Volatility Timing Using ETF Options: Evidence from Hedge Funds*

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Abstract

We find that hedge funds' positions in exchange-traded fund (ETF) options contain volatility information about underlying ETF returns. Greater hedge fund option demand predicts higher variance of ETF returns over the following quarter and on days of macroeconomic news. The predictive power holds for options on equity and non-equity (e.g., fixed income, currency) ETFs. A tracking portfolio of straddles based on funds' straddle positions earns quarterly abnormal returns of 7.95%. Net of fees, funds using ETF straddles deliver lower risk and higher benchmark-adjusted returns than nonusers. We conclude that ETF options are an important venue for market volatility timing strategies.

Keywords: Hedge funds, Exchange-traded funds, Options, Volatility timing
JEL Codes: G11, G12, G23

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1. Introduction

Exchange-traded funds (ETFs) are increasingly popular as investment vehicles. Since the first ETF was introduced in the early 1990s, as of 2022, the ETF industry has $7 trillion in assets under management (AUM) in the United States (U.S.), accounting for about 35% of the volume in U.S. equity markets. ETFs have an even larger footprint in options markets and account for nearly 40% of the daily volume of all options traded.[1] While much of this growth is undoubtedly due to ETFs providing low-cost portfolio diversification, an open question is whether investors also use the ETF marketplace for informed trading. By their very nature, ETFs emphasize the systematic over idiosyncratic factors in asset returns, suggesting that ETFs are a natural vehicle for acting on information about aggregate market fundamentals. However, existing empirical studies conclude that investment professionals use ETFs to manufacture passive indexing strategies and that their trading in ETFs can introduce noise in market prices.[2] These findings neither imply nor are implied by informed trading. In addition, no prior work examines how investors trade on ETFs in the options markets – an important omission because options markets are often the preferred venue for trading on information, particularly volatility information.[3] In this paper, we examine whether investors use the ETF marketplace to trade on market volatility information by studying the ETF options positions of hedge fund managers over the period of 2007–2022.

Our setting is well-suited to study informed trading about market volatility. Hedge fund managers face relatively few disclosure requirements, can earn enormous fees based on fund performance, and can implement diverse trading strategies using derivatives, including options. Such an environment attracts the best and brightest managers and enables us to detect informed trading if it exists. ETF options are also uniquely suited to investors with volatility information. Unlike traders with directional information about underlying asset prices, traders with volatility information can only use non-linear securities such as options. Therefore, ETF options, especially non-directional strategies like straddles, are an obvious vehicle for "volatility timing",

[1] See The Investment Company Institute Factbook (2021), The Options Clearing Corporation, and "ETF Options Break New Records,", 2022, https://www.nyse.com/data-insights/etf-options-break-new-records.

[2] See, e.g., Ben-David et al. (2017); Lettau and Madhavan (2018)

[3] See, e.g., Black and Scholes (1973); Merton (1973); Black (1975); Cox and Rubinstein (1985).

exploiting superior knowledge about the return volatility of several asset markets (e.g., equity, fixed income, commodity, currency). Finally, unlike hedge funds' positions in other derivatives on aggregate market indices such as index options, their positions in ETF options are publicly available via Form 13F filings. Hence, our setting offers a unique opportunity to investigate the volatility trading strategies of hedge fund managers across various markets and asset classes.

We first show that ETF option positions are prominent in hedge funds' portfolios. The nearly $1 trillion in aggregate notional value underlying their positions in ETF options represents more than two-thirds of the market value of their ETF share positions, a much larger fraction than that for funds' positions in individual equity options. ETF options cover many investment categories, including options on SPY (U.S. Large Cap), GLD (Gold), HYG (High Yield Corporate Bond), TLT (Treasury), and IYR (Real Estate). Therefore, our ETF setting provides a novel window into funds' informed trading across several asset markets, not just U.S. equities. In contrast, most studies of 13F filings exclude positions in ETF options and instead focus on the holdings of common shares issued by U.S. firms.[4]

Next, we undertake a comprehensive investigation into volatility timing ability as revealed by hedge funds' holdings of ETF options. We measure the synthetic payoff to a variance swap on the underlying ETF by the log difference between realized variance of ETF returns in quarter $t + 1$, and the model-free implied variance of ETF returns at the end of quarter t. In our sample, the average variance swap payoff is -74%, consistent with a negative variance risk premium documented in prior work. However, we contribute by showing that ETFs associated with greater hedge fund option demand realize greater (i.e, less negative) variance swap payoffs over the following quarter even after controlling for a number of other variables. For example, an increase in the percentage of hedge funds holdings a straddle on an ETF from 0% to 100% predicts a higher variance swap payoff of 45%. In sum, when hedge funds report holding ETF options, variance tends to increase.

Does the volatility information in hedge funds' option positions translate into profitable trading strategies in the options market? To address this question, we use option price data to

[4]One exception is Aragon et al. (2019b) who show that hedge funds use put options on equity ETFs to hedge equity market risk while buying equities sold in distressed by other investors.

construct hold-to-maturity straddle returns for each ETF in our sample.[5] We find that greater hedge fund demand for options on ETFs, especially straddle positions, predicts greater straddle returns. Specifically, we regress quarter t+1 straddle return for ETF i ($r_{i,t+1}^{straddle}$) on hedge fund demand for straddles on ETF i in quarter t ($STRA_{i,t}$). The coefficient is positive and significant (t-statistic = 2.76). Furthermore, we construct a tracking portfolio that is long ETF straddles with positive hedge fund straddle demand and short ETF straddles with zero hedge fund straddle demand. The long-minus-short portfolio earns quarterly alpha of 7.95% (t-statistic = 2.40) after adjusting for the Fama-French 5 factors augmented with momentum, liquidity, and option-based factors. We conclude that the volatility information contained in hedge funds' ETF options positions has significant economic value.

We further show that hedge fund option demand predicts realized variance on days with macroeconomic news, including days with Federal Open Market Committee statements and releases of key employment and inflation data. This suggests that hedge funds are successful at forecasting important new information that generates large movements in ETF prices. In addition, the predictive power is present in both equity and non-equity ETFs such as those tracking the U.S. Treasury and currency markets. This aligns with earlier studies indicating that macroeconomic news is associated with substantial price volatility in these markets.[6]

We also examine whether the informed nature of hedge funds' ETF option holdings benefits their investors. We divide the hedge fund sample into those that report holding at least one ETF straddle during the quarter (ETF Straddle Users) and those that do not (Non-Straddle Users). We then compute monthly portfolio returns for each group as the equal-weighted average of net returns of funds in the portfolio. We find that ETF Straddle Users deliver higher after-fee returns, lower return volatility, and a higher Sharpe ratio as compared to Non-Straddle Users. Moreover, ETF Straddle Users earn an annualized alpha of 4.56% (t-statistic = 2.72). Taken together, hedge fund managers use ETF options to profit from volatility information and share these rents with investors in the form of after-fee performance.

A natural question is which type of trader is on the other side of hedge funds' informed purchases of ETF options and, therefore, writing ETF options ahead of unexpected increases in

[5]See, e.g., Goyal and Saretto (2009); Heston et al. (2021)

[6]See, e.g., Cutler et al. (1988), Jones et al. (1998), Balduzzi et al. (2001), and Evans and Lyons (2008).

