemption(%)	-0.02	1.39	2.29	-5.29	-1.36
Flow reinvestment(%)	0.00	0.01	0.01	0.00	0.00
Flow sales(%)	9.61	5.79	7.01	17.34	20.41

Table 3: Derivative Allocation Across ETF Categories

The table presents the fraction of gross notional amounts by derivative categories (DerivCat) for each ETF group. There are five categories of derivatives: futures (FUT), forwards (FWD), options (OPT), swaps (SWP), and warrants (WAR). ETFs are grouped into three types: active, passive, and leveraged. Furthermore, for each derivative category within each ETF group, we report the fraction of gross notional amounts by their payoff profile. For futures, we report the fraction of the gross notional amounts for their long positions. For forwards, we report the fraction for long USD. Similarly, for options, we report the fractions for long (short) call and long (short) put positions. Swaps are divided into long, short, and long-short categories. For warrants, we report the fraction for long positions.

DerivCat	Active	Passive	Leveraged
FUT	13.17%	**77.14%**	1.87%
Long	76.66%	**99.73%**	78.26%
FWD	0.16%	**19.23%**	0.00%
Long USD	71.45%	74.14%	0.00%
OPT	**79.70%**	0.76%	0.46%
Long Call	5.20%	23.05%	5.34%
Short Call	32.80%	67.07%	11.10%
Long Put	34.43%	0.59%	79.99%
Short Put	27.58%	9.29%	3.57%
SWP	6.92%	2.87%	**97.67%**
Long	18.74%	84.10%	75.99%
LongShort	1.55%	11.30%	0.17%
Short	79.71%	4.61%	23.85%
WAR	0.05%	0.00%	0.00%
Long	100.00%	100.00%	100.00%

Table 4: The Fraction of Derivative Users by ETF Types Across Derivative Strategies

The table reports the fraction of fund numbers across five derivative strategies for derivative users in the ETF industry: token users, passive, active, and leveraged. The ETFs are classified into five derivative strategies using derivative holding data and K-means clustering technique. For each ETF type, we calculate the fraction of ETF numbers in each derivative category.

	Token users	Passive	Active	Leveraged
FX Hedge	7.61%	**23.68%**	1.50%	0.00%
Long Non-option Derivative Equity	**91.10%**	**49.12%**	6.31%	**50.63%**
Short Non-option Derivative Equity	0.32%	0.88%	2.40%	**44.94%**
Covered Call and Put Protection	0.81%	**21.05%**	**58.26%**	2.53%
Complex Options Strategies	0.16%	5.26%	**31.53%**	1.90%

Table 5: ETF Flow Sensitivity to Fees and Past Performance

The table presents the flow sensitivity of ETFs to their fees and past performance. Panel A displays the results for passive ETFs, while Panel B reports on active ETFs. The dependent variable is ETF flows in month $t+1$, calculated as $(TNA_{t+1} - TNA_t \times Return_{t+1})/TNA_t$, where t is last month, $t+1$ is current month. The independent variables are shown in the first column. We use five performance measures in the five models: cumulative return, CAPM alpha, Fama-French four-factor alpha, Fama-French five-factor alpha, and Sharpe ratio. The panel regressions are conducted for each of these measures, as displayed in the last five columns. In Panel A, the dummy variable *Derivative* denotes whether the ETF is identified as a passive ETF that uses derivatives. In Panel B, *Derivative* is 1 if the ETF is an active derivative-based ETF. Our control variables include turnover ratio, the natural logarithm of fund size, and past-year return volatility, without past-year return volatility included when testing the Sharpe ratio. The time-fixed effect at the calendar-month level is included. Standard errors are clustered at both the ETF and calendar-month levels. The overall adjusted R^2 is reported. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Panel A: Passive ETFs

	Fund Flows$_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
Performance	0.204***	0.133***	0.114***	0.076***	0.055***
	(12.33)	(12.48)	(11.20)	(8.59)	(14.91)
Performance	-0.023	0.012	0.028	0.045*	-0.001
× Derivative	(-0.98)	(0.47)	(1.32)	(1.74)	(-0.25)
Expense Ratio	-0.053***	-0.053***	-0.049***	-0.056***	-0.044***
	(-5.41)	(-5.45)	(-4.99)	(-5.64)	(-4.42)
Expense Ratio	0.015	0.018	0.015	0.016	0.012
× Derivative	(0.75)	(0.91)	(0.74)	(0.77)	(0.64)
Derivative	0.015	0.019	0.021	0.026	0.024
	(0.71)	(0.93)	(1.00)	(1.23)	(1.19)
Control Variables	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.025	0.025	0.022	0.016	0.028
Calendar-month FE	Yes	Yes	Yes	Yes	Yes
Observations	43,757	43,757	43,757	43,757	43,657

Panel B: Active ETFs

	Fund Flows$_{t+1}$				
	(1)	(2)	(3)	(4)	(5)
Performance	0.085***	0.095***	0.083***	0.056***	0.028***
	(5.63)	(6.49)	(6.02)	(3.76)	(3.72)
Performance × Derivative	-0.010	-0.039	-0.047*	-0.030	-0.004
	(-0.37)	(-1.40)	(-1.89)	(-1.11)	(-0.61)
Expense Ratio	-0.042***	-0.038**	-0.038**	-0.046***	-0.043***
	(-2.47)	(-2.25)	(-2.19)	(-2.69)	(-2.55)
Expense Ratio × Derivative	0.066***	0.066***	0.066***	0.07***	0.069***
	(2.95)	(3.05)	(3.02)	(3.16)	(3.13)
Derivative	0.061**	0.067***	0.071***	0.069***	0.075***
	(2.23)	(2.55)	(2.71)	(2.62)	(2.75)
Control Variables	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.009	0.011	0.009	0.007	0.010
Calendar-month FE	Yes	Yes	Yes	Yes	Yes
Observations	12,448	12,448	12,448	12,448	12,328

