Flow-Induced Demand Pressure from Option-Trading ETFs

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Abstract

The assets under management of option-trading exchange-traded funds (ETFs) have grown more than 120-fold since 2018. This paper exploits option-trading ETFs to examine how flow-induced demand pressure and exogenous rollover trade demand pressure affect the implied volatility surface. I show that demand pressure from these ETFs significantly affects implied volatility surface, with the magnitude of the effect varying with option characteristics—particularly moneyness and days to expiration—due to differences in option vega. In addition, liquidity frictions also explain the magnitude of impact. These findings suggest that flow-induced demand pressure plays an important role in shaping both the term structure and moneyness curve of implied volatility.

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1 Introduction

The assets under management (AUM) of option-trading exchange-traded funds (ETFs) reached \$125 billion by the end of June 2024, representing a more than 120-fold increase since 2018. These ETFs represent a specialized subset of exchange-traded funds that employ options, either independently or in combination with underlying assets, to achieve targeted investment objectives. Investor flows from mutual funds (Chang et al., 2015; Lou, 2012; Pavlova and Sikorskaya, 2023) and ETFs (Easley et al., 2021; Brown et al., 2021) are known to affect the prices and volatilities of underlying assets, with recent studies highlighting the impact of flows from specific ETF segments, such as leveraged ETFs (Davies, 2022). Option-trading ETFs, particularly covered call ETFs, have recently drawn attention from many practitioners who are concerned that rising investor inflows—and the resulting increase in written call options—may have contributed to the suppression of the VIX index.[1] Despite their increasing market presence and media attention[2], the price implications of the rapidly expanding option-trading remain largely unexplored.

This paper evaluates impact of flow-induced demand pressure from option-trading ETFs on implied volatility surface. I proxy for flow-induced demand pressure at the option level by mapping ETF fund flows to the specific option mandated in each fund's prospectus. The decomposition from ETF flow to granular option level demand, based on days to expiration, moneyness, option type (call/put) and underlying asset, enables analysis of heterogeneous impact of demand pressure on implied volatility.

Furthermore, to address potential endogeneity in ETF fund flows, I exploit the mechanical nature of rollover trades. ETFs that implement predefined option strategies with minimal discretion systematically roll over the same type of option contracts upon the expiration of existing positions. Rollover trades are exogenous because they are mechanically determined by the ETF's predefined strategy and predefined outcome period, rather than market conditions or managerial discretion. This rule-based structure provides a sharp identification, as the resulting demand pressure is unrelated to contemporaneous information or price movements

[1] JPMorgan blames JPMorgan for suppressed volatility and Structured products and the 'broken VIX' discourse.

[2] See more, Bank for International Settlements (BIS) associates drop in VIX with proliferation of yield-enhancing structured products, such as covered call ETFs. Conversely, research from the Chicago Board Options Exchange (CBOE) argues that the impact of option income ETFs on the VIX is minimal. In addition, a note from AQR on Option-based ETF performance.

of underlying.

Flow-induced demand pressure significantly impacts the implied volatility of associated options while controlling for past implied volatility level and underlying asset return, consistent with the hypothesis that increased buying (selling) pressure raises (lowers) option prices and, in turn, implied volatility. Plausibly exogenous rollover demand pressure confirms the significant effect: a one-standard-deviation increase in buying pressure from rollovers results in a 0.008 standard deviation increase in implied volatility on average.

While the average measure of price impact remains statistically modest, the high granularity of dataset in this study allows a further investigation of price impact across options with varying characteristics. The effect of demand pressure on implied volatility is theoretically inversely related to an option's vega, which reflects an option's price sensitivity to changes in implied volatility (Gârleanu et al., 2009). As option vega varies with option characteristics such as moneyness and days to expiration, a given level of demand pressure can have heterogeneous effects on implied volatility. Consistent with the theory, the strongest effects are observed in near expiry options and those that are deep in- or out-of-the-money, where vega is typically lower. The difference in the magnitude of impact is substantial. A one-standard-deviation increase in buying pressure can result in an increase in implied volatility of up to 38.1 standard deviations, depending on option characteristics. These results highlight the role of demand pressure in contributing to the term structure and moneyness curve of implied volatility surface.

Prior research has documented the existence of volatility smiles and smirks, attributing these patterns, in part, to demand-driven price pressures (Bollen and Whaley, 2004; Xing et al., 2010). Building on this literature, I show that flow-induced demand pressure has a more pronounced impact on in-the-money (ITM) options compared to out-of-the-money (OTM) options. This highlights the role of demand pressure in shaping the asymmetry of the implied volatility surface.

To study the impact of market frictions on price pressure effects, I focus on the measures of liquidity in the option market. In less liquid markets, market makers face greater difficulty in hedging their exposures (delta, vega, etc.) efficiently and at low cost. As a result, they require greater compensation for bearing these risks, which leads to elevated implied volatility. Consistent with prior research showing that liquidity influences option pricing and implied volatility patterns (Chou et al., 2011; Brenner et al., 2001; Etling and Miller, 2000), I find that in less liquid option markets, flow-driven demand pressure can exert a stronger influence on implied volatility.

Finally, this paper investigates the impact of option-trading ETFs on the VIX index. By incorporating all rollover trades involving option contracts that could potentially affect the VIX index, the analysis finds that the demand pressure from these ETF-driven trades has an economically small and statistically insignificant effect. This limited impact is largely attributable to the narrow overlap between the specific option contracts used in the VIX calculation and those actively traded by option-trading ETFs, which constrains their direct influence on the VIX.

Options provides important information for the underlying assets returns, and facilitates the price discovery process for the underlying assets. Under no-arbitrage theory, option prices should be independent of investor demand, as payoffs can be replicated using the underlying asset and a risk-free asset. However, due to hedging constraints and exposure to informed trading, option market makers cannot fully offset inventory risk (Muravyev, 2016; Gârleanu et al., 2009; Dim et al., 2024; Staer, 2017). Consequently, demand pressure affects option prices as market makers adjust prices to manage risk (Bollen and Whaley, 2004; Eaton et al., 2024; Hu et al., 2023).

While flow-induced demand pressure is well studied in other asset classes, such as equities (Chang et al., 2015; Lou, 2012) and commodities (Tang and Xiong, 2012), research in the options market remains limited. Recent studies (Eaton et al., 2024; Lipson et al., 2023; Bryzgalova et al., 2023) emphasize the growing influence of demand pressure from retail option investors. Additional work has focused on ultra-short-term instruments like zero-days-to-expiration (0DTE) options, where demand shocks can lead to sharp price movements and volatility spikes (Vilkov, 2024; Beckmeyer et al., 2023; Dim et al., 2024). However, the role of institutionally aggregated demand—such as that generated by systematic trading in ETFs—remains largely unexplored. ETF-induced demand is structural by design, and thus may have a more persistent and systemically relevant impact on option pricing.

This paper contributes to several strands of literature. Firstly, it aligns with a substantial body of research that suggests demand pressures can significantly affect asset prices. Flow-induced demand is well documented in equities (Coval and Stafford, 2007; Ben-Rephael et al., 2012), with ETF flows shown to predict both future returns (Brown et al., 2021; Lou, 2012) and stock volatility (Lazo-Paz, 2024). Evidence from the options market suggests similar effects on option prices and implied volatility. Bollen and Whaley (2004) show that net buying pressure, particularly for index puts, is associated with changes in implied volatility. Gârleanu et al. (2009) develop a theoretical model in which option demand alters the pricing kernel, impacting both option prices and volatility. More recently, Eaton et al. (2024) find that retail option demand significantly affects implied volatility. Building on this literature, the present paper provides novel evidence that institutional demand—arising from systematic trading by option-trading ETFs—also contributes to option pricing dynamics.

Second, this paper relates to the literature on the shape of the implied volatility surface. Prior research shows that its features—such as term structure (Mixon, 2007; Vasquez, 2017), moneyness (Dennis and Mayhew, 2002; Pan, 2002; Xing et al., 2010; Yan, 2011), and option type (Bali and Hovakimian, 2009; Cremers and Weinbaum, 2010; An et al., 2014; Han and Li, 2021)—contain information on the underlying asset. This paper suggests that the flow-driven demand price pressure, which does not appear to contain private information, also plays a part in the shape of implied volatility surface.

This paper contributes to the literature on asset management vehicles that employ derivatives, particularly options. Cici and Palacios (2015) examine mutual fund option usage, identifying motives such as income generation and portfolio insurance, but also documenting underperformance among funds engaging in speculative strategies. Aragon and Martin (2012) analyze hedge funds' option positions, emphasizing their informed volatility timing in a less regulated environment. This study complements their work by focusing on ETF option strategies and their broader market implications.

The remainder of the paper is organized as follows. Section 2 provides an overview of option-trading ETFs and decomposes their strategies. Section 3 discusses the data and flow-induced demand pressure variable, and presents descriptive statistics. Section 4 and 5 present empirical results that demand pressure from option trading ETFs affects implied volatility surface. Section 6 investigates the impact of option trading ETFs on VIX index. Section 7 concludes.

2 Institutional Details and Data

2.1 Overview of Option Trading ETFs

Option-trading ETFs represent a specialized subset of ETFs that utilize options alone or in conjunction with underlying assets to achieve specific investment objectives. These ETFs typically implement well-defined option strategies, such as covered calls, buffers, or spreads, to generate income or manage risk. By strategically integrating options, these funds provide investors with exposure to various risk-return profiles, making them suitable for different market conditions and investment goals.

Table 1 exhibits the snapshot of fund management firms that offer option-trading ETFs. Column (1) shows the number of option trading ETFs, column (2) - (4) show the number of ETFs, dead funds and all funds offered by the firms. The main providers of option trading ETFs are firms that specialize in ETFs, such as Innovator, First Trust, Elevate(YieldMax), Global X, and Pacer. Besides, large fund management firms also enter this market to complete their product profiles, i.e., BlackRock, State Street Global Advisors.

Figure 1 shows the growth trajectory of option-trading ETFs and their total AUM over time. By the end of June 2024, there are 423 option-trading ETFs, collectively managing an AUM of $125 billion. While relatively small compared to the broader ETF market, option-trading ETFs is growing at a faster speed than the broader ETF market.

The proportion of an option-trading ETF's total market value allocated to options varies considerably depending on the strategy it employs, as will be discussed in detail in Section 2.3. Some ETFs, e.g., buffer ETFs, use options as their primary means of obtaining market exposure, with options comprising up to 99% of their total portfolio market value. In contrast, others employ options as an overlay on top of the underlying securities to enhance income, accounting for a very small fraction of their total portfolio market value. Quantifying the volume of option contracts traded by ETFs is challenging as transactional-level data of ETFs is unavailable. Therefore, this paper seeks to measure flow-induced demand pressure by fund flow and predefined option strategy, rather than directly quantifying the volume of option trades.

2.2 Flex Options

More than 90% of the option-trading ETFs in the sample utilize FLexible EXchange Options (hereafter FLEX options). FLEX options[3] are exchange-traded, non-standardized options that allow investors to customize key contract terms, including strike prices, expiration dates, and exercise styles. In terms of market share, FLEX options currently make up nearly 1.7% of the total listed options volume, with peak days topping 2 million contracts, or 4% of the market[4].