ETF price volatility. While short positions are not reported in Form 13F filings, we shed light on this question using data from the Commodities and Futures Trading Commission (CFTC). Specifically, we collect the aggregate long and short positions of large traders in the VIX futures markets – a venue for traders to capitalize on volatility information about the aggregate U.S. stock market. We find that the net long (i.e., long minus short) position of Levered Funds is a positive and significant predictor of VIX futures payoffs. Since the Levered Funds category includes hedge funds, this evidence supports our earlier conclusions that hedge funds are informed traders with regards to market volatility. In contrast, the net long position of Asset Managers (e.g., mutual funds) actually predicts lower VIX futures payoffs. This suggests that mutual funds are often on the opposite side of hedge funds' informed volatility bets, consistent with existing evidence that option usage by mutual funds is associated with either no performance advantages or underperformance relative to nonusers (Cici and Palacios (2015)).

We contribute to a growing literature on how ETFs impact the informativeness of market prices. For example, Ben-David et al. (2018) find that short-term liquidity traders in ETF markets can move the prices of underlying stocks away from their fundamental values.[7] In contrast, other studies show that ETFs can enhance price efficiency by allowing investors to efficiently hedge market risk and/or incorporate industry and sector-related information into underlying stock prices.[8] We show that an important group of informed traders – hedge funds – use ETF options to trade on volatility information about market fundamentals. This suggests that ETF option prices convey important information about market volatility.

We also contribute to existing work on how institutional investors use ETFs and other derivatives as investment vehicles.[9] For example, Sun and Teo (2022) find that hedge funds do not use ETF shares for informed trading, but that the presence of ETF positions in hedge fund portfolios is symptomatic of agency problems.[10] As we show, a very different picture emerges for ETF options positions in that they strongly predict the volatility of ETF prices.

[7] See, also, Israeli et al. (2017) and Da and Shive (2018). Ben-David et al. (2023) find that ETF sponsors potentially exacerbate overvaluation in underlying stock markets by catering to investors' extrapolative beliefs.

[8] See, e.g., Antoniou et al. (2023), Huang et al. (2021), Glosten et al. (2021), Ernst (2020), and Bhojraj et al. (2020).

[9] See, e.g., Koski and Pontiff (1999); Deli and Varma (2002); Chen (2011); Aragon et al. (2019a); Kaniel and Wang (2020).

[10] See, also, Cumming and Monteiro (2022) and Joenväärä and Salehi (2018).

This makes sense because options markets are often a preferred venue for informed traders. We also build on the findings of Aragon and Martin (2012) that hedge funds' holdings of individual equity options predict the volatility of underlying equity returns.[11] We use data on ETF option positions and show that hedge funds are also informed about systematic volatility across several asset markets, especially on days with macroeconomic news releases. Hence, the volatility information of informed traders extends beyond the idiosyncratic volatility of U.S. stock fundamentals.

There is mixed evidence of volatility timing for mutual funds. Busse (1999) finds that mutual funds are successful at reducing their portfolio exposure to the market before market volatility subsequently increases.[12] More recently, however, Ferson and Mo (2016) find that mutual funds engage in adverse volatility timing behavior – increasing market exposure when market volatility is high – due to adverse incentives. We find evidence of successful volatility timing among hedge funds – an industry where fund managers are free to use derivatives and where managers' performance-based compensation and personal capital investment help align their incentives with those of investors.

Finally, our study is related to prior work examining the economic benefits from volatility timing across asset markets and over time. For example, Fleming et al. (2001) find that volatility timing can generate significant economic benefits and note that "because volatility timing requires active trading, hedge funds are a likely source for further empirical evidence (p. 351)."[13] Indeed, we show that hedge funds actively use ETF options to capitalize on market volatility information and generate significant investment gains for fund investors.

2. Sample and Variables

In this section, we detail the data sources utilized in our empirical analysis, the classification of hedge fund option positions, the construction of key variables, and the summary statistics of

[11] See, also, Ni et al. (2008) who find that aggregate non-market maker net demand for volatility in the market for individual equity options positively predicts the realized volatility of underlying stocks.

[12] See, also, Chen and Liang (2007) and Cao et al. (2013) for evidence of market return timing and liquidity timing by hedge funds.

[13] See, e.g., Fleming et al. (2001, 2003), Boguth et al. (2011), Ang (2014), Moreira and Muir (2017, 2019), and Cederburg et al. (2020).

our sample.

2.1. Data Sources

2.1.1. ETFs and ETF Options Traded on U.S. Exchanges

We construct the sample of ETFs listed on U.S. exchanges using securities information from CRSP, Morningstar Direct, and ETF Global.[14] We extract information from CRSP for all securities with a share code of 73 and then merge this data with the ETFs available in Morningstar Direct and ETF Global. We exclude actively managed ETFs, leveraged ETFs, and volatility ETFs.[15] We form investment objectives of ETFs based on Region (e.g., North America) and Focus (e.g., Financial Sector) provided by ETF Global database. For example, the investment objectives for SPDR S&P 500 ETF Trust (SPY), iShares iBoxx $ High Yield Corporate Bond ETF (HYD), and SPDR Gold Shares (GLD) are North America/Large Cap, North America/High Yield, and Global/Gold, respectively. The returns of ETFs with the same investment objective are highly correlated due to their focus on the same asset market. Figure 1 shows that the average pairwise correlation of ETFs within the same category is around 0.8, and is rarely below 0.6. For instance, the pairwise correlation of monthly returns between GLD and IAU, two gold ETFs, is nearly one.

Our options data come from OptionMetrics IvyDB US. This database contains a complete historical record of end-of-day data on all U.S. exchange-traded options, including options on ETFs. The data include daily observations of the option's symbol, closing bid and ask quotes, volume, and open interest. It also includes the high, low, and closing prices for the underlying equity or index. We use these data to create straddle returns as described in Section

[14] Morningstar Direct and ETF Global are leading providers of ETF data and have been widely used in academic studies (see, e.g., Ben-David et al. (2017); Shim (2019); Hong et al. (2022)).

[15] There are in total 11 volatility ETFs traded on the U.S. exchanges, including leveraged volatility ETFs and short volatility ETFs (see https://www.etf.com/topics/volatility). The largest one, Simplify Volatility Premium ETF (SVOL), was launched on May 12th 2021 and has an AUM of $603 million as of 2022, which is below the median AUM of $1,003 million in our ETF sample. The second largest one, ProShares Short VIX Short-Term Futures ETF (SVXY), was launched on October 3rd 2011 and has an AUM of $339 million as of 2022. We also find that hedge fund advisors rarely trade volatility ETFs according to their 13F filings. For example, during the 2011-2022 period, we only observe Stadion Money Management LLC held calls on SVXY in 2014Q1 and Boothbay Fund Management LLC held puts on SVXY in 2016Q3. Therefore, volatility ETFs are unlikely to be significant investment vehicles for hedge funds due to their limited number and relatively small AUMs, which can lead to lower liquidity.

2.4. We merge our sample of ETFs with the underlying securities of exchange-traded options in OptionMetrics.

Trading in ETF options surged in the mid-2000s. For example, the total trading volume for ETF options in 2007 was approximately 0.6 billion contracts and half of the trading volume for equity options. In 2014, the trading volume for ETF options reached about 1.5 billion contracts and have since maintained a comparable trading volume to equity options.[16] Additionally, hedge fund managers have been actively using ETF options since 2007, as disclosed in their 13F filings (see Section 2.5). Therefore, our empirical analysis focuses on the period from 2007 onward.