Table 6: Derivative Use and ETF Fees

The table presents the results from the panel regressions of ETF fees on derivatives use and derivative relative contribution. The dependent variables are fees charged by passive ETFs and active ETFs, measured by expense ratios in month t+1. Panel A reports for passive and active ETFs including derivative users and nonusers. The independent variable in Panel A is a dummy variable (*Derivative*), where 1 represents the ETF using derivatives and 0 denotes the nonusers. *Size* is the natural logarithm of fund total net assets. Panel B focuses exclusively on derivative-using ETFs. The independent variable is *Derivative Relative Contribution (DC)*, defined as the absolute value of the signed derivative return (DR) divided by the sum of the absolute values of both DR and non-derivative return (non-DR). DR captures the return attributed to changes in the value of derivative positions, and non-DR captures the return from the rest of the portfolio. *Fund age* is the distance between the fund inception date and 2024. *Turn ratio* is the turnover ratio downloading from CRSP. *Illiquidity* is measured as the relative quoted spread, calculated by dividing the bid-ask spread by the mid-quote, where the mid-quote is the average of the bid and ask prices. The time-fixed effect at the calendar-month level and index-fixed effect are included. Standard errors are clustered at both the ETF and calendar-month levels. The overall adjusted R^2 is reported. *$p < .1$; **$p < .05$; ***$p < .01$.

Panel A: Difference between Derivative Users and Nonusers

	Fee_{t+1} of Passive ETFs				Fee_{t+1} of Active ETFs			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Derivative	-0.352***	-0.403*	-0.420**	-0.288*	0.400***	0.321***	0.324***	0.274***
	(-5.91)	(-1.91)	(-2.36)	(-1.70)	(7.42)	(5.36)	(5.37)	(4.17)
Size		0.024	0.101**	0.112**		-0.014	-0.027	-0.039
		(0.54)	(2.18)	(2.38)		(-0.62)	(-1.13)	(-1.56)
Fund age			-0.293***	-0.320***			0.043	0.057
			(-2.95)	(-3.11)			(1.08)	(1.42)
Turn ratio				0.066***				0.044***
				(2.92)				(3.13)
Illiquidity				0.040***				-0.018
				(2.86)				(-0.81)
Calendar-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Index FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Adjusted R^2	0.037	0.682	0.687	0.692	0.064	0.305	0.307	0.326
Observations	31,225	31,225	31,225	30,687	18,769	18,769	18,769	17,630

Panel B: Derivative Relative Contribution and ETF Fees

	ETF Fees_{t+1}	
	Passive ETFs	Active ETFs
DC	-0.019	0.087**
	(-0.50)	(2.19)
Size	0.118**	-0.034
	(2.40)	(-0.87)
Turn ratio	-0.011	0.029
	(-0.31)	(1.07)
Illiquidity	0.035*	-0.002
	(1.77)	(-0.06)
Fund age	-0.465**	0.030
	(-2.29)	(0.46)
Calendar-month FE	Yes	Yes
Index FE	Yes	Yes
Adjusted R^2	0.715	0.260
Observations	9,975	9,118

Table 7: Derivative Use and Tracking Errors in Passive ETFs

The table presents the results from the panel regressions of monthly tracking errors on derivatives use for passive ETFs. The independent variable is a dummy variable (Derivative), where 1 represents the ETF using non-token derivatives. The dependent variable in each regression (each column of the table)is an ETF index tracking measure calculated from net-of-fee fund returns. They are $|ETF - Index|$, $|NAV - Index|$, and $|ETF - NAV|$. $|ETF - Index|$ and $|NAV - Index|$ are absolute values of the average daily return differences between ETF(NAV) returns and their index returns for each month. $|ETF - NAV|$ is the absolute value of the average daily return differences between ETF returns and net asset value (NAV) returns for each month. Our control variables include the natural logarithm of fund total net assets (Size); *Fund age*, the distance between the fund inception date and 2024; *Turn ratio*, the turnover ratio from CRSP; *Illiquidity*, the relative quoted spread, calculated by dividing the bid-ask spread by the mid-quote, where the mid-quote is the average of the bid and ask prices; *Expense ratio*, the fund expense ratio from CRSP. The time-fixed effect at the calendar-month level and index-fixed effect are included. Standard errors are clustered at both the ETF and calendar-month levels. The overall adjusted R^2 is reported. *$p < .1$; **$p < .05$; ***$p < .01$.

	Tracking Errors_{t+1}		
	$\lvert ETF - Index\rvert$	$\lvert NAV - Index\rvert$	$\lvert ETF - NAV\rvert$
Derivative	-0.005	-0.024	-0.010
	(-0.65)	(-1.54)	(-1.12)
Size	-0.016	-0.013	0.001
	(-1.19)	(-0.98)	(0.53)
Fund age	-0.001	-0.002	0.001
	(-0.12)	(-0.18)	(0.26)
Turn ratio	0.006	0.022	0.003
	(1.07)	(1.02)	(0.79)
Illiquidity	0.006**	0.008	0.001
	(2.11)	(1.37)	(0.25)
Expense ratio	0.001	-0.015	-0.015
	(1.00)	(-1.10)	(-1.23)
Calendar-month FE	Yes	Yes	Yes
Index FE	Yes	Yes	Yes
Adjusted R^2	0.147	0.032	0.020
Observations	28,775	28,775	30,687

Table 8: Derivatives Use and Active ETF Performance

The table presents the results from the panel regressions of monthly fund performance measures on derivatives use and derivative relative contribution for active ETFs. Panel A reports for both derivative users and nonusers. The key independent variable is a dummy (Derivative) equal to one for derivative users. Panel B focuses exclusively on derivative-using active ETFs. The independent variable is *Derivative Relative Contribution (DC)*, defined as the absolute value of the signed derivative return (DR) divided by the sum of the absolute values of both DR and non-derivative return (non-DR). The dependent variables are rolling 12-month measures, evaluated each month t+1 using net-of-fee returns. Return measures include: cumulative return (*CRet*), Fama-French five-factor alpha (*Alpha5*), and Sharpe ratio (*Sharpe*). Risk measures include: total volatility (*Total*), downside volatility (*Downside*), market beta *Market*, maximum drawdown *Max DD*, the 95% Value at Risk *VaR 95%*. *Market* is the coefficient estimate from regressing an ETF's excess return on the market excess return. *Max DD* is the largest observed percentage decline from a peak in cumulative net value. *VaR 95%* is defined as the 5th percentile of the return distribution. Our control variables include *(Size)*, *Fund age*, turnover ratio *Turn ratio*, and *Expense ratio*. *Illiquidity* is calculated by dividing the bid-ask spread by the mid-quote, that is the average of the bid and ask prices. The calendar-month and index fixed effects are included. Standard errors are clustered at both the ETF and calendar-month levels. The overall adjusted R^2 is reported. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