The primary distinction between FLEX options and standardized options lies in their level of customization. Standardized options provide a predefined grid of strike prices and expiration dates, whereas FLEX options allow participants to tailor these parameters to meet their specific needs. Unlike standardized options, whose prices are listed in an options chain, FLEX options utilize a request-for-quote (RFQ) process[5]. This process involves soliciting quotes from the exchange and may include negotiations to arrive at a mutually agreeable price.

Demand pressure to FLEX options does not directly affect the prices of standardized option contracts, which are used to derive the implied volatility surface. However, it influences the implied volatility surface indirectly through the arbitrage activities of market makers. The process to offset and hedge FLEX options essentially involve both FLEX options and standardized options by market makers[6]. As a result, this facilitates the transmission of demand pressure between the FLEX options market and the standardized options market, establishing a connection between the two. Therefore, the implied volatility surface from FLEX options and standardized options should theoretically align under the assumption of perfect arbitrage by market makers.

[3]Introduced in 1993, and mainly cater to institutional investors, FLEX options combine the flexibility of over the counter(OTC) option contracts with the transparency and low default risk of standard exchange-traded options, as the counterparty is the Options Clearing Corporation (OCC), same as standard exchange-traded options.

[4]https://www.cboe.com/insights/posts/flex-appeal-enhanced-flex-functionality-on-cboe-platforms-and-data/

[5]https://www.optionseducation.org/news/the-basics-of-flex-options

[6]See page 20 of CBOE Margin Manual

2.3 Strategies of Option-trading ETFs

For each option-trading ETF, the option strategy is detailed in its fund prospectus. Using this information, I classify the strategies of option-trading ETFs into distinct strategy buckets as summarized in Table 2. The classification framework is structured around two key dimensions. The first dimension differentiates between ETFs that trade options on individual stocks and those that trade options on an index or passive ETF, such as SPY[7]. The majority of option-trading ETFs engage in trading index options or options on passive ETFs, while a smaller subset, particularly those employing overlay or credit spread strategies, trade options on individual or a group of stocks, e.g., AAPL.

The second dimension considers the extent to which ETFs hold options as a dominant portion of their total assets. Among ETFs that trade options on an index or passive ETF, the extent of option exposure varies based on the strategy. ETFs utilizing buffer strategies may allocate up to 99% of their portfolio market value to options when employing deep-in-the-money call options (e.g., option with a strike price at 1% of the underlying asset price) as a substitute for directly holding the underlying asset. Alternatively, some ETFs directly hold stocks while layering options to achieve a specific return profile. ETFs that follow credit spreads, covered call, collar, and barrier strategies typically maintain direct holdings in underlying securities while incorporating options as an additional layer to modify risk-return characteristics.

Figure 2 presents the growth of AUM across option-trading ETF strategies over time. Covered call and buffer ETFs have emerged as the most dominant. As of September 2024, ETFs utilizing buffer strategies collectively manage $45 billion, while covered call ETFs oversee an average of $73 billion. This highlights the increasing investor interest in income-generating and risk-mitigating option strategies.

Buffer ETFs. Buffer ETFs have monthly series, and they offer defined outcomes, such as partial downside protection and capped upside growth—over a specified time frame, mostly one year, some for two years, starting from the first day of their designated month series. They attract flow from risk-averse investors. The defined outcome is often realized by combining options contracts with one-year maturity (or two years, depending on the specified time frame

[7] Appendix A shows detailed information of the underlying passive ETFs.

of the outcome period) with strike prices tied to the price of the underlying asset on the first day of the designated month series, the cap, and the buffer. The underlying asset of options traded by buffer ETFs are mostly passive ETFs and Index.

To illustrate the mechanics of a Buffer ETF, consider the Innovator U.S. Equity Power Buffer ETF – January Series (ticker: PJAN). This ETF follows a structured outcome strategy based on a defined one-year investment period, running from January 1 to December 31 each year. For the current outcome period, spanning January 1, 2025, to December 31, 2025, the ETF offers a predefined cap of 12.03% and a buffer of 15%[8]. This implies that the ETF is designed to provide downside protection against the first 15% of losses in the SPY, while gains are capped at 12.03% over the specified period. Both the cap and buffer levels are subject to adjustment at the start of each new outcome period with minor fluctuations. At the end of each defined outcome period, investor holdings are automatically transitioned into a new one-year outcome window. This means that upon the expiration of the current option contracts, the ETF roll over its option positions forward to establish a new set of defined outcomes for the following year.

The defined outcome is achieved by a buffer option strategy (see Table 12). Specifically, for Innovator US equity power buffer ETF January series, the option strategy involves buying deep-in-the-money call options on SPY to gain exposure to it, writing out-of-money call options, long at-the-money put options, and short in-the-money put options. All these options will expire on December 31st, 2025. The resulting payoff plot of the option strategy is shown in the left panel of Figure 3.

Covered Call ETFs. Covered call ETFs represent the earliest form of option-trading ETFs. The first such fund, the Invesco S&P 500 BuyWrite ETF (ticker: PBP), was launched in 2007, offering investors exposure to a covered call strategy based on the S&P 500 Index. From 2007 to 2018, the option-trading ETF landscape was predominantly shaped by funds employing covered call strategies. Over time, the market has diversified to include ETFs that sell call options on broad indices, passive ETFs, or individual stocks.

Covered call ETFs follow an income-enhancement strategy by holding a long position in equities—either in a passive ETF or a portfolio of stocks—while simultaneously writing call options on all or part of the same underlying assets. Compared to buffer ETFs, which

[8] Both specified before fees.

may allocate up to 99% of their portfolio to options, covered call ETFs typically have much smaller option exposure. In addition, covered call ETFs generally have greater discretion in writing options compared to buffer ETFs, except in cases where they track a predefined buy-write index.

As an example, the Invesco S&P 500 BuyWrite ETF implements a buy write strategy on the S&P 500 Index. This approach mirrors the methodology of the CBOE S&P 500 BuyWrite Index (BXM), which maintains a long position in a portfolio replicating the S&P 500 Index while simultaneously writing a one-month-to-maturity call option on the index with a strike price approximately equal to the current index level. The right panel of Figure 3 illustrates the payoff profile associated with this option strategy.

3 Sample Description

3.1 ETF Sample

To measure the demand pressure of option-trading ETF on implied volatility, I zoom into buffer ETFs to take advantage of their predefined option strategies.

The buffer ETF universe is an ideal subset for identification. First, achieving the predefined buffer strategy requires options with specified strike prices and expiration dates. Any future inflows within the defined outcome period into the buffer ETF will lead to purchase or write the same options defined at the start of the outcome period. This allows the breakdown of ETF flows into specified option contracts, enabling the mapping of ETF flow into the demand pressure for each option. In contrast, ETFs with more discretion trade options with strike prices and expiration dates that vary over time, and this information is not readily available.

There are 266 buffer ETFs in the sample and on average accounts for near 35% of the total option-trading ETF AUM.

3.2 Data Sources

Option trading ETFs are first flagged in the Morningstar database, including all US-domiciled ETFs that are in the Morningstar category of derivatives income or defined outcomes with a base currency of US dollars. There are 423 option-trading ETFs flagged. Then these flagged option trading ETFs are merged by ticker and the latest available CUSIP (if the ticker is not available) with the Center for Research in Security Prices (CRSP) database for monthly fund characteristics such as total net assets. The daily ETF shares outstanding data is sourced from Bloomberg.

Additionally, I manually collected detailed option strategy information for each option-trading ETF from its fund prospectus. I select buffer ETFs and covered call ETFs which mechanically track a buy-write index based on description in the fund prospectus. For buffer ETFs, I record the buffer and the cap range, underlying asset of the options, define outcome period length, defined monthly series. For covered call ETFs, I record underlying asset of options.

The above information makes it possible to determine key details on the option contracts that are traded by these ETFs such as the first purchase time of constituent options, their expiration dates, moneyness at the time of first purchase, long or short positioning, shares of each option in the strategy, and whether the options are calls or puts[9].

In addition, I employ daily ETF holding data from Morningstar to verify the strategies implemented by these ETFs. This dataset offers information on the option contracts and the market values of each option position held by the ETF. Since a predefined option strategy can be executed using various combinations of options and underlying assets, the holding data is useful in identifying the exact strategy structure adopted by each ETF [10].

The sample includes 266 buffer ETFs. All of these ETFs trade options on either index and mostly on passive ETFs. On average the extended sample account for 62% of the total option-trading ETF AUM and holds on average 63% options shares of all shares held by

[9] An example is presented in Table 12

[10] A limitation of the daily Morningstar holding data is the lack of detailed characteristics for each option contract. Specifically, option contracts are listed separately without clear information on strike prices or maturities. Nonetheless, distinguishing the number of the type of option contracts used is sufficient for the purposes of this study.

option-trading ETFs over the sample period and 90% of all option shares starting from 2021.

The daily implied volatility, option price, option volume, option open interest, and option Greeks data are sourced from OptionMetrics. Moneyness is calculated as the ratio of the strike price to the underlying price, minus one, for put options and one minus the ratio of the strike price to the stock price for call options. To estimate implied volatility, I average across options that have the same underlying asset, type (call/put), and days to expiration, and fall in the same moneyness buckets defined in the subsequent sections. The sample period for the empirical analysis in this paper spans from January 2018 to June 2023, as implied volatility data is only available up to June 2023.

3.3 Key Variables

ETF Flow. I measure ETF inflows and outflows using daily relative changes in shares outstanding. ETF shares are created and redeemed in response to changes in investor demand. When investor demand increases, the market price of the ETF rises above its Net Asset Value (NAV), incentivizing authorized participants to create new shares by exchanging underlying assets for ETF shares. This process continues until the market price aligns with the NAV. Consequently, changes in shares outstanding serve as an indicator of investor interest in the ETF. While in mutual fund literature, fund flow is usually measured by the change in AUM after accounting for fund returns, the unique double-layer liquidity structure of ETF allows for the separation of capital flow from ETF return[11].

$$flow_{k,t} = \frac{Shrout_{k,t} - Shrout_{k,t-1}}{Shrout_{k,t-1}}$$

Option Level Flow-induced Demand Pressure. I construct the option-level flow-induced demand pressure by the following steps. Firstly map flow to buffer ETF k at day t, i.e., $flow_{k,t}$, into specific options mandated in its fund prospectus at time t. To do so, I multiply the flow by the share of options $shares_{idsc,k,t}$ incorporated in the strategy implemented. The option characteristics include underlying asset i, days to expiration d, moneyness bucket s,

[11] One potential caveat of daily ETF flow is that ETFs often report shares outstanding use either "T+1" accounting or "T" accounting, and the reporting standard of a single ETF can change over time with the change records unavailable (Yousefi et al., 2024; Staer, 2017).

and option type (call/put) c. Additionally, $shares_{idsc,k,t}$[12] captures the long or short position of the option. A positive value indicates that the ETF takes a long position in the option, while a negative value implies a short position. Secondly, summing up across K ETF to the option-level flow-induced demand pressure.

$$OptionFlow_{idsc,t} = \sum_{k=1}^{K} flow_{k,t} \times shares_{idsc,k,t}$$

The option strategy of a buffer ETF during an outcome period remains unchanged. However, the $shares_{idsc,k,t}$ changes over time. The change occurs because new ETF inflows(outflows) lead to additional option purchases/write(option settlements) at varying days to expiration d and varying moneyness s than those of the initial option contracts acquired at the beginning of the defined outcome period. These discrepancies arise due to changes in the underlying asset price and the passage of time.