In total, we identify 978 optionable ETFs traded on U.S. exchanges from 2007 to 2022. Our ETF universe offers broad regional coverage, encompassing North America, Asia-Pacific, Europe, Emerging Markets, and Developed Markets. In terms of asset class coverage, the majority of ETFs are specialized in equity markets (819). The remaining ETFs are distributed across various asset classes, including commodities (19), currencies (11), fixed income (119), multi-assets (19), and real estate (30).

2.1.2. 13F Fillings and Portfolio Holdings of Institutional Investors

Instituted in 1978, Section 13(f) of the Exchange Act of 1934 mandates that all institutional investors, including hedge fund investment advisors, managing accounts with 13(f) security assets exceeding $100 million must make quarterly public disclosures of their portfolio holdings via Form 13F within 45 days following the end of each quarter. Furthermore, institutional investors report aggregated holdings across all individual funds managed under the same management company.

The required disclosures cover a range of securities, including exchange-traded stocks, ETFs, equity options, warrants, convertible bonds, and shares of closed-end investment companies. Reporting is mandatory for all long positions exceeding either ten thousand shares or a market value of $200,000. Short positions are not required to be disclosed. Form 13F filings

[16] The Options Clearing Corporation (OCC) provides monthly summaries of all equity and ETF option trading volumes by exchange (https://www.theocc.com/market-data/market-data-reports/volume-and-open-interest/daily-volume).

provide detailed information, including the issuers of the securities, the type of security, CUSIP, and the number and market value of each security held by institutional investors. For option positions, the filings must include whether the option is a call or put, and the CUSIP and dollar amount owned in terms of the underlying securities, rather than the options themselves. Strike prices and maturities of option positions are not required to be disclosed.[17] As we discuss in Section 2.2, we follow Aragon and Martin (2012) and use option positions disclosed in 13F filings to construct various measures of hedge fund option demand.

All 13F filings can be downloaded from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system, but they require considerable processing due to their manual formatting. Our empirical analysis utilizes the 13F institutional holdings data from WhaleWisdom, a commercial database that provides a comprehensive set of reported 13F positions, including stocks, options, and other types of securities. In contrast, other databases frequently used in academic research, such as Thomson Reuters and Factset, primarily focus on the stock holdings of institutional investors.

2.1.3. *Identifying Hedge Fund Investment Advisors in 13F Institutions*

We identify hedge fund investment advisors in 13F institutions using the names of hedge fund companies listed in commercial hedge fund databases: Eurekahedge, Hedge Fund Research (HFR), Morningstar, and Lipper TASS.[18] We manually match these hedge fund companies to the financial institutions reported in WhaleWisdom by firm names.

Some hedge fund investment advisors engage in market making in the options markets, facilitating trading and providing liquidity to other options traders. As our research focuses on whether hedge fund managers use ETF options for informed volatility trading, we concentrate on the end users of options in our paper by excluding the six hedge fund firms identified as option market makers by the Financial Conduct Authority. We also exclude hedge fund investment advisors whose products are primarily funds of funds.[19] Our final sample consists of 615

[17] For further details on the reporting requirements for exchange-traded options on Form 13F, see Aragon and Martin (2012).

[18] We extend our gratitude to Vikas Agarwal for providing the list of hedge fund manager names.

[19] See https://www.fca.org.uk/publication/documents/market-makers-authorised-primary-dealers.pdf. The six firms are Credit Suisse, Evnine & Associates Inc, Gemsstock Ltd., Mitsubishi UFJ Asset Management Ltd., Morgan Stanley, and TD Asset Management Inc. Our qualitative results are unchanged if we do not impose filters

hedge fund advisors from 2007 to 2022.

2.1.4. Hedge Fund Net-of-Fee Performance

For our empirical analyses concerning hedge fund performance, we obtain the net-of-fee monthly returns of hedge funds reporting to Lipper TASS from 2007 to 2022. To mitigate potential survivorship bias, we include both live and defunct funds in our analysis. It is common for funds to report return data before their listing date in the database. Since well-performing funds are more likely to list, for example, after an incubation period, the backfilled returns tend to be higher than the non-backfilled returns. To address this backfill and incubation bias, we follow the approach of Jorion and Schwarz (2019) and retain only the returns after the listing date of each fund in the database. We exclude funds of funds and funds whose returns are not reported in U.S. dollars. Our final sample includes 862 unique hedge funds from 366 hedge fund investment advisors in WhaleWisdom.

2.2. Classification of Hedge Fund Option Positions

We follow Aragon and Martin (2012) and classify ETF option positions into one of four types: directional call, directional put, nondirectional call, and nondirectional put. Specifically, an ETF call position of a hedge fund advisor is directional if the advisor does not simultaneously report a put option position in ETFs of the same investment objective.[20] Similarly, we classify a put option position as directional if the advisor does not simultaneously report a share or call option position in ETFs of the same investment objective. A protective put position is defined as a pair of ETF shares and nondirectional puts on ETFs of the same investment objective. Furthermore, this criterion defines a straddle position as a pair of nondirectional calls and puts on ETFs of the same investment objective. Due to the high correlation of ETFs in the same investment objective, we consider a hedge fund's option positions in ETFs within the investment objective in our classification; a hedge fund holding a call option on GLD and a put

for option market makers and funds of funds.

[20]Our results do not materially change if we expand the set of nondirectional calls to include call positions without any accompanying share or put position. Such positions may constitute long covered call positions, which should be categorized as non-directional.

option on IAU is interpreted as a straddle position on the gold market, rather than two separate directional positions.

2.3. *Realized Volatility, Implied Volatility, and Variance Risk Premium*

The realized variance (RV_{t+1}) is defined as the sum of squared daily returns over the next quarter.[21] We compute the forward-looking model-free implied variance (IV_t) developed in Bakshi et al. (2003). Specifically, IV_t is calculated by applying formula (7) in Theorem 1 of Bakshi et al. (2003) to a collection of out-of-the-money puts and calls on the Volatility Surface of OptionMetrics. For a given day t, IV with τ days to maturity, indicated by $IV(t,\tau)$, is calculated from the following formula,

$$IV(t,\tau) = \frac{2e^{r\tau}}{\tau}\left\{\int_{S_t}^{\infty} \frac{1-\ln(K/S_t)}{K^2} \times C(t,\tau;K)dK + \int_{0}^{S_t} \frac{1-\ln(K/S_t)}{K^2} \times P(t,\tau;K)dK\right\},$$

where K is the strike price, S_t is the current (spot) stock price, r is the risk-free rate, and $C(t,\tau;K)$ ($P(t,\tau;K)$) is the price of a call (put) on day t.[22] We use the data of options with 91-day maturity on the Volatility Surface to compute IV and match the quarterly horizon of portfolio disclosures.