Panel A: Difference between Derivative Users and Nonusers

	Return Measures			Risk Measures				
	Cret	Alpha5	Sharpe	Total	Downside	Market	Max DD	VaR_95
Derivative	-0.006	0.001	0.219***	-0.069***	-0.033***	-0.369***	-0.052***	0.026***
	(-0.33)	(1.16)	(3.48)	(-6.54)	(-5.54)	(-8.30)	(-5.54)	(5.91)
Size	0.012*	0.000	0.043	-0.001	0.000	-0.011	0.000	0.000
	(1.89)	(-0.66)	(1.43)	(-0.27)	(-0.06)	(-0.61)	(0.01)	(0.16)
Fund age	-0.004	0.000	-0.062*	0.004	0.006**	-0.004	0.010***	-0.002
	(-0.70)	(-0.97)	(-1.78)	(1.03)	(2.41)	(-0.18)	(2.77)	(-1.35)
Turn ratio	0.000	0.000	-0.044*	-0.003**	0.000	-0.034***	-0.002*	0.001
	(-0.02)	(-1.40)	(-1.84)	(-2.11)	(-0.30)	(-4.05)	(-1.76)	(1.51)
Illiquidity	-0.023***	-0.002*	-0.156***	0.017***	0.011***	0.044**	0.022***	-0.009***
	(-2.80)	(-1.68)	(-4.42)	(3.20)	(3.36)	(2.47)	(3.90)	(-3.34)
Expense ratio	-0.002	0.000	-0.033	-0.001	-0.001	-0.007	0.001	0.002
	(-0.59)	(0.67)	(-1.08)	(-0.42)	(-0.59)	(-0.52)	(0.46)	(1.21)
Calendar-month & Index FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.086	0.083	0.081	0.301	0.215	0.474	0.192	0.261
Observations	11,791	11,894	17,611	17,611	16,741	17,630	17,611	13,911

Panel B: Derivative Relative Contribution and ETF Performance

	Sharpe	Total	Downside	Market	Max DD	VaR_95
DC	0.135**	-0.029***	-0.026***	-0.107***	-0.026***	0.012***
	(2.66)	(-4.20)	(-3.68)	(-4.15)	(-3.68)	(3.83)
Size	0.049	0.001	0.004	-0.004	0.004	-0.002
	(1.16)	(0.16)	(0.69)	(-0.16)	(0.69)	(-0.50)
Fund age	-0.025	-0.014**	-0.007	-0.093**	-0.007	0.007**
	(-0.40)	(-2.09)	(-1.05)	(-2.11)	(-1.05)	(2.05)
Turn ratio	-0.018*	-0.003***	-0.003***	-0.039***	-0.003***	0.001**
	(-1.78)	(-2.81)	(-2.93)	(-8.44)	(-2.93)	(2.32)
Illiquidity	-0.153***	0.022***	0.028***	0.055***	0.028***	-0.012***
	(-3.03)	(3.40)	(3.55)	(2.64)	(3.55)	(-3.19)
Expense ratio	0.006	-0.005	-0.005	-0.015	-0.005	0.004*
	(0.13)	(-1.14)	(-1.06)	(-0.83)	(-1.06)	(1.76)
Calendar-month & Index FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.138	0.329	0.240	0.461	0.240	0.292
Observations	9,112	9,112	9,112	9,118	9,112	7,300

Table 9: What Drives Investors' Demand to Active Derivative-using ETFs?

The table presents the results from the panel regressions of monthly fund flows on derivatives use for active ETFs. The dependent variable is ETF flows in month $t+1$, calculated as $(TNA_{t+1} - TNA_t \times Return_{t+1})/TNA_t$, where t is last month, $t+1$ is current month. The independent variables are shown in the first column. The first one is a dummy variable (Derivative), where 1 represents the ETF using non-token derivatives. Other variables include the natural logarithm of fund total net assets (Size); *Fund age*, the distance between the fund inception date and 2024; *Turn ratio*, the turnover ratio from CRSP; *Illiquidity*, the relative quoted spread, calculated by dividing the bid-ask spread by the mid-quote, where the mid-quote is the average of the bid and ask prices; *Expense ratio*, the fund expense ratio from CRSP; *Sharpe ratio*, past annualized Sharpe ratio; *Max DD*, refers to the maximum drawdown, defined as the largest observed percentage decline from a peak in cumulative net value over the past 12 months. The time-fixed effect in the calendar-month and index level are included. Standard errors are clustered at both the ETF and calendar-month levels. The overall adjusted R^2 is reported. $^*p < .1$; $^{**}p < .05$; $^{***}p < .01$.

	Fund Flow$_{t+1}$			
Variable	(1)	(2)	(3)	(4)
Derivative	0.074***	0.041	0.044	0.065**
	(2.62)	(1.47)	(1.52)	(2.09)
Max DD		-0.088***	-0.079***	-0.061***
		(-4.12)	(-3.76)	(-2.88)
Sharpe ratio	0.083***	0.043	0.052*	0.067***
	(3.43)	(1.53)	(1.94)	(2.71)
Expense ratio	-0.028	-0.027	-0.025	-0.038*
	(-1.45)	(-1.43)	(-1.32)	(-1.90)
Size			-0.104***	-0.108***
			(-6.23)	(-5.85)
Fund age			-0.063***	-0.055***
			(-4.08)	(-3.79)
Turn ratio				-0.008
				(-1.39)
Illiquidity				-0.030**
				(-2.33)
Calendar-month & Index FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.024	0.028	0.041	0.039
Observations	18,769	18,769	18,769	17,630

References

Agarwal, V., Ren, H., Shen, K. and Zhao, H. (2023), 'Redemption in kind and mutual fund liquidity management', *The Review of Financial Studies* **36**(6), 2274–2318.

Agarwal, V., Ruenzi, S. and Weigert, F. (2017), 'Tail risk in hedge funds: A unique view from portfolio holdings', *Journal of Financial Economics* **125**(3), 610–636.