An increase in $OptionFlow_{idsc,t}$ suggests an increased flow-induced demand pressure, and it can be originated from one or more of the following: (1) an increase in ETF inflows directed toward this type of option, (2) a rise in the shares of long positions in the option, or (3) a decrease in the shares of short positions in the option. Regardless of the specific cause, all these scenarios reflect an increase in buying pressure or a decrease in the short-selling pressure for that option type. Conversely, a decrease in $OptionFlow_{idsc,t}$ signals a decline in buying intensity or an increase in short-selling pressure for the option.

3.4 Descriptive Statistics

Table 3 shows the overview of all the option-trading ETFs (423 in total) from January 2018 to June 2024. Throughout this period the average daily option-trading ETF flow is 1.04% and the average yearly return of option-trading ETF is 9.3% with an average yearly expense ratio of 0.8%.

Table 4 lists ETFs with the highest AUM and highest percentage of non-zero daily flows in the buffer and covered call ETF sample. Three covered call ETFs offered by Global X have the highest AUMs among others. Those covered call ETFs track various buy-and-write

[12] As an example, for covered call strategy, the share of at-the-money call option is -1 at t the time of first purchase of this option.

indices such as CBOE Nasdaq-100 BuyWrite V2 Index.

Non-zero daily flow of an ETF is the percentage of the non-zero daily flow, where flow is defined as the daily percentage change in shares outstanding. It is common for the number of shares outstanding of an ETF to remain unchanged on certain days, due to the relatively large minimum size required for creation or redemption units (Ivanov and Lenkey, 2019). Therefore, non-zero daily flow measures the frequency at which an ETF experiences net share creation or redemption activity, capturing the liquidity of the ETF.

4 Empirical Results

4.1 Flow-Induced Demand Pressure and IV

In this section, I examine flow-induced demand pressure and its impact on implied volatility. Since option market makers cannot hedge perfectly due to market frictions and are sensitive to inventory risk (Muravyev, 2016), demand pressure can have effects on option prices and implied volatility (Gârleanu et al., 2009), with increased flow-induced buying demand pressure elevates the option price and leads to a higher implied volatility.

To test the relationship between flow-induced demand pressure and implied volatility, I estimate the following pooled regression:

$$IV_{idsc,t} = \alpha + \beta \times OptionFlow_{idsc,t} + X + FE_t + FE_i + FE_d + FE_s + FE_c + \varepsilon_{idsc,t} \quad (1)$$

Where $IV_{idsc,t}$ denotes the average implied volatility of options written on the underlying asset i, observed at time t, where the options belong to days to expiration bucket d, the moneyness bucket s, and are of type c. $OptionFlow_{idsc,t}$ is the flow-induced demand pressure to the corresponding option at time t. I include fixed effect on all the option characteristics and time. X denotes a set of control variables including $ret_{i,t}$, the return of the underlying asset i at time t; $shrout_{i,t}$, the number of shares outstanding for asset i at time t; and $lagIV_{idsc,t-7}$, the average implied volatility of the option over the preceding seven days.

Table 5 reports the results of the pooled regression on flow-induced demand pressure. Column (1) - (3) present the specifications with all fixed effects. Column (4) - (8) show results with subsets of fixed effects. Positive coefficients on flow-induced demand pressure suggest that buying demand pressure originating from ETFs leads to increase in option prices and implied volatility, in line with theoretical expectations.

Flow-induced demand pressure is plausibly influenced by the return of the underlying asset, as investors tend to adjust their holdings of ETFs in response to changes in the underlying asset's performance. I find that the return of the underlying asset is statistically significantly and negatively correlated with implied volatility. Specifically, when controlling for the average implied volatility over the preceding seven days, the estimated coefficient on the asset return is -0.005. In addition, prior literature identifies the liquidity of the underlying asset as an important determinant of implied volatility (Cetin et al., 2006). However, in the present analysis, the effect of liquidity is not found to be statistically significant. Furthermore, the empirical results confirm the well-documented persistence of implied volatility, as reflected in statistically significant coefficients close to 0.97.

In column (3), the coefficient is not statistically significant including all the fixed effects. In column (4) - (8), several coefficients remain statistically significant at the 5% or 10% levels, depending on the specific combination of fixed effects applied. A one-standard-deviation increase in flow-induced demand pressure to option leads to a 0.00002 standard deviation increase in the implied volatility.

The pooled regression has two potential concerns. Firstly, past implied volatility contains predictive information on future implied volatility, making it difficult to isolate the impact of demand pressure without sharp identification. Therefore, in Section 5, I exploit the mechanical roll over trades as exogenous shocks to better identify and quantify the impact.

Secondly, the pooled regression shows the average effect of flow-induced demand pressure across option contracts with heterogeneous characteristics, such as varying moneyness and days to expiration. While the implied volatility of certain contracts may exhibit greater sensitivity to demand pressure, the average effect can potentially be masked by less sensitive contracts. The granularity of the dataset, however, enables a more detailed examination of these heterogeneous effects across different types of option contracts as shown in the Section 4.2.

4.2 Heterogeneous Impact on IV

The previous section documents the aggregate impact of flow-induced demand pressure on implied volatility. In this section, I investigate how demand pressure has heterogeneous effect on implied volatility of option with varying characteristics, including days to expiration, moneyness and underlying asset.

One source of the heterogeneity comes from option vega. Option vega measures the sensitivity of an option's price to changes in the implied volatility. It is a function of option contract parameters, such as days to expiration, moneyness, underlying asset prices and volatility level, see Figure 4. Options with longer maturity and those are near the money exhibit higher vega compared to those with shorter maturities or those are deep in- or out-of-the-money holding other parameters fixed.

Holding the underlying asset fixed, a given change in the option price resulting from demand pressure is expected to lead to a larger impact on the implied volatility of options with lower vega. Consequently, the strongest effects in implied volatility are expected to be observed in options with shorter maturities or those that are deep in- or out-of-the-money.

To examine the heterogeneous impact of demand pressure on options with varying characteristics, I conduct group regressions based on days to expiration, moneyness, underlying asset, and option type (call or put). I begin by focusing on heterogeneity across moneyness.

$$IV_{idsc,t} = \alpha + \sum_{s=1}^{S} \beta_s \, OptionFlow_{idsc,t} \mathbb{1}\{Moneyness_{idsc,t} = s\} + X + FE + \varepsilon_{idsc,t} \tag{2}$$

Where $Moneyness_{idsc,t}$ represents the moneyness bucket of the option. I include all fixed effects except for moneyness, the characteristic of interest in the specification, and I denote them as FE for simplicity. All other notations are consistent with those defined in Equation (1).

Table 6 shows that in-the-money (ITM) options display a stronger estimated effect as their moneyness increases, particularly when the options are further in-the-money and exhibit lower vega. This pattern is consistent with the hypothesis that demand pressure exerts a greater influence on the implied volatility of options with lower sensitivity to volatility changes (i.e., lower vega). The magnitude of this effect is substantial: for ITM options with moneyness between 0% and 10%, the estimated coefficient is 0.0001, whereas for options with moneyness between 50% and 60%, the coefficient increases markedly to 6.46. This contrast highlights the pronounced role of demand pressure in shaping implied volatility when vega is low.

The estimated coefficient for options with moneyness greater than 60% remains at 0.0001. This diminished estimate likely reflects the imprecision introduced by aggregating option flow and implied volatility over such a broad moneyness interval. This result underscores the importance of employing granular defined buckets to accurately identify the impact of demand pressure on implied volatility.

Demand pressure, in general, has a more significant impact on in-the-money (ITM) options than out-of-money (OTM) options. The discrepancy between ITM option and OTM option could be related to the relative trading volume (Bollen and Whaley, 2004), as discussed in Section 4.3. Previous research records the existence of volatility smirk, and relates demand pressure to this phenomenon (Bollen and Whaley, 2004; Xing et al., 2010). In line with this perspective, this paper contributes to the literature by showing that flow-induced demand pressure also plays a role in shaping the asymmetry of the implied volatility surface of options.

A key limitation of the current approach—grouping options based on a single characteristic—is that the resulting groups remain heterogeneous along other relevant dimensions. For instance, options categorized within the 0%–10% ITM moneyness range may still differ significantly in terms of underlying asset (e.g., SPY vs. EEM) and days to expiration (e.g., 10 days vs. 100 days). Therefore, the estimated coefficients could be potentially biased by the composition of options along other characteristics dimensions. To address this issue, I implement a more granular grouped regression by segmenting the sample along multiple dimensions: days to expiration, moneyness, and underlying asset, characteristics are related to the sensitivity of implied volatility to demand shocks. The estimated coefficients from this multidimensional grouped regression are presented in Figure 5.

In Figure 5, the estimated coefficients are plotted against days to maturity (x-axis, left) and moneyness (y-axis, right) in each subplot, where each subplot corresponds to options written on a common underlying asset. Several key observations emerge. First, implied volatility of options that are either deep in-the-money or deep out-of-the-money exhibit heightened sensitivity to demand pressures induced by option ETFs. This is evidenced by the upward tilting surfaces of the estimated coefficients at both extremes of the moneyness dimension. Second, options on QQQ and SPY tend to display lower sensitivities, on average, relative to options on other underlyings. This pattern may be partially attributed to higher liquidity in these markets, a hypothesis further examined in Section 4.3. Finally, along the maturity dimension, the estimated coefficients are negative for near expiry options (those with fewer than 10 days to maturity) that are deeply away from money. This pattern arises because the implied volatility of such options changes substantially as they approach expiration. The average implied volatility of the preceding seven days, used as a control, fails to capture the level of implied volatility as it is highly non-linear and convex near maturity. To alleviate the concern of negative estimates, a further analysis using lag one day implied volatility is shown in Appendix D. For options with longer maturities, the coefficients decrease with time to maturity, consistent with theoretical predictions.

4.3 Liquidity of Option Market

Market makers are required to provide liquidity and accommodate customer order imbalances and thus their position often deviates substantially from the desired level. Therefore, they require compensation for inventory risk (Muravyev, 2016), leading to increase in both option price and implied volatility.

In this section, I assess whether the price effect of demand pressure is amplified in option contracts with lower liquidity. In illiquid markets, market makers face greater difficulty in hedging their exposures (delta, vega, etc.) efficiently and at low cost. As a result, they require greater compensation for assuming these risks, which is reflected in higher option premiums and, consequently, elevated implied volatility.