We measure volatility that has not yet been incorporated into option prices using the logarithmic difference between the realized variance of the ETF returns in the quarter t+1, and the implied model-free variance of the ETF returns at the end of the quarter t. We denote this log difference as r_{t+1}^{VS} because it can be interpreted as the log return to a synthetic variance swap (VS) written on the underlying ETF.[23]

We also construct the ex-ante variance risk premium (VRP_t) and include it as a control variable in our regression analysis. VRP_t is defined as the log difference between the expected objective variance ($\mathbb{E}_t(RV_{t+1})$) and the model-free implied variance (IV_t) at the end of each quarter. $\mathbb{E}_t(RV_{t+1})$ is estimated from the Heterogenenous Autoregressive Model (HAR) used to

[21] For robustness, we also use the high-frequency return data from TAQ and measure RV as the sum of the squared overnight and 15-minute intraday returns on trading days within a quarter. The results (not tabulated) are similar to those of our baseline analysis.

[22] We thank Grigory Vilkov for sharing the Python codes to implement interpolation routine and computation of IV in parallel (Vilkov, 2018).

[23] See, e.g., Carr and Wu (2009) and Heston et al. (2022).

predict future realized variance. The model uses the current implied variance and the past one, five, 21, and 63-day realized variances as predictors. Realized variances are computed using an expanding window and high-frequency, 15-minute returns using TAQ data.[24]

2.4. *Straddle Returns*

We construct straddle returns using tradable call and put contracts following the methodologies proposed in the option pricing literature.[25] Straddle returns are based on traded option contracts and, therefore, provide a direct measure of the economic benefits of volatility timing. Our straddle formation starts at the quarter end to match the reporting dates of 13F fillings. Specifically, on the last trading day of each quarter, we select near-the-money call and put options with identical strike prices, set to expire in the third month of the following quarter. For each call-put pair, we require the delta of the call option to be between 0.25 and 0.75, and both open interest and implied volatility to be positive and non-missing. We focus on options where early exercise is rarely optimal by excluding ETFs that pay dividends in excess of 1% of the underlying share price before the option's expiration date. Option prices are determined using the midpoint of the best bid and offer quotes from OptionMetrics. We construct a delta-hedged straddle using each call-put pair, holding it until maturity. This involves maintaining the call and put with weights proportional to $-\Delta_P S_t C_t$ and $\Delta_C S_t P_t$, respectively, where Δ is the option's delta, and C_t and P_t are the bid-ask midpoints of the call and put. These weights are always positive, sum to one, and are typically close to a 50/50 split. The straddle return is calculated as the weighted average of the hold-to-maturity returns on the call and put, based on the split-adjusted price of the underlying stock at expiration.

2.5. *Summary Statistics*

[Insert Table 1 near here]

[24]The method follows Bekaert and Hoerova (2014), Lochstoer and Muir (2022), Bogousslavsky (2021) and Jiang et al. (2021)

[25]See, e.g., Goyal and Saretto (2009) and Heston et al. (2021)).

Panel A of Table 1 shows summary statistics of our sample of hedge fund positions. The total number of positions held in ETF shares is 106,421. The average position size is $9.55 million. The total number of positions held in ETF options is 10,209 (1797+3927+1618+2867) and about 10% of the total number of ETF positions. The total notional value of ETF option positions is nearly one trillion dollars (0.72 trillion) and 71% of the total market value of the ETF share positions.[26]

[Insert Figure 2 near here]

Figure 2 plots the time series of the aggregate positions of hedge funds for options and underlying securities, both for ETFs and individual stocks. Strikingly, the notional value of options on ETFs held relative to the value of ETF shares held in the aggregate hedge fund portfolio is vastly larger than that for individual stocks, in particular during recent periods. This highlights the importance of ETF options in hedge fund investment strategies.

Panel B of Table 1 reports summary statistics of variables in the regressions. In our sample, the average return to going long the synthetic variance swap of an ETF is -74% if we regard the forward cost (i.e., the variance swap rate) as the initial investment. By comparison, Carr and Wu (2009) report a -66% average return for long 30-day synthetic variance swap contracts on the S&P 500 index. The average return of ETF straddles that expire in the third month of the next quarter is -2% in our sample. Likewise, Heston et al. (2021) report a negative average return (-5% per month) for straddles on individual stocks. The negative returns of variance swaps and straddles are consistent with variance buyers willing to accept a negative average excess return to hedge away upward movements in stock market volatility.[27]

[Insert Table 2 near here]

Table 2 provides a list of the ETF options that hedge fund advisors use most frequently. The top-ranked ETF options are SPDR S&P ETF Trust, iShares Russell 2000 ETF, Invesco QQQ Trust, SPDR Gold Shares, and Financial Select Sector SPDR Fund. Besides equities and gold, several othr asset markets are represented in commonly held ETF options, including high-yield

[26]This is from (1797*59.96+3927*87.5+1618*40.28+2867*72.01)/(106421*9.55).

[27]See, e.g., Coval and Shumway (2001), Bakshi and Kapadia (2003) and Eraker and Wu (2017).

bonds (HYG), silver (SLV), and real estate (IYR). Our list also includes many ETFs cited by practitioners as having the most liquid options.[28]

Table 2 also lists the most frequent hedge fund users of ETF options. The top users include Polar Asset Management Partners, Mariner Investment Group, Caxton Associates, and Pine River Capital Management. These managers are known to pursue trading strategies across asset classes and geographies and aim to generate returns independent of market direction.[29]

3. Evidence on Informed Volatility Trading of Hedge Funds

In this section, we examine the volatility timing ability of hedge fund managers based on their holdings of ETF options. We first explore whether hedge funds' demand for ETF options can predict future ETF volatilities and straddle returns. We then investigate whether hedge funds' straddle demand can be used to implement profitable straddle trading strategies in the options market.

3.1. Baseline Results

Our baseline results are derived from the following pooled OLS regressions at the ETF and year-quarter level:

$$r^{VS}_{i,t+1} = b_1 NDIR_{i,t} + b_2 DIR_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1},$$

$$\text{or} \quad r^{VS}_{i,t+1} = b_1 STRA_{i,t} + b_2 PPUT_{i,t} + b_3 BEAR_{i,t} + b_4 BULL_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1},$$

where $r^{VS}_{i,t+1}$ denotes the log return of the synthetic variance swap on ETF i in quarter t+1 (see details in Section 2.3). $NDIR_{i,t}$ represents the non-directional demand for ETF i's options at the end of quarter t, measured by the proportion of hedge fund advisors who hold non-directional

[28] Sumit Roy, "ETFs With The Most Liquid Options," July 22, 2022, https://www.etf.com/sections/features-and-news/etfs-most-liquid-options

[29] According to Prequin, the strategy descriptions include "...seeks a low volatility/low beta profile such that the dominant source of returns is not dependent upon market direction..." (Polar), "...a wide range of diversified mandates..." (Mariner), "...trades across asset classes including fixed income, currencies, commodities and equities, and geographic regions..." (Caxton), and "...focuses on relative value trading across a wide range of markets, regions, and asset classes..." (Pine River).

options positions in ETF i among all hedge fund advisors holding shares or options in ETF i, and $DIR_{i,t}$ is similarly defined for directional options demand.We further decompose the non-directional options demands into straddle ($STRA$) and protective put ($PPUT$), and the directional options demands into directional put ($BEAR$) and directional call ($BULL$). $\mathbf{X}_{i,t}$ represents the vector of control variables, including hedge fund demand for ETF shares, the log of market capitalization, the log of share trading volume, the ratio of option trading volume to share trading volume, the lagged one-month ETF return, the cumulative ETF return over the past 1 to 12 months, and the ex-ante variance risk premium (VRP). Since VRP can contribute to the variance swap payoff, we include VRP as a control variable to ensure that the coefficients on hedge fund option demands effectively capture informed trading about future volatility shocks.[30] All specifications include fixed effects for the ETF investment objective and year-quarter. Standard errors are clustered by year-quarter.