Agarwal, V., Ruenzi, S. and Weigert, F. (2024), 'Unobserved performance of hedge funds', *The Journal of Finance* **79**(5), 3203–3259.

Antoniewicz, R. S. and Heinrichs, J. (2014), 'Understanding exchange-traded funds: How etfs work', *Jane, Understanding Exchange-Traded Funds: How ETFs Work (September 30, 2014)* .

Aragon, G. O. and Martin, J. S. (2012), 'A unique view of hedge fund derivatives usage: Safeguard or speculation?', *Journal of Financial Economics* **105**(2), 436–456.

Atilgan, Y., Demirtas, K. O., Gunaydin, A. D. and Oztekin, M. (2024), 'Performance implications of hedging with industry etfs', *Global Finance Journal* **61**, 100990.

Bae, K. and Kim, D. (2020), 'Liquidity risk and exchange-traded fund returns, variances, and tracking errors', *Journal of Financial Economics* **138**(1), 222–253.

Barth, D., Kahn, R. J., Monin, P. and Sokolinskiy, O. (2024), 'Reaching for duration and leverage in the treasury market', *Available at SSRN* .

Ben-David, I., Franzoni, F., Kim, B. and Moussawi, R. (2023), 'Competition for attention in the etf space', *The Review of Financial Studies* **36**(3), 987–1042.

Bordalo, P., Gennaioli, N. and Shleifer, A. (2016), 'Competition for attention', *The Review of Economic Studies* **83**(2), 481–513.

Chen, Y. (2011), 'Derivatives use and risk taking: Evidence from the hedge fund industry', *Journal of Financial and Quantitative analysis* **46**(4), 1073–1106.

Choi, J., Kim, M. and Randall, O. (2023), 'Hidden duration: Interest rate derivatives in fixed income funds', *Available at SSRN* .

Cici, G. and Palacios, L.-F. (2015), 'On the use of options by mutual funds: Do they know what they are doing?', *Journal of Banking & Finance* **50**, 157–168.

Deli, D. N. and Varma, R. (2002), 'Contracting in the investment management industry:: evidence from mutual funds', *Journal of Financial Economics* **63**(1), 79–98.

Easley, D., Michayluk, D., O'Hara, M. and Putniņš, T. J. (2021), 'The active world of passive investing', *Review of Finance* **25**(5), 1433–1471.

Frino, A., Lepone, A. and Wong, B. (2009), 'Derivative use, fund flows and investment manager performance', *Journal of Banking & Finance* **33**(5), 925–933.

Gennaioli, N., Shleifer, A. and Vishny, R. (2015), 'Money doctors', *The Journal of Finance* **70**(1), 91–114.

Gilstrap, C., Petkevich, A., Teterin, P. and Wang, K. (2024), 'Lever up! an analysis of options trading in leveraged etfs', *Journal of Futures Markets* **44**(6), 986–1002.

Hitzemann, S., Sokolinski, S. and Tai, M. (2022), 'Paying for beta: Leverage demand and asset management fees', *Journal of Financial Economics* **145**(1), 105–128.

Huang, S., O'Hara, M. and Zhong, Z. (2021), 'Innovation and informed trading: Evidence from industry etfs', *The Review of Financial Studies* **34**(3), 1280–1316.

Huang, S., Song, Y. and Xiang, H. (2020), 'The smart beta mirage', *Journal of Financial and Quantitative Analysis* pp. 1–32.

Kaniel, R. and Wang, P. (2024), 'Unmasking mutual fund derivative use', *Working Paper* .

Khomyn, M., Putniņs, T. and Zoican, M. (2024), 'The value of etf liquidity', *The Review of Financial Studies* **37**(10), 3092–3148.

Koski, J. L. and Pontiff, J. (1999), 'How are derivatives used? evidence from the mutual fund industry', *The Journal of Finance* **54**(2), 791–816.

Merton, R. C. (1998), 'Applications of option-pricing theory: twenty-five years later', *The American Economic Review* **88**(3), 323–349.

Natter, M., Rohleder, M., Schulte, D. and Wilkens, M. (2016), 'The benefits of option use by mutual funds', *Journal of Financial Intermediation* **26**, 142–168.

A Appendix

A.1 Payoff Profile Determination

We extract the payoff profile for options, swaptions, and swaps is missing as there is distinct information reported for derivative holdings based on their category. We further identify it by incorporating more information.

We first consolidate swaptions into the options category due to their similarity to options and their relatively small proportion. For option contracts, investments can be made by either purchasing or writing options, which include call options and put options. We identify the payoff profile of options as long(short) call, long(short) put, where the long(short) corresponds to purchase(writing).

For swap contracts, the N-PORT filings provides information on both payers and receivers. After a thorough manual review, we categorise swap contracts into three types:

1) fixed receivers and floating payers;

2) floating receivers and fixed payers;

3) floating receivers and floating payers.

We identify swap contracts of type 1 as a short position because they lose as payers when the underlying value of the floating side increases. Similarly, swap contracts of type 2 are identified as a long position. For swap contracts in type 3, one case is that the payment is made or received based on reference rates such as "1-month LIBOR + spread", and "1-month Euribor + spread". We identify assets other than reference rates as their underlying assets for this case, and then we classify the long/short position based on whether they are receivers and payers. For example, one ETF called Direxion Daily S&P 500 Bull 3X Shares[13], there is a swap contract in their N-PORT filing of 30, September 2019 showing that they would receive a Total Return Swap Contract of S&P 500 Index and pay a 1-month Libor + spread. We identify this swap contract as a long position because their underlying asset is the return of the S&P 500 Index and they gain as the return of the S&P 500 Index increases. Another case in swap contracts of type 3 is that both legs are based on assets other than reference

[13] https://www.sec.gov/Archives/edgar/data/1424958/000114554919053539/xslFormNPORT-P_X01/primary_doc.xml

rates, we cannot identify whether they are long or short positions and we put their payoff profile as "long short". The IQ Hedge Multi-Strategy Tracker ETF provides an example for this case in their filing of 30, September 2019 as well, one of their swap contracts shows that the reference asset for both receipt and payment is "ISHARES S&P SMALL-CAP 600 GROWTH ETF"[14].