I employ three measures of option liquidity for each option—average open interest, average option volume, and average bid-ask spread—calculated over the preceding seven-day period. Specifically, I estimate the following specifications:

$$IV_{idsc,t} = \alpha + \beta \times OptionFlow_{idsc,t} \times Liquidity_{idsc,t} + X + FE + \varepsilon_{idsc,t} \tag{3}$$

$$IV_{idsc,t} = \alpha + \beta \times (OptionFlow_{idsc,t}/Vega_{idsc,t}) \times Liquidity_{idsc,t} + X + FE + \varepsilon_{idsc,t} \tag{4}$$

Where $Liquidity_{idsc,t}$ represent for the liquidity proxies for the option contracts. Other notations are consistent with the baseline regression (1). In addition, I also scaled option demand pressure by option vega, $Vega_{idsc,t}$,to account for the potential bias originating from heterogeneous impact across option contracts.

Column (1) -(3) in Table 7 indicate that more liquid option contracts—those characterized by higher open interest and trading volume—exhibit lower sensitivities of implied volatility to demand pressure. This suggests that greater market depth enables market makers to absorb order flow and manage inventory risk more effectively, thereby mitigating the impact of trading activity on option prices. Column (4) - (6) confirm the results is not biased by the heterogeneous impact of demand pressure on implied volatility across varying contracts.

5 Rollover Trade Demand Pressure

In this section, I exploit the mechanical rollover trades as exogenous demand shocks to better identify and quantify the demand pressure impact on implied volatility.

Buffer ETFs, which follow predefined option strategies with minimal managerial discretion, systematically roll over the same type of option contracts upon the expiration of existing positions. These trades mark the beginning of a new outcome period for the ETFs. Demand pressure shocks from rollover trades provide an ideal setting for identifying the price impact for two key reasons. First, demand pressure from rollover trade is less subject to endogeneity than flow-induced demand pressure due to the mechanical nature rollover trades. Second, the volume of rollover trades is typically larger than that of flow-induced trades, enhancing the visibility of their impact.

The rollover trades are typically not executed on a single day; rather, they are generally spread over a few days following the start date of the defined outcome period, although the majority of the trades tend to occur on the first day. I do not record the exact time frame of trading but rather the date of major purchase.

I start by documenting the events that each buffer ETF purchases a specific option contract at time t. The demand pressure from the rollover trade depends on the size of the buffer ETF. Therefore, I multiply the shares outstanding of the ETF at the time of rollover by the shares of the specific option needed for the strategy as a proxy for the rollover demand pressure. Then I aggregate across ETFs to the option level as before:

$$Rollover_{idsc,t} = \sum_{k=1}^{K} Shrout_{k,t} \times Shares_{idsc,k,t}$$

For each rollover event, I compare the implied volatility of the option contract on the day it is purchased by a buffer ETF with the implied volatility of similar option contracts from a control group. The control group comprises contracts that share identical characteristics—specifically, the same underlying asset i, days-to-maturity bucket d, moneyness bucket s, and option type c—but are observed on days sufficiently distant from any ETF purchase activity (i.e., more than five days apart)[13]. The selection methodology for the control group is identical to the approach used in Pastor and Veronesi (2013). To mitigate day-to-day fluctuations in implied volatility, I follow Pastor and Veronesi (2013) and use the average implied volatility of the treated option contracts within a three-day window around day t.

To identify and quantify the impact of rollover trade-induced demand pressure on implied volatility, I estimate the following regression specification:

$$\overline{IV}_{idsc,t,e} = \alpha + \beta Rollover_{idsc,t,e} + FE_i + FE_d + FE_s + FE_c + FE_e + \epsilon_{idsc,t} \tag{5}$$

where $\overline{IV}_{idsc,t,e}$ denotes the average implied volatility of options written on underlying asset i, of option type c, moneyness bucket s, and days-to-maturity bucket d, observed within a three-day window centered on rollover day t, and corresponding to rollover event e. The variable $Rollover_{idsc,t,e}$ captures the demand pressure associated with rollover event e, and is equal to zero for control group where no rollover event takes place. The regression includes rollover event fixed effect FE_e on top of option characteristics fixed effects applied as above. All other notations are consistent with those defined in Equation (1).

Table 8 reports an estimated coefficient of 0.008, which is positive and statistically significant at the 1% level. This result indicates that days on which buffer ETFs engage in rollover buying leads to higher implied volatility in the affected option contracts, relative to days without such transactions. Conversely, rollover selling leads to lower implied volatility. These findings provide evidence that demand pressure from option-trading ETFs exerts a meaningful influence on implied volatility.

[13] Option contracts are defined by characteristics, but not by unique contract identifier. This ensures that fluctuations in implied volatility due to differences in days to expiration and moneyness are properly controlled.

6 Demand Pressure and VIX

In this section, I address whether option-trading ETFs have an impact on the VIX. Media coverage suggests that increasing inflows into covered call ETFs may have contributed to the observed decline in VIX, as these ETFs systematically write call options on the index, thereby exerting persistent selling pressure that dampens implied volatility as reflected in the VIX. Institutional analyses present divergent perspectives on the influence of option-trading ETFs on the VIX. For example, Bank for International Settlements (BIS) associates drop in VIX with proliferation of yield-enhancing structured products, such as covered call ETFs. Conversely, research from the Chicago Board Options Exchange (CBOE) offers a different perspective, arguing that the impact of option income ETFs on the VIX is minimal.

The VIX, or the CBOE Volatility Index, is a widely used measure of the market's expectation of near-term volatility, derived from option prices on the S&P 500 index (SPX). Often referred to as the "fear gauge," the VIX reflects the market's consensus view of future volatility over the next 30 calendar days. It is calculated using a wide range of SPX call and put options with maturities that bracket the 30-day target horizon[14]. I focus on the rollover trades of option-trading ETFs to examine their impact on the VIX, as such trades are more plausibly exogenous. I select the subset of rollover trades that potentially have an impact on VIX: trade on options on S&P 500 index (SPX) with days to maturity between 23 and 37 days to match options used in calculating VIX.

All relevant trades in this analysis originate from covered call ETFs which short at-the-money option contracts, as buffer ETFs typically roll over option contracts with days to expiration aligned with their defined outcome periods, which are significantly longer than one month and therefore fall outside the scope of the VIX calculation.

I run the following regressions to recover the impact on VIX at time t when there is a relevant trade happen:

$$\Delta VIX_t = \alpha + \beta Rollover_{idsc,t} + \overline{\Delta VIX}_{t-7:t-1} + \epsilon_{idsc,t} \tag{6}$$

[14] Specifically, the VIX is constructed using SPX options with days to expiration between 23 and 37 days, and combines information from two adjacent maturities through linear interpolation to produce a constant 30-day measure of implied volatility. The calculation incorporates a broad grid of of both at-the-money (ATM) and out-of-the-money (OTM) options.

Where ΔVIX_t denotes the change in the VIX on day t, defined as the difference between the VIX index level on the day of the option trade and its level on the preceding day, $t-1$. $Rollover_{idsc,t}$ represents the option-level rollover trade intensity at time t, as defined in Equation (5). I control for the average change in the VIX over the preceding seven trading days, $\overline{\Delta VIX}_{t-7:t-1}$. Alternatively, as a robustness analysis, I also consider the average VIX index change over the three preceding days, $\overline{\Delta VIX}_{t-3:t}$, to account for transitory effects and reduce the impact of idiosyncratic daily noise. Furthermore, I examine whether rollover trading activity exerts an effect on the level of the VIX index.

Column (1)-(4) in Table 9 indicates that, for both measures of VIX change, the coefficients are positive, suggesting that the rollover selling activity of covered call ETFs may contribute to a decrease in the VIX. Column (5) shows that the same result holds for the level of VIX index. However, these effects are economically small and statistically insignificant. The set of options used in the VIX calculation represents only a narrow subset of the broader universe of options actively traded by option-trading ETFs. This limited intersection of option contracts reduces the direct influence that the trading activities of option-trading ETFs have on the VIX.

However, while the current impact remains statistically insignificant, the rapid growth in AUM within these funds suggests potential future implications. As the AUM of covered call ETFs continues to expand, the volume of options transactions associated with these funds is likely to increase correspondingly. This escalation in demand pressure could amplify their influence on the options market, potentially leading to more pronounced effects on implied volatility measures such as the VIX.

7 Conclusion

The AUM of option-trading exchange-traded funds (ETFs) have increased significantly in recent years. These funds represent a specialized and rapidly expanding segment of the ETF market, utilizing options—either independently or in conjunction with underlying assets—to pursue specific investment objectives. This paper investigates the strategy compositions of option-trading ETFs and examines the impact of demand pressure originating from these funds on the options market.

This paper demonstrates that demand pressure significantly affects implied volatility, consistent with the hypothesis that flow-induced demand raises option prices and, in turn, implied volatility. To more precisely identify this effect, I use mechanical rollover trades as an exogenous shock. The results reinforce the main finding: demand pressure from option-trading ETF has a significant impact on implied volatility.

The magnitude of this effect varies systematically with option characteristics—particularly moneyness, days to expiration, and the underlying asset—driven by differences in vega. As predicted by theory, the impact is inversely related to vega, with the strongest effects observed in near expiry and deep in- or out-of-the-money options. The analysis also reveals that flow-induced demand pressure has a stronger effect on in-the-money (ITM) options compared to out-of-the-money (OTM) options, highlighting its role in shaping the asymmetry of the implied volatility surface.

Additionally, the paper examines whether demand pressure originating from option-trading ETFs contributes to the suppression of the VIX. The estimated effect is economically small and statistically insignificant. This is likely because the set of options used in the VIX calculation represents only a narrow subset of the broader universe of options actively traded by these ETF. Nonetheless, since this paper confirms that demand pressure affects implied volatility—indicating that market makers cannot perfectly hedge—continued growth in the size and option trading intensity of these "sell volatility" ETFs could potentially lead to more pronounced effects on aggregate measures of volatility, such as the VIX, in the future.

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Table 1: Management Firms of Option-Trading ETFs

This table exhibits the snapshot by fund management firms that offer option-trading ETFs. Column (1) shows the number of option-trading ETFs offered by the firm. The option-trading ETFs is flagged from Morningstar, as described in Section 3.2. Columns (2)–(3) show the number of ETFs and dead funds managed by the firm. Column (4) shows the total number of funds offered by the firm. The data from column (2)-(4) are from Center for Research in Security Prices Database(CRSP).