[Insert Table 3 near here]

Table 3 reports the regression results. Columns (1) to (3) show that the coefficients of $NDIR$ and DIR are both positive and significant. Specifically, the coefficient of $NDIR$ in column (3) is 0.389 (t-statistic = 3.31), indicating that the log return of the variance swap increases by 38.9% when the proportion of hedge funds holding non-directional ETF options increases from 0% to 100%. This evidence supports our hypothesis that hedge fund managers are informed volatility traders because both their nondirectional and directional ETF option demands are positively associated with future unexpected ETF volatilities.

Columns (4) to (6) of Table 3 shows the results for the finer partitions of option demand. The demand for straddle and bull options are positive and significant predictors of future ETF volatilities. For example, the coefficient on $STRA$ is 0.451 (t-statistic of 2.94), indicating that an increase in hedge fund straddle demand from 0% to 100% is associated with an increase of 45.1% in variance swap returns. The coefficient on demand for bear options is also positive and marginally significant. The results suggest that hedge funds' demand for ETF options, especially straddle and bull positions, predicts future unexpected volatility and are consistent

[30] A simple decomposition shows that $r^{VS}_{i,t+1} = VolShock_{i,t+1} + VRP_{i,t}$, in which $VolShock_{i,t}$ represents future volatility shock, $\log(RV_{i,t\to t+1}) - \log(E_t(RV_{i,t\to t+1}))$.

with informed volatility trading by hedge fund managers.

3.2. *Equity VS Non-Equity ETFs*

The ETF landscape is diverse, encompassing various asset classes with actively traded options on U.S. exchanges. Our sample consists of 819 unique equity ETFs, 119 fixed-income ETFs, 19 multi-asset ETFs, 19 commodity ETFs, 11 currency ETFs, and 30 real estate ETFs. While previous research on hedge fund trading has primarily focused on U.S. equity positions reported in Form 13F, our analysis of ETFs provides insights into hedge funds' informed trading activities across a broad spectrum of asset markets, not limited to U.S. equities. Therefore, we examine whether hedge funds' ability to time volatility is restricted to equity markets or extends to other asset classes as well. To explore this question, we replicate the analyses from Section 3.1 for both equity and non-equity ETF subsamples.

[Insert Table 4 near here]

Table 4 presents the results; columns (1) and (2) focus on equity ETFs, while columns (3) and (4) focus on non-equity ETFs. For both equity and non-equity ETFs, the slope coefficients on *NDIR* and *DIR* are positive and significant, indicating that skilled hedge fund managers leverage their volatility information through both equity and non-equity ETF options. We further decompose the hedge fund option demands into four types in columns (2) and (4). The coefficients are positive and significant for straddle and bull option positions for both equity and non-equity ETFs. These findings suggest that ETF options are an essential instrument for hedge fund managers to trade volatility across diverse asset markets, and their ability to time volatility is pervasive across these markets, not just limited to the equity market.

3.3. *Hedge Fund Straddle Demand and ETF Straddle Returns*

We now examine whether the volatility signals derived from hedge fund ETF option holdings can be effectively transformed into profitable trading strategies in the options market. To this end, we evaluate the predictability of hedge fund option demand for future straddle returns.[31] Specifically, we employ the following pooled OLS regressions:

$$r^{Straddle}_{i,t+1} = b_1 NDIR_{i,t} + b_2 DIR_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1},$$
$$\text{or} \quad r^{Straddle}_{i,t+1} = b_1 STRA_{i,t} + b_2 PPUT_{i,t} + b_3 BEAR_{i,t} + b_4 BULL_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1},$$

where $r^{Straddle}_{i,t+1}$ denotes the straddle return of ETF i in quarter t+1 as described in Section 2.4. In addition to the control variables outlined in Table 3, $\mathbf{X}$ also includes the average straddle return over the past year to control for the known momentum in straddle returns (Heston et al. (2021)). All specifications include fixed effects for the ETF investment objective and year-quarter. Standard errors are clustered by year-quarter.

[Insert Table 5 near here]

Column (3) of Table 5 reveals that the coefficient on hedge fund non-directional option demand ($NDIR$) is positive and significant (coef. = 0.347, t-statistic = 1.97) whereas the coefficient on hedge fund directional option demand ($DIR_{i,t}$) is not. Moreover, a finer partitioning of $NDIR$ shows that hedge fund straddle demand ($STRA$) strongly predicts straddle returns. This finding aligns with our priors as the straddle demand variable closely mirrors the option strategy used to generate straddle returns. Specifically, the coefficient on $STRA$ is 0.598 (t-statistic = 2.76), suggesting a 60% increase in returns when the proportion of hedge funds holding straddle positions rises from 0 to 100%. These results support the notion that hedge fund straddle demand harbors valuable information about future straddle returns, consistent with the idea of informed volatility trading by hedge funds.

[Insert Figure 3 near here]

To further illustrate our findings, we examine hedge funds' demand for straddles on three popular ETFs, each representing a distinct asset class. Figure 3 plots hedge fund straddle demand at quarter-end for the Invesco QQQ Trust (ticker: QQQ), the iShares iBoxx $ High Yield

[31] The option pricing literature is broadly divided into two approaches. The first focuses on the difference between realized and implied variances to approximate the returns on variance swaps, while the second examines average returns on option portfolios. The continuous-time equivalence of these approaches has been demonstrated by Britten-Jones and Neuberger (2000), with full empirical reconciliation shown in Heston et al. (2022).

Corporate Bond ETF (ticker: HYG), and the SPDR Gold Trust (ticker: GLD). Additionally, we plot the corresponding straddle returns in the subsequent quarter (i.e., the return plotted at the end of quarter t reflects the straddle return in quarter t+1). As shown in the figure, hedge fund straddle positions are strong predictors of future ETF straddle returns; the correlations between straddle demand and subsequent straddle returns for QQQ, HYG, and GLD are 0.10, 0.30, and 0.28, respectively.

3.4. Portfolios of ETF Straddles

We now examine the profitability of ETF straddle portfolios based on hedge funds' straddle demand. To this end, we create two distinct portfolios of ETF straddles, labeled "HF" and "Other." Specifically, we assign the straddle of ETF i to the HF portfolio if at least one hedge fund advisor holds straddle positions in ETF i (i.e., $STRA$ is greater than zero). Otherwise, it is allocated to the Other portfolio. These straddle portfolios are rebalanced at the end of each quarter, with the return of each portfolio calculated as the equal-weighted average return of its individual straddles.

[Insert Table 6 near here]

Panel A of Table 6 shows summary statistics of the returns on straddle portfolios. The average return to the HF portfolio is 1.46% per quarter; in contrast, the Other portfolio generates an average return of -3.43%. The difference, 4.89% per quarter, corresponds to the average return on an "HF-minus-Other" portfolio that is long the HF portfolio and short the Other portfolio. Its annualized Sharpe ratio is 0.54. Moreover, the positive average return on the HF portfolio contrasts sharply with the negative average return on straddles of individual stocks (Heston et al. (2021)).