A.2 The Underlying Asset Classes of Derivatives Used by ETFs

In this subsection, we examine the underlying asset classes of derivatives used by ETFs. Derivative users are classified by combining their six underlying asset categories with their payoff profiles. The underlying asset categories are DCO (derivative-commodity), DCR (derivative-credit), DE (derivative-equity), DFE (derivative-foreign exchange), DIR (derivative-interest rate), and DO (derivatives-other). The payoff profiles are Long, Short, LongShort, Long USD, and Short USD, resulting in a total of fifteen categories. Panel A in Table A1 illustrates the breakdown of derivative use by active, passive, and leveraged ETFs across underlying asset categories, including commodities, credit, equity, foreign exchange, and interest rates. Panel B presents the fraction of gross notional exposure by underlying asset type for each derivative category.

Panel A reports the fraction of derivative users that hold a certain position in each ETF category. It shows that 84% of active ETFs hold long positions of equity derivatives and 70% of them hold short positions of equity derivatives. The fraction of active ETFs that use derivatives belonging to any other category asset category is much smaller and typically less than 10%. 83.6% of passive ETFs use long equity derivatives and only 6% of passive ETFs use short equity derivatives. It implies that derivatives used by passive ETFs may be driven by their investment objective to closely track their benchmarks. The other main underlying asset category of derivatives that passive ETS use is the foreign exchange category. 15% of passive ETFs use short USD derivatives while nearly 17% of passive ETFs use long USD derivatives. This highlights their need to manage foreign exchange risks, which can be driven by their indices which include assets from non-U.S. markets.

[14] https://www.sec.gov/Archives/edgar/data/1415995/000175272419201517/xslFormNPORT-P_X01/primary_doc.xml

Leveraged ETFs mainly use long and short equity derivatives and long swap and warrant positions. Specifically, 51.9% of leveraged ETFs use equity derivatives with long positions and 48.1% of them with short positions. Notably, 21.6% of these ETFs use derivatives based on other assets instead of common financial assets like equities and commodities.

Panel B of Table A1 shows that notional amounts of futures, options, swaps, and warrants focus on equity. Interestingly, all of the forward derivative exposure comes from exposure to foreign exchange derivatives.

A.3 Derivative Holdings and Prospectus' Strategy Description

It is worth examining whether ETFs' actual derivative use aligns with the descriptions provided in their prospectus. A prospectus is a formal document required by and filed with the Securities and Exchange Commission (SEC) that provides details about an investment offering to the public. The prospectus can help investors make more informed investment decisions because it contains a host of relevant information about the investment. The SEC encourages investors to read prospectuses before making their investment decisions.

To investigate this, we download fund prospectuses from the SEC website, extracting the Principal Investment Strategy sections. We then identify derivative-related sentences, removing common words like "fund", "ETF", and "assets", which are not directly related to derivative use. The filtered sentences are then analysed for word frequency, with more commonly occurring words given greater prominence in the resulting word clouds presented in Figure A2.

Figure A2 shows that, in general, there is consistency between actual ETF derivative use and stated derivative use by ETFs in their prospectuses. In particular, Table 3 show that passive ETFs appear to use derivatives for hitting their target benchmark using futures but also for managing foreign exchange risk through USD forwards. When we compare this with what passive ETFs say they do in their prospectuses, the word cloud of passive ETFs in Panel (a) shows that the most frequently mentioned derivative-related term is "futures contract", followed by "call option", "put option", and "currency forward". This lines up with their derivative holdings.

For active ETFs, they use equity options for hedging and return enhancement, with the majority of their derivative allocation in equity options. Consistently, the word cloud of active ETFs in Panel (b) shows that the most prominent derivative-related term is "FLEX Option" (Flexible Exchange Options). It suggests that many derivative-based active ETFs use customised option contracts instead of standardized option contracts in their holding. Leveraged ETFs mainly use swaps in Table 3 and additionally hold a large proportion of cash. Consistently, the word clouds for leveraged ETFs shown in Panel (c) emphasise "swap agreements" and "money market".

A.4 Risk-Return Asymmetry in Active Derivative-based ETFs

We manually reviewed the fund prospectuses and official websites of all 416 active derivative-using ETFs to identify the key features emphasized in their investment strategies. Based on this review, we classified the ETFs into two main categories: (1) downside protection ETFs, which mention that they use derivatives for mitigating losses during market downturns, and (2) option income ETFs, which describe in their investment strategies that they use options to generate stable income. These two strategies represent the primary use cases of derivatives among active ETFs.

Next, to evaluate their performance relative to benchmarks, we also manually identified and matched appropriate benchmarks for those ETFs that missed benchmark information in the datasets obtained from Morningstar and Bloomberg. In particular, we observe that nearly half of these funds are benchmarked against the S&P 500, including 181 buffer ETFs categorised as downside protection ETFs. These funds typically use derivatives to cap losses within a specified range of S&P 500 declines. Additionally, 26 ETFs are benchmarked to individual stocks, including four linked to Tesla and two to Apple, and primarily aim to generate income by selling options on the underlying stocks.