Firm Name	(1) # Option-Trading ETF	(2) # ETF	(3) # Dead Funds	(4) # All
Innovator	126	139	7	143
First Trust	94	264	33	302
Allianz	38	37	464	606
WisdomTree	30	2	0	3
PGIM Investments	26	46	17	105
Global X	17	152	62	155
PACER FUNDS TRUST	13	51	4	54
The Opportunistic Trader	12	15	1	15
Calamos Investments	8	9	0	13
Kurv	6	7	0	7
BlackRock	5	472	38	560
Neos Funds	4	6	0	6
Invesco	4	372	144	376
ProShares	3	151	7	152
Nationwide Fund Advisors	3	8	276	591
Goldman Sachs	2	45	2	45
Amplify ETFs	2	39	10	39
JP Morgan	2	75	444	1012
KraneShares	2	43	11	43
Roundhill Investments	1	20	5	22
Peerless ETFs	1	1	0	1
REX Shares	1	11	0	14
AdvisorShares	1	54	36	54
State Street Global Advisors	1	141	13	182
PeakShares	1	1	0	1
Swan Capital Management	1	2	0	2
TappAlpha	1	1	0	1
TrueMark Investments LLC	1	1	0	1
Unity Wealth Partners	1	148	69	161
Summit Global Investments	1	5	0	5
Main Management Fund Advisors	1	4	0	4
Nicholas Wealth	1	2	0	2
Natixis Funds	1	6	3	6
Morgan Stanley	1	2	4	44
AllianceBernstein	1	15	18	95
Kensington Asset Management	1	0	0	2
Innovative Portfolios LLC	1	2	2	4
Fidelity Investments	1	65	31	544
Exchange Traded Concepts LLC	1	65	34	65
Defiance	1	24	9	24
Cullen Funds	1	1	0	1
Barclays Capital Inc	1	0	112	122
Aptus Capital Advisors	1	6	0	6
YieldMax ETFs	1	1	0	1
The Opportunistic Trader	1	1	1	1
Total	423	2512	1857	5592

Table 2: Classification of Option-Trading ETFs by Strategy and Underlying Asset

This table categorizes option-trading ETFs based on two key dimensions: (1) the type of underlying asset (index/passive ETF or individual stocks) and (2) the role of options in the fund's portfolio (primary or non-primary). A primary option trade strategy refers to strategies where options constitute a dominant portion of the ETF's portfolio market value, while a non-primary option trade involves using options as a complementary layer for income generation or risk management.

Option Exposure	**Strategy**	**Underlying Asset**
Primary Option Trade	buffer	index or passive ETF
Non-Primary Option Trade	credit spreads	index or passive ETF, individual stock
	barrier	index or passive ETF
	buffer	index or passive ETF
	collar	index or passive ETF
	covered call	index or passive ETF, individual stock
	floor	index or passive ETF
	active layer	index or passive ETF, individual stock

Table 3: Descriptive Statistics of Option Trading ETFs

This table presents the descriptive statistics of option-trading ETFs. Shrout represents the shares outstanding of ETFs in millions. Flow measures the daily percentage change in shares outstanding. AUM refers to assets under management in millions of dollars. Turnover Ratio indicates the trading turnover of ETFs. Expense Ratio is the annualized expense ratio in percentage. Return represents the annualized return of ETFs in percentage. Shrout and Flow are reported at a daily frequency, whereas the other variables are of monthly frequency. The sample period spans from January 2018 to June 2024 and includes all 423 option-trading ETFs.

	N	St. Dev.	Mean	Min	25th	50th	75th	Max
Shrout	195,173	25.312	5.849	0.010	0.620	1.900	4.700	468.330
Flow (%)	195,173	27.861	1.044	−88.235	0.000	0.000	0.000	8,450.000
AUM	9,616	509.345	163.784	0.200	16.000	54.150	142.625	8,302.700
Turonover Ratio	7,936	1.958	0.410	0.000	0.000	0.000	0.060	28.990
Expense Ratio (%)	8,454	0.136	0.796	0.380	0.770	0.790	0.850	1.850
Return (%)	9,427	43.727	9.292	−380.623	−13.304	11.547	31.342	837.863

Table 4: Option Trading ETF with Highest AUM and Highest Non-Zero Daily Flows

This table reports two subsets of buffer and covered call ETF sample: Panel A presents the top 10 ETFs ranked by assets under management (AUM), while Panel B lists the top 10 ETFs with the highest frequency of non-zero daily flows. The first three columns display the ETF name, ticker symbol, and the specific option strategy employed. The Option Ticker refers to the underlying asset on which the ETF writes or trades options. AUM is reported in millions of U.S. dollars. Non-zero Flows represents the proportion of trading days with non-zero changes in shares outstanding, where flow is defined as the daily percentage change in shares outstanding. Average Flows denotes the mean daily flow of the ETF in percentage.

Panel A: Top 10 AUM Option Trading ETFs

ETF Name	ETF Ticker	Strategy	Option Ticker	AUM	Non-Zero Flows	Average Flows
Global X NASDAQ 100 Covered Call ETF	QYLD	covered call	NDX	8209.5	63.17	0.26
Global X S&P 500 Covered Call ETF	XYLD	covered call	SPX	2895.1	26.53	0.26
Global X Russell 2000 Covered Call ETF	RYLD	covered call	RUT	1385.2	39.86	0.54
Innovator US Equity Power Buffer ETF-Jan	PJAN	buffer	SPY	1129.9	37.58	1.04
Innovator US Equity Power Buffer ETF-Apr	PAPR	buffer	SPY	958.9	34.09	2.01
FT Cboe Vest US Equity Buffer ETF-Feb	FFEB	buffer	SPY	853.6	31.23	1.07
FT Cboe Vest US Equity Buffer ETF-Mar	FMAR	buffer	SPY	829.5	34.02	0.76
Innovator US Equity Power Buffer ETF-Dec	PDEC	buffer	SPY	791.1	31.04	1.36
FT Cboe Vest US Equity Buffer ETF-Dec	FDEC	buffer	SPY	789.2	34.28	0.94
FT Cboe Vest US Equity Buffer ETF-May	FMAY	buffer	SPY	776.3	32.17	0.90

Panel B: Top 10 Non-Zero Flows Option Trading ETF

ETF Name	ETF Ticker	Strategy	Option Ticker	AUM	Non-Zero Flows	Average Flows
FT Vest US Equity Max Buffer ETF-June	JUNM	buffer	SPY	42.7	100.00	120.82
FT Vest US Equity Max Buffer ETF-Mar	MARM	buffer	SPY	212.9	64.62	17.30
Global X NASDAQ 100 Covered Call ETF	QYLD	covered call	NDX	8209.5	63.17	0.26
FT Vest Nasdaq-100 Mod Buffr ETF-May	QMMY	buffer	QQQ	104.7	57.14	56.81
Innovator Growth-100 Power Buffer ETF-Jun	NJUN	buffer	QQQ	34.2	50.00	44.44
FT Vest US Equity Enhance & Mod Buffer ETF-May	XMAY	buffer	SPY	41.6	50.00	18.05
Innovator Intl Dev Power Buffer ETF-Jun	IJUN	buffer	EFA	19.3	44.44	22.86
Calamos S&P 500 Struct Alt Prot ETF-May	CPSM	buffer	SPY	117.1	44.19	23.69
AllianzIM US Large Cap 6M Buffer10-Jun/Dec ETF	SIXD	buffer	SPY	168.9	42.11	83.92
Innovator Defined Wealth Shld ETF	BALT	buffer	SPY	624.1	40.29	1.35

Table 5: Flow-Induced Demand Pressure on Implied Volatility: Pooled Regression

This table presents the regression results for the following specifications:

$$IV_{idsc,t} = \alpha + \beta \times OptionFlow_{idsc,t} + X + FE_t + FE_i + FE_d + FE_s + FE_c + \varepsilon_{idsc,t}$$

Where $IV_{idsc,t}$ denotes the average implied volatility of options written on the underlying asset i, observed at time t, where the options belong to days to expiration bucket d, the moneyness bucket s, and are of type c. $OptionFlow_{idsc,t}$ is the flow-induced demand pressure to the corresponding option at time t. I include fixed effect on all the option characteristics and time. X denotes a set of control variables including $ret_{i,t}$, the return of the underlying asset i at time t; $shrout_{i,t}$, the number of shares outstanding for asset i at time t; and $lagIV_{idsc,t-7}$, the average implied volatility of the option over the preceding seven days. The t-statistics are reported in parentheses. Standard errors are clustered at time and underlying asset level. Coefficients reported are scaled by variable standard deviation. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	$IV_{idsc,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$OptionFlow_{idsc,t}$	0.0007	0.0007	0.0001	0.0002*	0.0002**	0.0002**	0.0001	0.0001
	(1.10)	(1.06)	(1.35)	(2.36)	(2.88)	(2.91)	(1.79)	(1.79)
$ret_{i,t}$		-0.006	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
		(-1.60)	(-8.98)	(-8.23)	(-8.62)	(-8.46)	(-9.39)	(-9.39)
$shrout_{i,t}$		0.008	-0.004	-0.003	-0.003	-0.004	-0.002	-0.002
		(0.146)	(-0.471)	(-0.383)	(-0.374)	(-0.519)	(-0.290)	(-0.290)
$lagIV_{idsc,t-7}$			0.988***	0.965***	0.966***	0.967***	0.976***	0.976***
			(117.6)	(141.7)	(138.8)	(143.4)	(119.7)	(119.7)
Fixed-effects								
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underlying Asset	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Moneyness	Yes	Yes	Yes				Yes	Yes
DTE	Yes	Yes	Yes			Yes		
Option Type	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,405,039	1,352,004	1,346,936	1,346,936	1,346,936	1,346,936	1,346,936	1,346,936
R^2	0.525	0.524	0.929	0.928	0.928	0.928	0.928	0.928
Within R^2	0.000	0.000	0.850	0.925	0.924	0.893	0.908	0.908

Table 6: Heterogeneous Impact of Moneyness

This table presents the regression results for the following specifications:

$$IV_{idsc,t} = \alpha + \sum_{s=1}^{S} \beta_s \, OptionFlow_{idsc,t} \mathbb{1}\{Moneyness_{idsc,t} = s\} + X + FE + \varepsilon_{idsc,t}$$

Where $IV_{idsc,t}$ denotes the average implied volatility of options written on the underlying asset i, observed at time t, where the options belong to days to expiration bucket d, the moneyness bucket s, and are of type c. $OptionFlow_{idsc,t}$ is the flow-induced demand pressure to the corresponding option at time t. I include fixed effect on all the option characteristics and time except for moneyness, the characteristic of interest in the specification. X denotes a set of control variables including $ret_{i,t}$, the return of the underlying asset i at time t; and $lagIV_{idsc,t-7}$, the average implied volatility of the option over the preceding seven days. The t-statistics are reported in parentheses. Standard errors are clustered at time and underlying asset level. Coefficients reported are scaled by variable standard deviation. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	$IV_{idsc,t}$ (1)
$OptionFlow_{idsc,t}$ × ITM [0%-10%]	0.0001*
	(2.12)
$OptionFlow_{idsc,t}$ × ITM [10%-20%]	0.0009*
	(2.11)
$OptionFlow_{idsc,t}$ × ITM [20%-30%]	0.010*
	(2.07)
$OptionFlow_{idsc,t}$ × ITM [30%-40%]	0.122
	(1.09)
$OptionFlow_{idsc,t}$ × ITM [40%-50%]	7.13***
	(7.47)
$OptionFlow_{idsc,t}$ × ITM [50%-60%]	6.46***
	(7.20)
$OptionFlow_{idsc,t}$ × ITM [>60%]	0.0001*
	(2.14)
$OptionFlow_{idsc,t}$ × OTM [0%-10%]	0.0004
	(1.77)
$OptionFlow_{idsc,t}$ × OTM [10%-20%]	-0.0004*
	(-2.12)
$OptionFlow_{idsc,t}$ × OTM [20%-30%]	0.0005
	(0.214)
$OptionFlow_{idsc,t}$ × OTM [30%-40%]	-0.0008
	(-0.363)
$OptionFlow_{idsc,t}$ × OTM [40%-50%]	0.037
	(0.371)
$OptionFlow_{idsc,t}$ × OTM [50%-60%]	0.899
	(1.53)
$OptionFlow_{idsc,t}$ × OTM [>60%]	0.174
	(0.106)
$ret_{idsc,t}$	-0.005***
	(-8.47)
$lagIV_{idsc,t-7}$	0.977***
	(128.1)
Fixed-effects	
Time	Yes
Underlying Asset	Yes
DTE	Yes
Option Type	Yes
Fit statistics	
Observations	1,346,936
R^2	0.929
Within R^2	0.893