Panel B of Table 6 reports the results from time-series regressions of returns of the HF-minus-Other portfolio on various factors, including Fama and French (2015) five factors, momentum factor (r^{UMD}), Pástor and Stambaugh (2003) liquidity factor, and Agarwal and Naik (2004) option-based factors. The HF-minus-Other portfolio earns an alpha of 7.95% per quarter (t-statistic = 2.40) after adjusting for these factors, affirming the significant economic value of the volatility information contained in hedge funds' ETF straddle positions.

[Insert Figure 4 near here]

Figure 4 displays the time series performance of the "HF-minus-Other" straddle portfolio. Panel A illustrates the 5-year moving average returns of the HF-Other ETF straddle portfolio, while Panel B presents the 5-year moving average Sharpe ratios. The hedge fund straddle strategy has consistently delivered strong returns over time, with particularly notable performance in recent years.

The HF-minus-Other straddle portfolio and associated abnormal returns would be investable for a hypothetical copycat investor who can gain access to hedge fund option holdings *immediately* at each quarter-end. In reality, however, such holdings information may not be immediately available to copycat investors given the 45-day window between the quarter-end and when Form 13F filings must be filed with the SEC. We therefore cannot reject semi-strong form market efficiency as outlined by Fama (1970). Nevertheless, our findings indicate that hedge funds possess information about market volatility not yet reflected in options prices.

4. Additional Results

4.1. Do Hedge Funds Anticipate Volatility Related to Macro Announcements?

Previous research indicates that macro-news announcements can generate strong price reactions in financial markets, including stock, bond, and foreign exchange markets, and thus can be an important source of ETF volatility.[32] In this section, we investigate whether hedge funds possess private information about macro-news events that allows them to engage in informed trading of volatility. Specifically, we examine whether hedge fund demand for ETF straddles can predict unexpected volatility on days with scheduled macro news announcements.

We follow Hu et al. (2022) and focus on releases of macroeconomic news that occur on periodic, preannounced dates and are of great importance to the economy and financial markets.

[32] See McQueen and Roley (1993), Andersen et al. (2007), Flannery and Protopapadakis (2002), Anderson et al. (2003).

These releases include Federal Open Market Committee Statements (FOMC), Nonfarm Payroll Employment (NFP), Initial Claims for Unemployment Insurance (INC), the Preliminary Release of the Consumer Sentiment Index (CSI), Consumer Price Index (CPI), the Institute for Supply Management's Manufacturing Index (ISM), Gross Domestic Production (GDP), Industrial Production (IP), and Housing Starts (HST). Our data on macroeconomic news releases cover the period from January 2007 to September 2020.[33]

Table 7 reports the results of the following pooled OLS regression:

$$r_{i,t+1}^{VS,news} = bSTRA_{i,t} + \gamma \mathbf{X}_{i,t} + FEs + \varepsilon_{i,t+1},$$
$$news = Non\text{-}Macro,\ Macro,\ FOMC,\ NFP,\ CSI,\ INC,\ CPI,\ GDP,\ HST,\ IP,\ ISM$$

where $r_{i,t+1}^{VS,news}$ is the log difference between the macro-news driven realized variance $RV_{i,t\to t+1}^{news}$ and the end-of-quarter-t model-free option-implied variance $IV_{i,t}$.[34] $RV_{i,t\to t+1}^{news}$ is the annualized sum of squared daily returns on the day of and one day after the macro announcement in quarter $t+1$. We include the day after the macro announcement to account for potential delayed responses from investors. $r_{i,t+1}^{VS,Macro}$ is the realized variance of daily returns on the day of and one day after all days with macro announcements in quarter $t+1$; $r_{i,t+1}^{VS,Non-Macro}$ is the realized variance of daily returns over all other days in quarter $t+1$.

[Insert Table 7 near here]

The results are presented in Table 7. Column (2) shows that hedge fund straddle demand is a positive and significant predictor of unexpected volatility on days with regularly scheduled announcements of macro news (coeff. = 0.364, t-stat = 2.38). This suggests that hedge fund managers are adept at anticipating surprises in macro news and in discerning which asset classes or sectors are most sensitive to such surprises. Columns (3) through (11) further show that

[33] We thank Yucheng (John) Yang at Chinese University of Hong Kong for sharing data on the release dates of these macro-news announcements.

[34] Ideally, to extract the information of macro announcements from ETF option prices, the implied volatility should be measured right before the announcement day using option contracts expiring one-day after announcements. Alternatively, we can take the difference in the implied volatilities of two option contracts, one expiring right before and the other expiring after macro announcements. However, both methods are difficult to implement due to the lack of short-maturity option contracts during our sample period. Therefore, we still use the implied volatility at the end of the previous quarter.

$STRA$ is a positive and significant predictor of volatility on days with FOMC, NFP, CSI, INC, CPI, and GDP announcements. In contrast, $STRA$ has no predictive power for $r_{i,t+1}^{VS,Non-Macro}$. Overall, our findings establish macro news as one source of information through which hedge funds profit from volatility timing.

4.2. Use of ETF Options and Hedge Fund Performance

We now examine hedge funds' net-of-fees returns to assess whether fund investors gain from the volatility timing abilities of fund managers. Specifically, we compare the net-of-fees returns of hedge fund managers who hold at least one straddle position in the recent quarter (ETF straddle users) with those who do not (non-straddle users). We construct two portfolios of hedge funds: one comprising funds managed by ETF straddle users and the other comprising funds managed by non-straddle users. We rebalance the portfolios every quarter and record the monthly fund returns in the subsequent quarter. The portfolio return is calculated as the equal-weighted average of net-of-fee returns of funds in the portfolio. Our sample consists of TASS hedge funds whose advisors are in our pool of hedge fund advisors.

[Insert Table 8 near here]

Panel A of Table 8 presents summary statistics of the monthly returns of ETF straddle user and non-straddle user portfolios. Straddle users earn a higher monthly return than non-straddle users (0.51% vs. 0.45%) with a lower standard deviation (0.17% vs. 0.24%). The annualized Sharpe ratio of the straddle-user portfolio is larger than that of the non-straddle-user portfolio (1.03 vs. 0.65).

We also calculate the monthly returns of a spread portfolio that is long the portfolio of ETF straddle users and short the portfolio of non-straddle users. We then run time-series regressions of the monthly returns of the spread portfolio against several benchmarks: 1) the Fung and Hsieh (2004) seven risk factors; 2) the portfolios of hedge funds formed by the TASS primary categories: Global Macro (GM), Emerging Market (EM), Long/Short Equity (LS), Equity Market Neutral (EMN), Fixed Income Arbitrage (FIA), Multi-Asset Strategy (MS), and Options Strategy (OS); and 3) the CRSP value-weighted market return in excess of the risk-free rate and Agarwal and Naik (2004) option-based factors. Panel B of Table 8 shows that ETF straddle users significantly outperform non-straddle users. The long-short portfolio generates positive and significant alphas relative to all benchmarks. For example, the alpha estimated from the Fung and Hsieh (2004) seven-factor model is 4.56% per year (= 0.38% × 12), with a t-statistic of 3.29. Panel C repeats the performance evaluation analysis for the ETF straddle portfolio (i.e., the long leg of the spread portfolio) and confirms that ETF straddle users also substantially outperform various hedge fund benchmarks.