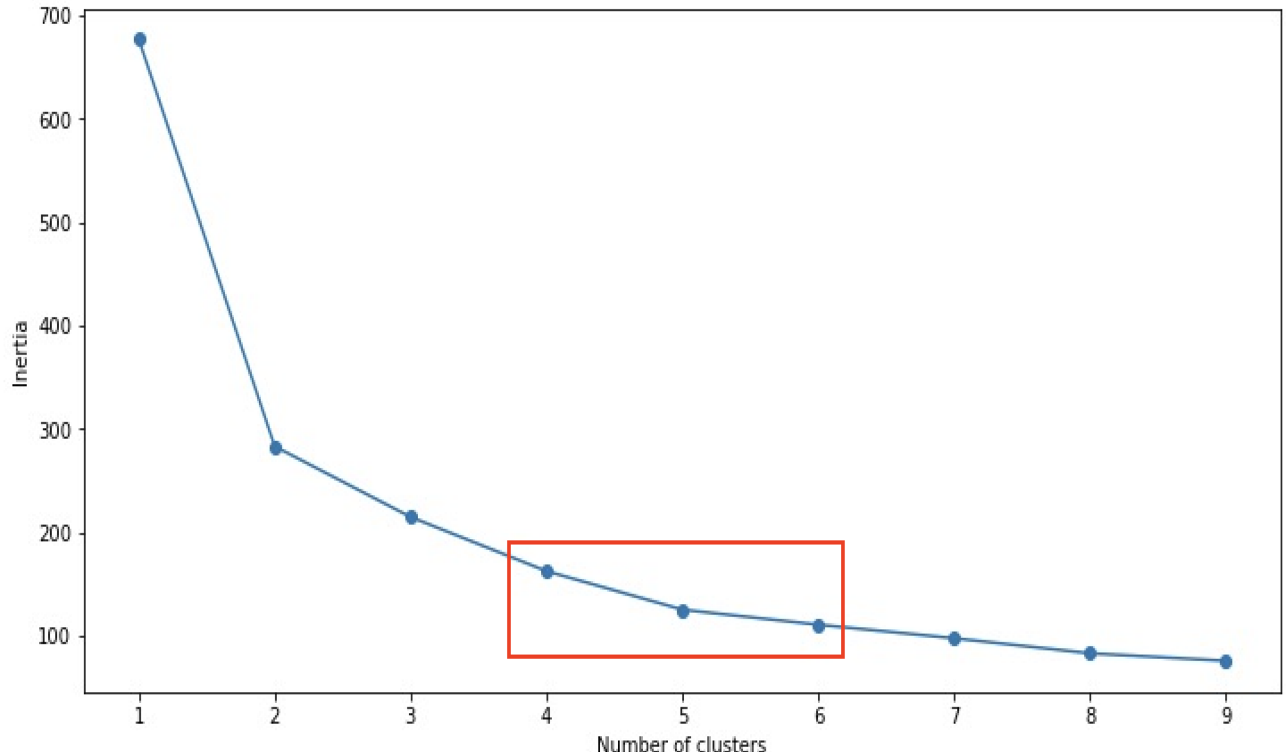
To examine the difference in risk-return asymmetry between the two categories of active ETFs, we visualise the relative return dynamics based on the performance of their benchmarks in Figure A3. Each graph includes three performance measures. Outperformance is defined as the percentage of months in which the ETF's excess return (ETF return minus benchmark return) is positive. *Upside (Downside) Capture* refers to the ETF's average return during months when the benchmark is up (down), divided by the benchmark's average return in those same months.

We find that the outperformance rate for both ETF types is below 45%, consistent with our earlier finding that these products are not primarily designed to outperform benchmarks, but rather to manage risk. Both downside protection and option income ETFs show a clear pattern: they tend to outperform their benchmarks when benchmark returns are negative and underperform when benchmarks rise. However, downside protection ETFs exhibit a more symmetric return profile than option income ETFs. In particular, downside protection ETFs capture 51% of downside market movements while retaining 54% of the upside, highlighting their hedging function without fully sacrificing gains.

In contrast, option income ETFs have an upside capture ratio of 0.66 and a downside capture of 0.74, indicating that an income-driven return profile can smooth returns but also comes out with a greater sacrifice of upside potential. This feature of option income ETFs also reflects the theoretical payoff structure of selling options, where income generation is conditional and depends on the moneyness of the underlying contracts. When markets rise significantly, the capped upside from short call positions can limit gains, leading to underperformance relative to benchmarks. As a result, while these strategies may reduce volatility and provide stable income, they come with a hidden cost: investors may forgo full participation in rising markets. This represents an implicit trade-off in addition to the higher fees typically charged by these products.

To summarize, this analysis suggests that both active ETF types create value in downside protection with different derivative strategies. Downside protection ETFs offer more effective tail risk management, whereas option income ETFs trade off some upside performance for greater return stability. These findings highlight the hedging intent behind active ETFs' use of derivatives.

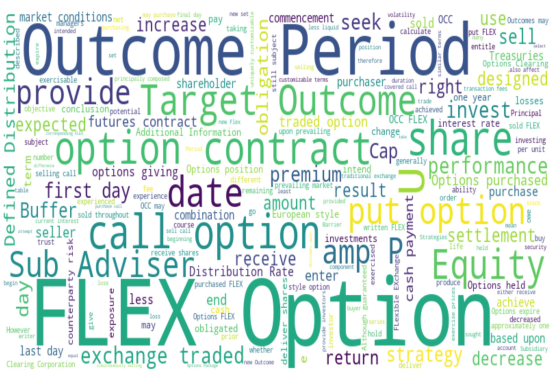
Figure A1: The Elbow Curve of K-Means Clustering



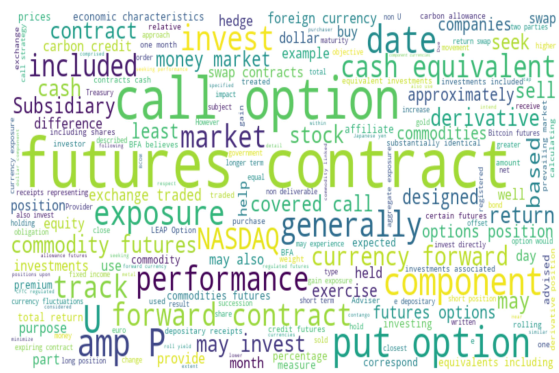
The figure shows the elbow curve of the K-means clustering process, where the x-axis represents the number of clusters and the y-axis shows inertia, a measure of cluster compactness. The curve initially drops steeply, indicating substantial improvement in clustering quality as the number of clusters increases. The rate of decrease in inertia slows around 4 to 6 clusters, highlighted by the red box. This "elbow" point suggests the optimal number of clusters, as adding more clusters beyond this point yields diminishing returns in reducing inertia.