Table 7: Flow-Induced Demand Pressure on Implied Volatility: Option Liquidity

This table presents the regression results for the following specifications:

$$IV_{idsc,t} = \alpha + \beta \times OptionFlow_{idsc,t} \times Liquidity_{idsc,t} + X + FE + \varepsilon_{idsc,t}$$

$$IV_{idsc,t} = \alpha + \beta \times (OptionFlow_{idsc,t}/Vega_{idsc,t}) \times Liquidity_{idsc,t} + X + FE + \varepsilon_{idsc,t}$$

Where $IV_{idsc,t}$ denotes the average implied volatility of options written on the underlying asset i, observed at time t, where the options belong to days to expiration bucket d, the moneyness bucket s, and are of type c. $OptionFlow_{idsc,t}$ is the flow-induced demand pressure to the corresponding option at time t. $Liquidity_{idsc,t}$ is the liquidity proxy for option contracts, including average option interest, option volume and bid ask spread calculated over the preceding seven-day period. $Vega_{idsc,t}$ is the option vega. I include fixed effect on all the option characteristics and time. X denotes a set of control variables including $ret_{i,t}$, the return of the underlying asset i at time t; $shrout_{i,t}$, the number of shares outstanding for asset i at time t; and $lagIV_{idsc,t-7}$, the average implied volatility of the option over the preceding seven days. $OpenInterest$, $OptionVolume$ and $Spread$ are the average open interest, average option volume, and average bid-ask spread—calculated over the preceding seven-day period. The t-statistics are reported in parentheses. Standard errors are clustered at time and underlying asset level. Coefficients reported are scaled by variable standard deviation. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	$IV_{idsc,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$OptionFlow_{idsc,t} \times OpenInterest$	-0.0001**					
	(-2.97)					
$OptionFlow_{idsc,t} \times OptionVolume$		-0.0002***				
		(-12.9)				
$OptionFlow_{idsc,t} \times Spread$			0.0001			
			(0.29)			
$(OptionFlow/Vega) \times OpenInterest$				-0.0001		
				(-0.19)		
$(OptionFlow/Vega) \times OptionVolume$					-0.001***	
					(-5.7)	
$(OptionFlow/Vega) \times Spread$						0.001
						(1.25)
$OptionFlow_{idsc,t}$	0.0001*	0.0001	0.0001			
	(2.08)	(1.51)	(0.87)			
$OptionFlow_{idsc,t}/Vega_{idsc,t}$				0.0001	0.0001	0.001
				(0.453)	(1.19)	(1.42)
$OpenInterest$	0.002			0.002		
	(1.19)			(1.24)		
$OptionVolume$		0.001*			0.002**	
		(2.17)			(3.51)	
$Spread$			-0.004			-0.006*
			(-1.61)			(-2.04)
$ret_{i,t}$	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(-8.51)	(-8.55)	(-8.51)	(-5.79)	(-5.8)	(-5.82)
$lagIV_{idsc,t-7}$	0.989***	0.988***	0.988***	0.987***	0.987***	0.987***
	(112.9)	(116.9)	(117.3)	(100.2)	(105)	(104.8)
Fixed-effects						
Time	Yes	Yes	Yes	Yes	Yes	Yes
Underlying Asset	Yes	Yes	Yes	Yes	Yes	Yes
Moneyness	Yes	Yes	Yes	Yes	Yes	Yes
DTE	Yes	Yes	Yes	Yes	Yes	Yes
Option Type	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,342,707	1,342,707	1,342,707	1,216,367	1,216,367	1,216,367
R^2	0.929	0.929	0.929	0.930	0.930	0.930
Within R^2	0.850	0.850	0.850	0.862	0.862	0.862

Table 8: Rollover Trade Demand Pressure on Implied Volatility

This table presents the regression results for the following specifications:

$$\overline{IV}_{idsc,t,e} = \alpha + \beta Rollover_{idsc,t,e} + FE_i + FE_d + FE_s + FE_c + FE_e + \epsilon_{idsc,t}$$

where $\overline{IV}_{idsc,t,e}$ denotes the average implied volatility of options written on underlying asset i, of option type c, moneyness bucket s, and days-to-maturity bucket d, observed within a three-day window centered on rollover day t, and corresponding to rollover event e. The variable $Rollover_{idsc,t,e}$ captures the demand pressure associated with rollover event e, and is equal to zero for control group where no rollover event takes place. The regression includes rollover event fixed effect FE_e on top of option characteristics fixed effects. The t-statistics are reported in parentheses. Standard errors are clustered at time and underlying asset level. Coefficients reported are scaled by variable standard deviation. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	$IV_{idsc,t,e}$ (1)	$\overline{IV}_{idsc,t,e}$ (2)
$Rollover_{idsc,t,e}$	0.008***	0.008***
	(4.60)	(5.11)
Fixed-effects		
Event	Yes	Yes
Underlying Asset	Yes	Yes
Moneyness	Yes	Yes
DTE	Yes	Yes
Option Type	Yes	Yes
Fit statistics		
Observations	23,591	23,781
R^2	0.367	0.366
Within R^2	0.000	0.000

Table 9: Rollover Trade Demand Pressure and VIX

This table presents the regression results for the following specifications:

$$\Delta VIX_t = \alpha + \beta Rollover_{idsc,t} + \overline{\Delta VIX}_{t-7:t-1} + \epsilon_{idsc,t}$$

Where ΔVIX_t denotes the change in the VIX on day t, defined as the difference between the VIX index level on the day of the option trade and its level on the preceding day, $t-1$. $Rollover_{idsc,t}$ represents the option-level rollover trade intensity at time t, as defined in Equation (5). I control for the average change in the VIX over the preceding seven trading days, $\overline{\Delta VIX}_{t-7:t-1}$. Alternatively, as a robustness analysis, I also consider the average VIX index change over the three preceding days, $\overline{\Delta VIX}_{t-3:t}$, to account for transitory effects and reduce the impact of idiosyncratic daily noise. In addition, I also consider if rollover trades have an impact on the level of VIX index. The t-statistics are reported in parentheses. Coefficients reported are scaled by variable standard deviation. ***, ** and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

	ΔVIX_t		$\overline{\Delta VIX}_{t-3:t}$		VIX_t
	(1)	(2)	(3)	(4)	(5)
$Rollover_{idsc,t}$	0.014	0.028	0.096	0.120	0.003
	(0.128)	(0.258)	(0.885)	(1.18)	(0.103)
$\overline{\Delta VIX}_{t-7:t-1}$		0.099			
		(0.898)			
$\overline{\Delta VIX}_{t-10:t-4}$				0.371***	
				(3.63)	
$lagIV_{idsc,t-7}$					0.969***
					(36.1)
Fit statistics					
Observations	87	87	87	86	87
R^2	0.000	0.010	0.009	0.146	0.940
Adjusted R^2	-0.012	-0.014	-0.003	0.125	0.939

Figure 1: Number of Option-trading ETFs and aggregate AUM over time

The left panel displays the number of option-trading ETFs over time, and the right panel shows their aggregate assets under management (AUM), expressed in billions of U.S. dollars.

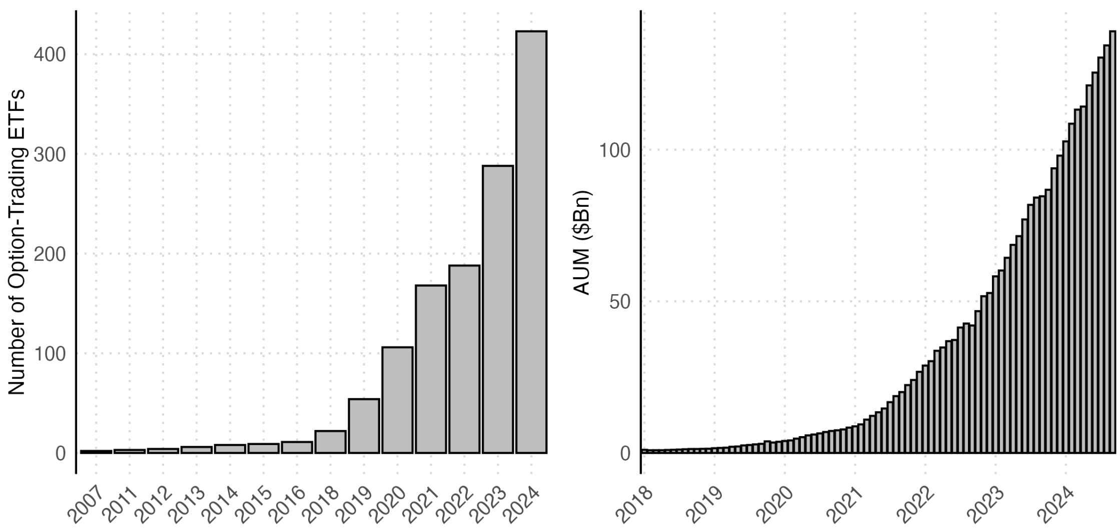


Figure 2: Assets Under Management by Strategy Buckets

The left panel of the figure illustrates the evolution of the number of option-trading ETFs over time, while the right panel presents the aggregate assets under management (AUM) of these ETFs, with both panels disaggregated by strategy category, both panels categorized by strategy bucket. Covered call strategy refers to ETFs that hold a long position in equities—either in a passive ETF or a portfolio of stocks—while simultaneously writing call options on all or part of the same underlying assets. Buffer strategy refers to ETFs that have defined outcomes with partial downside protection and capped upside growth over a specified time frame. Other strategies include credit spread, barrier, collar, floor and other active option layer strategies.