Our analysis supports the notion that ETF straddle users earn abnormal returns from informed volatility trading and that fund investors capture these profits. It is also possible that part of the abnormal returns of ETF straddle users may be due to broader investment skills that generate higher abnormal returns through strategies other than option trading. Nevertheless, fund investors achieve greater abnormal net-of-fee returns by investing in funds that use ETF straddles in their portfolios.

4.3. Volatility Trading in VIX Futures

In this section, we analyze aggregate trading data from the VIX futures market. The goal of this study is two-fold. The first is to assess the external validity of our main result. Our main results show that hedge funds are informed volatility traders in the ETF options market. If true, then we should find a similar pattern in other markets related to market volatility, like VIX futures. The second objective concerns market clearing: If hedge funds earn abnormal profits from informed volatility trading, it implies that other traders incur abnormal losses. By analyzing futures market data, we aim to identify which types of traders are on the losing end of volatility trading.

We use the weekly Commitment of Traders (COT) report issued by the US Commodity Futures Trading Commission (CFTC). The CFTC requires all reportable traders to report their current open futures positions each week. The report, updated every Thursday, provides aggregate long and short positions of investors categorized into five groups: Levered Funds (hedge funds), Asset Managers (pension funds, endowments, insurance companies, mutual funds, and institutional portfolio managers), Non-reportable (small investors), Dealers/Intermediaries (large banks and dealers in securities, swaps, and other derivatives), and Other Reportable (traders who primarily use futures to hedge business risk).

We conduct time-series regressions of the form:

$$r_{t+1}^{VIX} = a + bNP_t^{Investor} + \sum_{i=0}^{9} c_i r_{t-i}^{VIX} + \varepsilon_{t+1},$$

where $r_{t+1}^{VIX,Futures}$ is the return on VIX futures in period $t+1$, calculated as the percentage change in the near-maturity futures price.[35] $NP_t^{investor}$ is the net position, defined as $\frac{\text{Long Positions}-\text{Short Positions}}{\text{Open Interest}}$, which captures whether a type of investor is net long or short in aggregate. Observations are sampled weekly (Thursday to Thursday) from 2006 to 2022.

[Insert Table 9 near here]

The results are reported in Table 9. Column (1) shows that the coefficient on $NP^{investor}$ is positive and significant for hedge funds, indicating that larger net positions in VIX futures by hedge funds predict greater returns on VIX futures in the subsequent period. Conversely, Column (2) reveals a negative and significant coefficient on the net positions of asset managers, suggesting that larger long positions in VIX futures by asset managers predict lower returns. Overall, these findings provide further evidence that hedge funds are informed traders about market volatility, as their net positions in VIX futures positively predict VIX returns. This result corroborates the conclusions from our main analysis using hedge funds' holdings of ETF options, and also suggests that relatively uninformed volatility traders tend to be asset managers, given that their net positions negatively predict returns.

4.4. *Does ETF Option Demand Predict ETF Returns?*

Our analyses thus far focus on volatility timing by hedge funds through their use of ETF options. However, it is also interesting to know if hedge fund option positions contain information about the direction of future ETF returns.

[Insert Table 10 near here]

[35] See Aragon et al. (2020) for additional details on calculating VIX futures returns. Other studies of VIX futures include Mencia and Sentana (2013), Eraker and Wu (2017), and Cheng (2019).

To this end, we run pooled OLS regressions of future ETF returns on various hedge fund option demands,

$$
\begin{aligned}
& r^{ETF}_{i,t+1} = b_1 NDIR_{i,t} + b_2 DIR_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1}, \\
\text{or} \quad & r^{ETF}_{i,t+1} = b_1 STRA_{i,t} + b_2 PPUT_{i,t} + b_3 BEAR_{i,t} + b_4 BULL_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1}.
\end{aligned}
$$

Table 10 reports the regression results, in which none of the coefficients on $NDIR$, DIR, $STRA$, $PPUT$, and $BEAR$ are significant. The coefficient on $BULL$ is weakly significant, but indicates the wrong direction of future ETF price movements. We conclude that ETF option demand by hedge funds contains valuable information about future ETF volatility, but not the direction of ETF price movements. This "non-result" is consistent with recent studies finding no evidence of informed trading in ETF shares (Cumming and Monteiro (2022); Sun and Teo (2022)). Instead, our paper demonstrates that hedge funds use ETF options as an effective vehicle for volatility-timing.

4.5. *Does Stock Option Demand Predict Systematic Volatility?*

In this section, we explore the differences between the information revealed in hedge funds' ETF option positions and their stock option positions. Aragon and Martin (2012) discovered that hedge fund stock option positions predict both the direction and volatility of underlying equity returns over the 1999–2006 period. Given that a substantial portion of a stock's volatility is driven by its idiosyncratic component, we examine whether hedge funds use individual stock options primarily to target idiosyncratic stock volatility. If so, this would suggest that stock and ETF options serve distinct roles in hedge fund volatility timing strategies, because ETFs largely capture the systematic movement of asset returns.

We first revisit the main finding of Aragon and Martin (2012) using our sample of optionable stocks during the 2007-2022 period, providing an out-of-sample test of hedge funds' timing of stock volatility. We regress the log return of (synthetic) variance swaps in individual stocks (r^{VS}) on various measures of hedge fund demand for individual stock options, using the same model specifications as those in the ETF volatility timing analysis of Section 3.1. As shown in column (1) of Table 11, the coefficient on $STRA$ is positive and statistically significant, indicating that hedge fund straddle positions on individual stocks have strong predictive power for future stock volatility.

[Insert Table 11 near here]

We then examine the hypothesis that hedge funds use stock options to exploit their superior information about stock idiosyncratic volatility. To this end, we disentangle the systematic and idiosyncratic components of stock volatility using a matched ETF as the common factor driving systematic return volatility. Specifically, we use the *matched* ETF as the common factor driving the systematic component in the returns of a given stock, which allows us to measure the expected variance of the common factor by the ETF's forward-looking risk-neutral variance. A stock is matched to an ETF based on the sector or style classifications of this stock.[36] We define the systematic component of realized variance $RV_{j,t+1}$ of the stock j in the quarter $t+1$ as $\beta_{j,t}^2 \mathrm{RV}_{t+1}^{etf}$, where $\beta_{j,t}$ is estimated from regressions of the daily returns of the stock j on the daily returns of its matched ETF in the quarter t. The systematic component of implied variance of the stock j at the end of quarter t is measured by $\beta_{j,t}^2 \mathrm{IV}_t^{etf}$. The idiosyncratic component of RV (IV) of the stock j is defined as the difference between RV (IV) and its systematic component. r^{VS} can thus be decomposed accordingly into systematic and idiosyncratic components by taking the log difference between the corresponding systematic and idiosyncratic components of both realized and implied variances of individual stocks,

Table 11 presents the estimation results from pooled OLS regressions of the idiosyncratic and systematic components of r^{VS} against various hedge fund option demand in stock options. Columns (2) and (3) report the results for the sector-based decomposition, while columns (4) and (5) report the results for the style-based decomposition. When the dependent variable is the idiosyncratic component of r^{VS}, the coefficients on $STRA$ are positive and significant, as shown in columns (2) and (4). These results confirm that hedge funds use stock options to time the idiosyncratic component of stock volatility. When the dependent variable is the systematic

[36]For sector matching, we choose the 11 GICS-based sectors and use SPDR Sector ETFs as their tradable financial instruments. For style matching, we use the Russell 1000 Value, 1000 Growth, 2000 Value, and 2000 Growth ETFs as the tradable financial instruments for the size and value factors. For example, a financial stock is matched with the SPDR Financial Sector ETF (ticker: XLF), and a large-cap-growth stock is matched with the Russell 1000 Growth ETF (ticker: IWF).

component of r^{VS}, the coefficients on hedge fund straddle demand are not significant, suggesting that hedge funds do not use stock straddle positions to time the systematic component of stock volatility. These findings are in contrast to our main result of Section 3.1 that hedge funds' options positions in ETFs, which are concerned with systematic factors, are informative of future ETF volatilities.