Figure A2: Word-Cloud of Derivative-related Description in Fund Prospectus

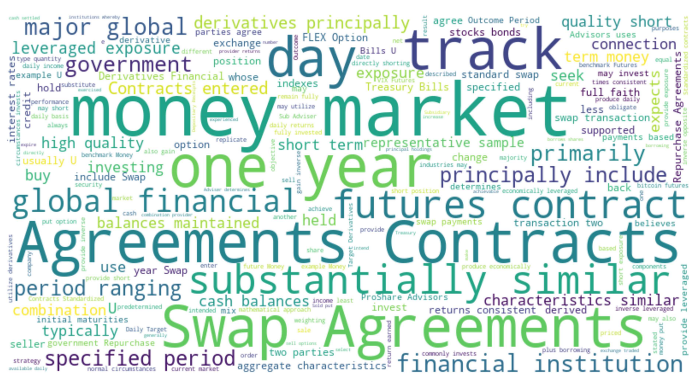
(a) Active Derivative-Based ETFs



(b) Passive Derivative-Based ETFs



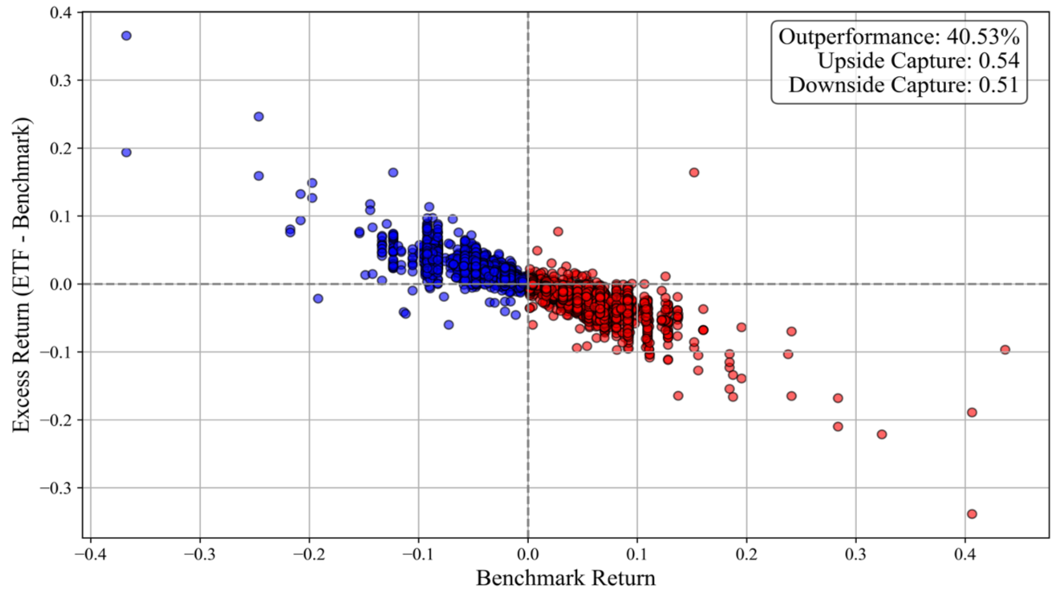
(c) Leveraged ETFs



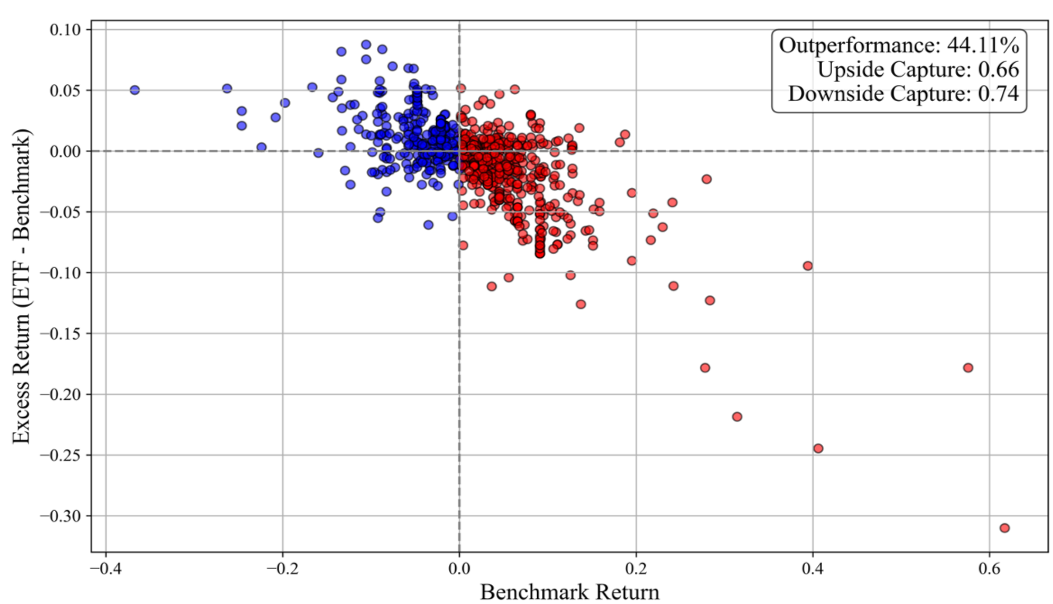
The figure shows the Word-Cloud of derivative-related discussions in the Principal Investment Strategy section of fund prospectuses. It focuses on derivatives-related content to visualise the frequency of key terms. The data is from Mutual Fund Prospectus Risk/Return Summary Data Sets provided by the SEC. We identify a list of derivatives-related keywords, including terms like "derivatives," "options," "futures," "swaps," and "hedging." Next, we remove common words like "fund," "ETF," and "assets," which are commonly found in financial documents but not directly related to derivatives analysis. The filtered sentences are analysed for word frequency, with more commonly occurring words given greater prominence in the resulting word cloud.

Figure A3: Excess Return Dynamics (Active ETFs vs. Benchmarks)

(1) Downside Protection ETFs



(2) Option Income ETFs



The figure plots the monthly excess returns of derivative-using ETFs relative to their benchmarks across varying market conditions. The x-axis shows the benchmark's monthly return, while the y-axis represents the ETF's excess return, calculated as the ETF return minus its benchmark return for the same month. Each point represents one ETF-month observation. Panel A displays results for downside protection ETFs, and Panel B for option income ETFs. *Outperfomance* measures the percentage of points with positive excess returns relative to the total points of excess returns. *Upside(Downside) Capture* the fund's average return in periods when the benchmark is up(down) divided by the benchmark's average return in those periods.

Table A1: Overview of Derivative Underlying Assets Allocation

The table reports the fraction of derivative users for each ETF category in Panel A and the fraction of gross notional exposure of underlying asset allocations for each derivative category in Panel B. Derivative users are classified by combining their six underlying asset categories with their payoff profiles. The underlying asset categories are DCO (derivative-commodity), DCR (derivative-credit), DE (derivative-equity), DFE (derivative-foreign exchange), DIR (derivative-interest rate), and DO (derivatives-other). The payoff profiles are shown in the second column, including Long, Short, LongShort, Long USD, and Short USD, resulting in a total of fifteen categories. In Panel A, we report the fraction of derivative users in these fifteen groups for each ETF category, where one unique series ID represents one derivative user. In Panel B, we report the average gross notional exposure of underlying assets for each derivative category. Derivatives are categorized as futures (FUT), forwards (FWD), options (OPT), swaps (SWP), and warrants (WAR).