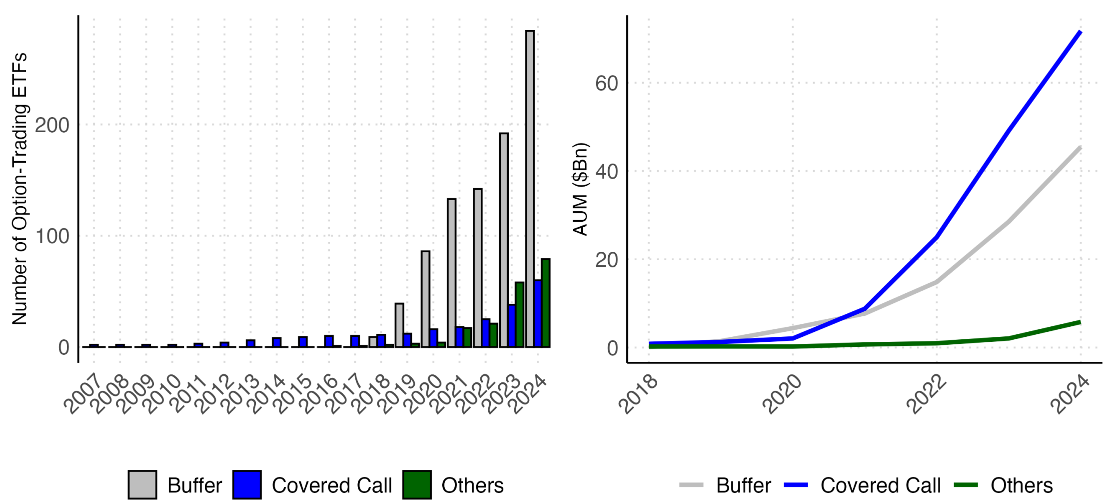


Figure 3: Payoff Profile of Buffer and Covered Call Strategies

This figure illustrates the theoretical payoff profile of buffer strategy and covered call strategy.

Innovator US Equity Power Buffer ETF. The left panel shows the buffer strategy payoff profile of Innovator US Equity Power Buffer ETF against varying underlying price, i.e., SPDR S&P 500 ETF Trust (SPY), at the end of its outcome period. The coral solid line shows the total payoff the option strategy. The black dashed line is the SPY price while other dashed lines indicate the payoff of constituent options. This strategy provides downside protection against the first 15% of losses in the SPY, while gains are capped at 12.03% over the defined outcome period.

Invesco S&P 500 BuyWrite ETF. The right panel shows the covered call strategy payoff profile of Invesco S&P 500 BuyWrite ETF against varying underlying price, i.e., S&P 500 (SPX), at its option maturity date. The coral solid line shows the total payoff the option strategy. The black dashed line is the SPX price while grey dashed lines indicate the payoff of short at-the-money call options.

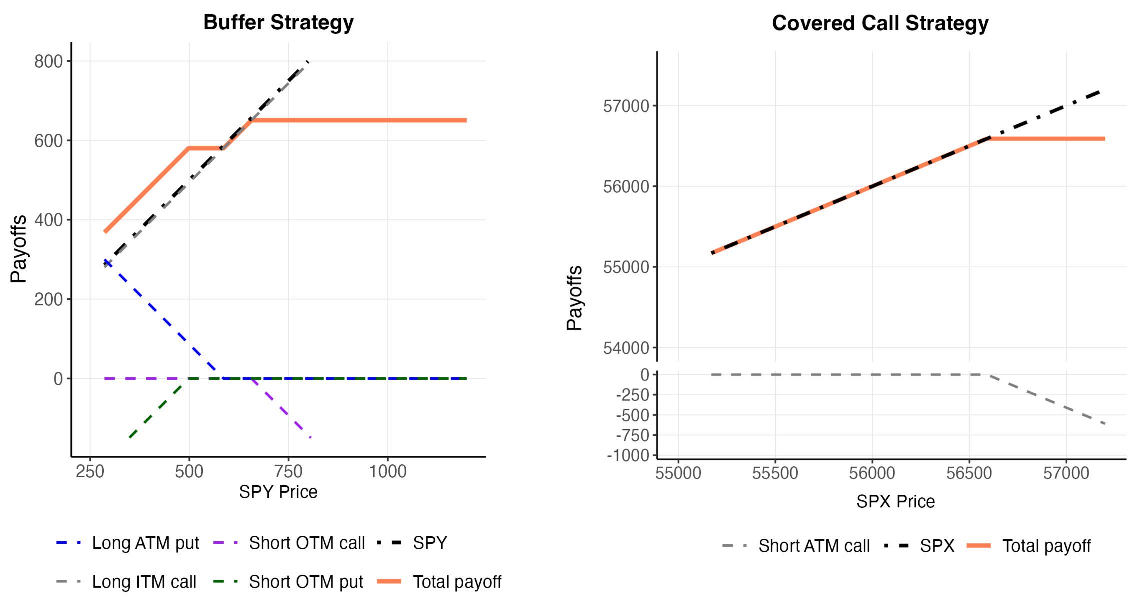


Figure 4: Vega Moneyness and Days to Expiration

This figure shows how option vega vary with moneyness and days to expiration. Generally, at-the-money(ATM) options have higher vega than in-the-money(ITM) or out-of-the-money(OTM) options. Long-dated options have greater vega than near-term options.

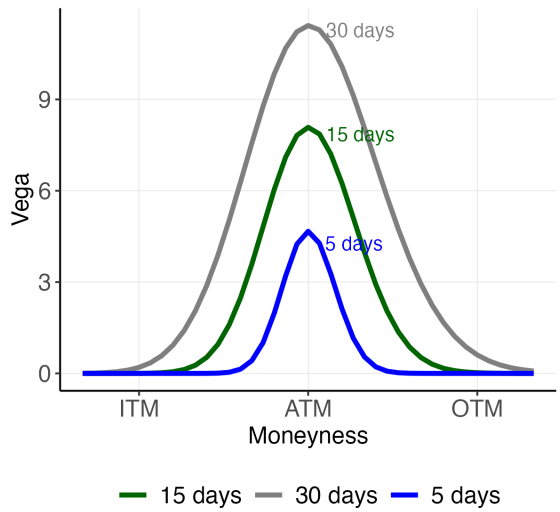
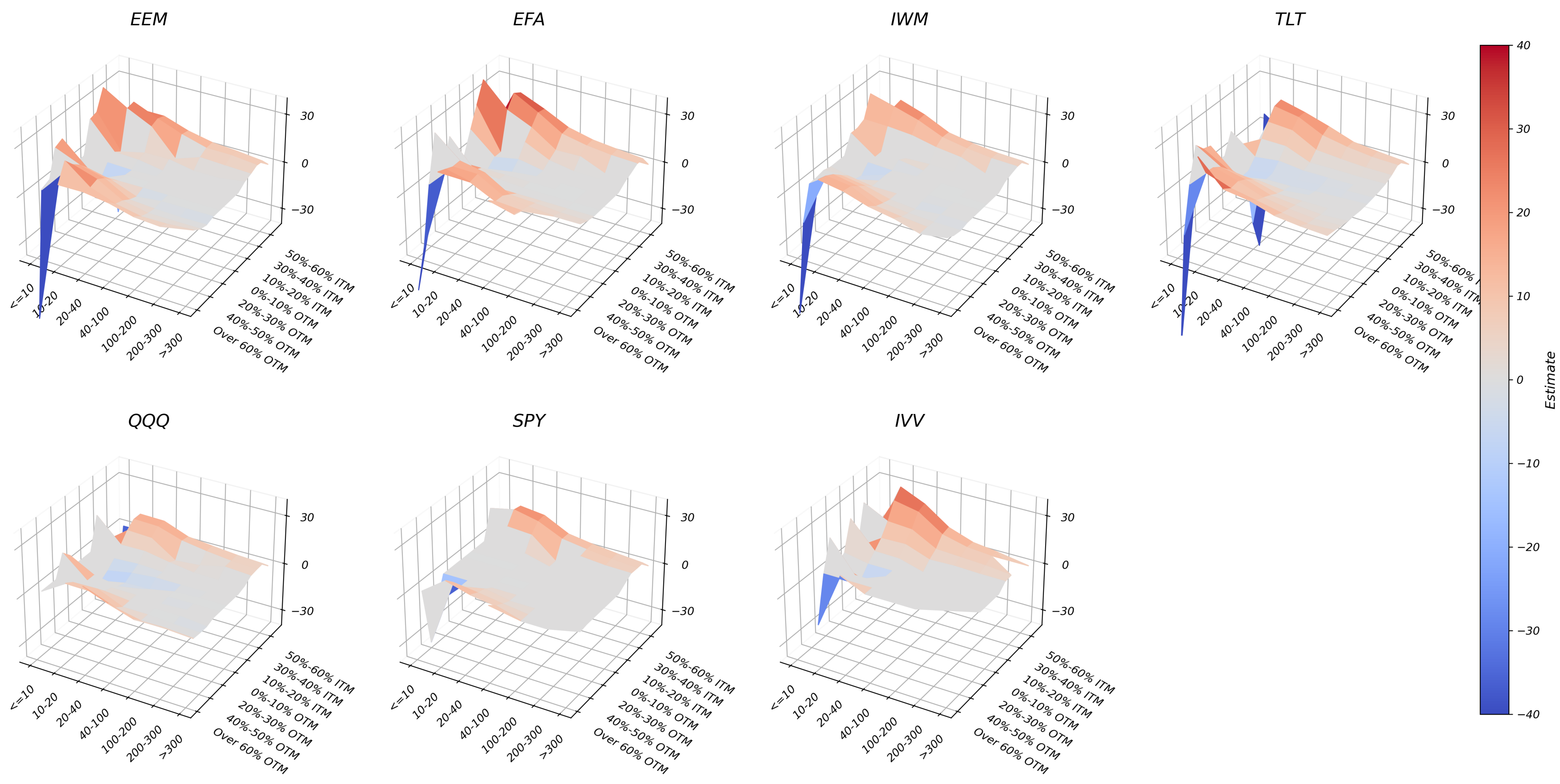


Figure 5: Estimate of Impact across Moneyness and Days to Expiration and Underlying Asset

This plot presents the estimated coefficients from the group regression of $IV_{idsc,t}$ on $OptionFlow_{idsc,t}$, incorporating various combinations of days to expiration, moneyness, and underlying asset groups. Only coefficients that are statistically significant at the 10% level are retained, while insignificant estimates are set to be zero. Coefficients reported are scaled by variable standard deviation. Standard errors are clustered at time and underlying asset level. The x-axis (left) shows the days to expiration grid, while the y-axis (right) shows the moneyness grid . The z-axis (vertical) shows the estimated coefficients. Short-term options exhibit the highest sensitivity to demand pressure, particularly those with fewer than 30 days to expiration. Deep in-the-money (ITM) and deep out-of-the-money (OTM) options generally show greater sensitivity compared to at-the-money (ATM) options.



Appendix A Underlying Passive ETFs

Table 10: Summary of Underlying Passive ETFs Used in Buffer Strategies

The buffer ETFs mainly implement buffer option strategies on several passive ETFs. This table shows the name, ticker, benchmark, market value, and shares outstanding of these passive ETFs. Market value is measured in billion US dollars and shares outstanding is in millions.