Panel A: Fraction of Derivative Users Across ETF Categories

AssetCategory	long_short	Active	Passive	Leveraged
DCO(derivative-commodity)	Long	0.064	0.025	0.000
DCO(derivative-commodity)	Short	0.051	0.011	0.006
DCR(derivative-credit)	Long	0.002	0.000	0.000
DCR(derivative-credit)	Short	0.002	0.000	0.000
DE(derivative-equity)	Long	**0.840**	**0.836**	**0.519**
DE(derivative-equity)	LongShort	0.004	0.024	0.025
DE(derivative-equity)	Short	**0.701**	0.063	**0.481**
DFE(derivative-foreign exchange)	Long	0.031	0.006	0.000
DFE(derivative-foreign exchange)	Long USD	0.048	**0.168**	0.000
DFE(derivative-foreign exchange)	Short	0.020	0.004	0.000
DFE(derivative-foreign exchange)	Short USD	0.037	**0.150**	0.000
DIR(derivative-interest rate)	Long	0.048	0.006	0.000
DIR(derivative-interest rate)	Short	0.035	0.003	0.000
DO(derivatives-other)	Long	0.007	0.022	**0.216**
DO(derivatives-other)	Short	0.002	0.001	0.099

Panel B: Fraction of Gross Notional Exposure Across Derivative Categories

AssetCategory	FUT	FWD	OPT	SWP	WAR
DCO(derivative-commodity)	0.054	0.000	0.000	0.032	0.000
DCR(derivative-credit)	0.000	0.000	0.000	0.000	0.000
DE(derivative-equity)	**0.927**	0.000	**0.999**	**0.902**	**0.975**
DFE(derivative-foreign exchange)	0.004	**1.000**	0.000	0.000	0.000
DIR(derivative-interest rate)	0.014	0.000	0.000	0.000	0.000
DO(derivatives-other)	0.001	0.000	0.001	0.065	0.025

Table A2: Examples of Prospectuses of Derivative-based ETFs

No.	Category	Principal Investment Strategies in Fund Prospectus
1	Passive	Global X S&P 500® Covered Call ETF: The Fund invests at least 80% of its total assets in the securities of the CBOE S&P 500 BuyWrite Index (the "Underlying Index"). The Underlying Index is comprised of two parts: (1) all the equity securities in the S&P 500® Index (the "Reference Index") in substantially similar weight as the Reference Index; and (2) short (written) call options on up to 100% of the S&P 500® Index.
2	Passive	iShares MSCI EAFE ETF: The Fund seeks to track the investment results of an index composed of large- and mid-capitalization developed market equities, excluding the U.S. and Canada. The Fund generally will invest at least 80% of its assets in the component securities of its Underlying Index and may invest up to 20% of its assets in certain futures, options and swap contracts, cash and cash equivalents.
3	Active	Goldman Sachs S&P 500 Core Premium Income ETF: The Fund seeks current income while maintaining prospects for capital appreciation. The Fund seeks to achieve its objective by investing primarily in a portfolio of stocks and selling call options. The Fund employs a dynamic options "overwrite" strategy whereby it sells (writes) call options on a varying percentage of the market value of the equity investments.
4	Active	YieldMax™AMZN Option Income Strategy ETF: The Fund's primary investment objective is to seek current income. The Fund uses a synthetic covered call strategy to provide income and indirect exposure to the share price returns of Amazon.com, Inc. ("AMZN"), subject to limits on potential gains.
5	Active	TrueShares Structured Outcome (November) ETF (NOVZ): The Fund is actively managed and employs a "buffer protect" options strategy using options to mitigate the first 8% to 12% decline in the S&P 500 Price Index performance over a 12-month period.
6	Active	Aptus Drawdown Managed Equity ETF: The Fund seeks capital appreciation with a focus on managing drawdown risk by purchasing exchange-listed put options while investing principally in U.S.-listed equity securities.
7	Leveraged	ProShares Ultra S&P500®: The Fund seeks daily investment results, before fees and expenses, that correspond to two times (2x) the daily performance of the S&P 500® Index by investing in derivatives, including swap agreements and futures contracts.
8	Leveraged	ProShares UltraPro Short S&P500: The Fund seeks daily investment results, before fees and expenses, that correspond to three times the inverse (-3x) of the daily performance of the S&P 500® Index by investing in derivatives, including swap agreements and futures contracts.

Table A3: Derivative Use and Risks in Buffer Protect ETFs

The table tests for the differences in fund risks and risk-adjusted returns between the portfolio of active ETFs using buffer protect strategies (Buffer ETFs) and the S&P 500 portfolio of passive ETFs (S&P 500 ETFs).The portfolios of all buffer (S&P 500 passive) ETFs comprise 181 (4) ETFs on average. *Total Risk* is the annual return volatility based on the standard deviation of the monthly net-of-fee return over the past 12 months. *Max Drawdown* is the largest observed percentage decline from the peak cumulative net value during the past 12 months. *VaR_95%* is calculated as 95% Value at Risk (VaR) by determining the 5th percentile of the returns distribution and *CVaR_95%* is the Conditional VaR, calculated as the average loss beyond this threshold. It measures the expected loss in extreme scenarios. *Buffer ETFs - S&P 500 ETFs* measures the spread of the mean variables between two portfolios, and t-difference is from a test of the null hypothesis that the spread of the mean variables is same as 0. $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.

	Total risk	**Max Drawdown**	**VaR_95%**	**CVaR**
Buffer ETFs	0.0921	0.1277	-0.0439	-0.0541
S&P 500 ETFs	0.1513	0.2388	-0.0683	-0.0895
Buffer ETFs - S&P 500 ETFs	-0.0592^{***}	-0.1111^{***}	0.0243^{***}	0.0354^{***}
t-difference	(-20.58)	(-14.30)	(16.23)	(17.17)