Name	Ticker	Benchmark Index	Market Value	Shares Outstanding
SPDR S&P 500 ETF Trust	SPY	S&P 500	430.2	879.1
Invesco QQQ Trust	QQQ	Nasdaq-100	230.5	489.7
iShares Russell 2000 ETF	IWM	Russell 2000	70.4	349.6
iShares MSCI EAFE ETF	EFA	MSCI EAFE	55.1	681.2
iShares MSCI Emerging Markets ETF	EEM	MSCI Emerging Markets	24.3	476.5

Appendix B Buffer ETFs In Detail

The Innovator US equity power buffer ETF January series above is an example of simple buffer ETF, where the payoff feature includes downside buffer and upside cap. While simple buffer ETFs are the most popular subcategory (194 simple buffer ETFs out of 266 buffer ETFs in my sample), there are also other buffer ETFs that provide alternative features other than the basic buffer and caps. Table 11 illustrates the detailed classification of buffer ETFs based on their distinctive payoff features.

Buffer ETFs exhibit a range of payoff features, but their underlying option strategies follow a basic principle: the total cost of the options (and any government bonds, if used) must match the ETF's net asset value at the start of the defined outcome period. This means that beneficial features—such as downside protection—come at a cost, usually in the form of a trade-off like an upside cap. In general, the more protection the ETF provides with its buffer, the lower the cap would be as a consequence of cost of option strategy.

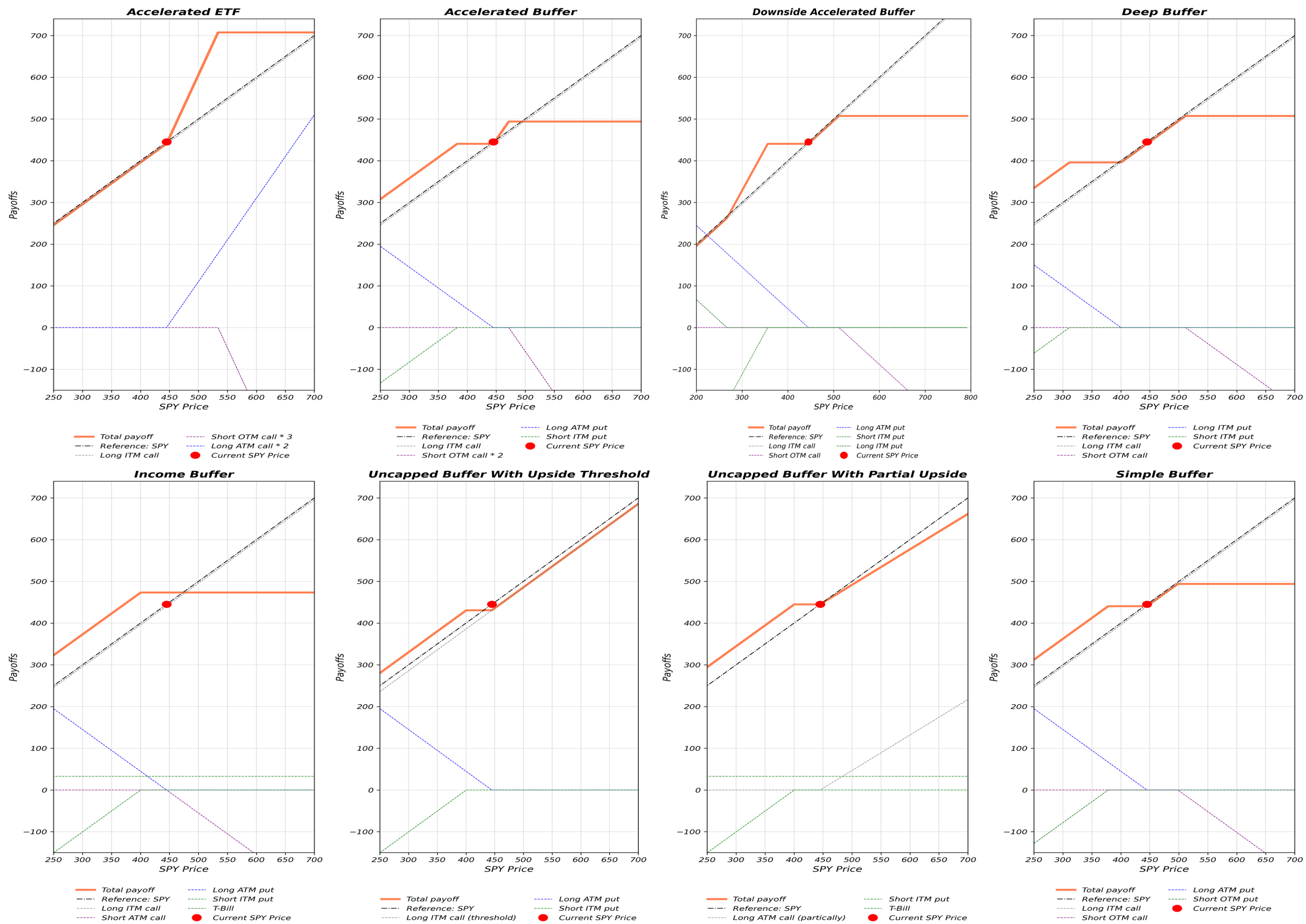
Table 11: Classification of Buffer ETF Categories and Payoff Features

Category	Representative ETF	Main Payoff Feature
Accelerated ETF	Innovator Growth Accelerated Plus ETF – Jan (QTJA)	Leverage on upside return, subject to cap
Accelerated Buffer	FT Vest U.S. Equity Enhanced Moderate Buffer ETF – Apr (XAPR)	Buffer and leveraged upside return until cap
Downside Accelerated Buffer	Pacer Swan SOS Flex (April) ETF (PSFM)	Buffer, upside cap, and leveraged downside below threshold
Deep Buffer	FT Vest U.S. Equity Deep Buffer ETF – Feb (DFEB)	Deep buffer and capped upside
Income Buffer	FT Vest U.S. Equity Buffer Premium Income ETF – Dec (XIDE)	Buffer with defined income generation
Uncapped Buffer with Upside Threshold	AllianzIM U.S. Equity Buffer 15 Uncapped Dec ETF (DECU)	Buffer with full upside beyond a threshold
Uncapped Buffer with Partial Upside	TrueShares Structured Outcome January ETF (JANZ)	Buffer with partial participation in upside return
Simple Buffer	FT Vest Emerging Markets Buffer ETF – Dec (TDEC)	Downside buffer and upside cap

Figure 6 presents illustrative payoff profiles for all categories of Buffer ETFs. While the combined payoff can theoretically be replicated through various combinations of constituent instruments, the daily holdings disclosures of the ETFs provide empirical confirmation of the implemented option strategy. This is critical, as a clear understanding of the strategy enables precise identification of the specific options purchased or sold by the Buffer ETFs.

Figure 6: Illustrative Payoff of Buffer ETFs

This figure displays the hypothetical payoff profiles of eight Buffer ETF categories. Each panel represents the combined payoff and individual instrument payoff of a buffer ETF. The horizontal axis corresponds to the price of the underlying asset (e.g., SPY) at the end of the outcome period, while the vertical axis reflects the resulting payoff.



Appendix C Data Construction

I provide a detailed example illustrating how information from the fund prospectus is translated into structural data, $share_{idsc,k,t}$. This variable is subsequently used to decompose the demand pressure exerted by buffer ETFs on specific option contracts.

Innovator U.S. Equity Power Buffer ETF – January Series (PJAN). PJAN is a simple buffer ETF with a predetermined buffer and cap level. According to the fund's prospectus:

> "The pre-determined outcomes sought by the Fund, which include the buffer and cap discussed below ('Outcomes'), are based upon the performance of the share price of the SPDR® S&P 500® ETF Trust (the 'Underlying ETF') **over an approximately one-year period from January 1 through December 31 of each year** (the 'Outcome Period)... The Cap is set on the first day of the Outcome Period and is **12.03%** prior to taking into account any fees or expenses charged to shareholders... The Fund seeks to provide shareholders that hold Shares for the entire Outcome Period with a buffer (the 'Buffer') against the **first 15%** of Underlying ETF losses during the Outcome Period."

From the above, I collect the details of the outcome period, the predetermined buffer and cap levels, as well as any other specified payoff features.

The next step involves backing up the option strategy of the ETF. Table 12 shows the options that replicates the payoff of PJAN in the outcome period from Jan 1st 2025. With the underlying price and predetermined cap/buffer, I am able to back out the strike price of options. The outcome period also defines the maturity of these options, which is set to expire on December 31, 2025. While multiple combinations of option contracts can theoretically replicate the target payoff, I verify the specific strategy employed by the ETF by cross-checking the fund's disclosed option holdings.

Following the procedure outlined above, I am able to infer the value of $share_{idsc,k,t}$ on the first day of each outcome period. Over the course of the outcome period, $share_{idsc,k,t}$ evolves as the moneyness s and days to expiration d of the option change in response to movements

Table 12: Option Strategy for Innovator US Equity Power Buffer ETF January Series

This table shows the option strategy of Innovator US Equity Power Buffer ETF. The option strategy involves four options with different moneyness and strikes prices. Moneyness and Underlying Price are defined at the start of construction of the option strategy, i.e., Jan 1st 2025.

Option	Call/Put	Shares	Moneyness	Underlying Price	Strike Price	Strike/Underlying	Note
1	Call on SPY	1	Deep ITM	586.08	5.86	1%	SPY exposure
2	Call on SPY	-1	OTM	586.08	656.64	112%	Cap
3	Put on SPY	1	ATM	586.08	498.17	85%	Buffer
4	Put on SPY	-1	ITM	586.08	586.08	100%	

in the price of the underlying asset and passage of time, while the strike price and expiry date remains fixed. This allows me to explore the heterogeneous effects of demand pressure on option-implied volatility across different levels of moneyness and days to expiration.

By the above steps, I'm able to back out the $share_{idsc,k,t}$ at each outcome period start day. The $share_{idsc,k,t}$ changes as the moneyness change with the price change of the underlying asset dueing the outcome period (while strike price keeps unchanged). This change allows me to explore heterogeneous impact of demand pressure to option implied volatility with different moneynees.

Appendix D Demand Pressure and Near-expiry option

Implied volatility tends to vary substantially as options approach expiration. Consequently, using the 7-day average implied volatility may fail to accurately capture the prevailing level of implied volatility at the time of trading, potentially introducing bias into the estimation. To mitigate this concern, I restrict the analysis to a subsample of near-expiry options—defined as contracts with fewer than 10 days to maturity—and employ the one-day lagged implied volatility as a control for the prevailing volatility level.

Figure 7 illustrates that, consistent with the baseline results using the 7-day average, demand pressure has a stronger effect on options that are further out-of-the-money relative to those that are near-the-money. However, the estimated coefficients for deep in-the-money and deep out-of-the-money options are generally not statistically significant. This is likely attributable to the heightened volatility dynamics near expiration, which make it inherently difficult to fully control for implied volatility level.

Figure 7: Estimate of Impact for Near Expiry Options

This figure presents the estimated coefficients from the group regression of $IV_{idsc,t}$ on $OptionFlow_{idsc,t}$ for the near-expiry options, along with 10% confidence intervals. Coefficients reported are scaled by variable standard deviation. Standard errors are clustered at time and underlying asset level. The x-axis shows the moneyness grid . The y-axis (vertical) shows the estimated coefficients.