5. Conclusion

By their construction as composite securities, ETFs facilitate trading on systematic movements in different asset classes, industries, and geographic regions. Undoubtedly, for many investors, a key benefit of ETFs is in providing access to diversified portfolios at a relatively low cost. In this paper, we argue that another important use of the ETF marketplace, heretofore understudied, is informed trading about market fundamentals. ETF options, in particular, offer a unique device for informed traders to exploit superior information about return volatility. While the markets for these products have exploded in the last few decades, little remains known about their role in the portfolios of informed investors.

We analyze 15 years of portfolio disclosures of an important group of informed investors – hedge funds – to provide evidence that ETF options are used for informed trading about market volatility. Hedge funds' demand for ETF options strongly predicts greater realized return variance of the underlying ETF. The predictive power is particularly strong for simultaneous holdings of calls and puts (i.e., straddles) and for directional call positions, and is pervasive across both equity and non-equity ETFs. This predictability is not subsumed by forward-looking volatility expectations implied by option prices or an ex-ante variance risk premium, and is not found in hedge funds' demand for individual stock options. This highlights the unique character of ETF option positions in being informative about future systematic volatility.

In terms of economic magnitudes, buying straddles in which hedge funds take straddle positions on ETFs and selling straddles in which hedge funds do not take straddle positions on ETFs delivers a long-short portfolio alpha of 7.95% when held to maturity. We do not claim these are achievable returns for other "copycat" investors because they exclude transaction costs and ignore the average 45-day reporting lag following the end of each quarter. Nevertheless, our analysis of after-fee portfolio returns reveals that, compared to nonusers, users of ETF straddles have lower return standard deviation, higher Sharpe ratios, and higher excess returns relative to a style benchmark. Thus, investors in hedge funds capture significant investment gains from fund managers' volatility timing ability.

Additional evidence shows that hedge funds' demand for ETF options has predictive power for large price movements on days with scheduled releases of macroeconomic news, such as statements of the FOMC. In addition, data from aggregate position data of large traders in the VIX futures markets corroborates our main findings on the informative nature of hedge funds' ETF option holdings, while also shedding light on other traders, like mutual funds, who do not appear to successfully time market volatility.

Overall, we conclude that the ETF option market is a useful tool for investors to exploit information about market volatility. A broader implication of our research is related to price efficiency. In a Kyle (1985)-type framework, the presence of informed traders spurs market makers to adjust price in response to demand. The extent to which informed volatility trading in the ETF option market impacts option prices is a fruitful area for research.

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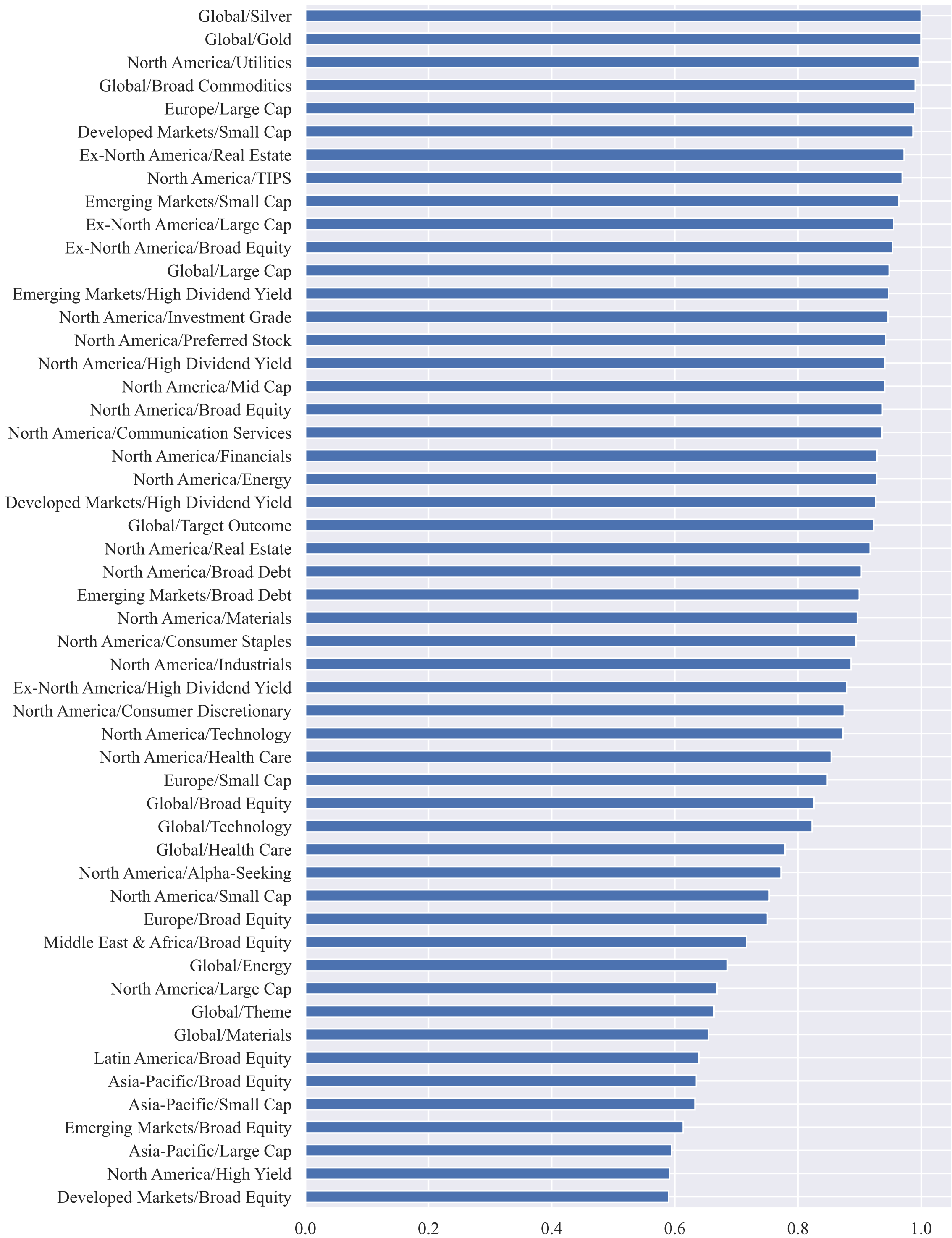

Fig. 1. **Pairwise Correlations of Returns of ETFs with Different Investment Objectives**
This figure plots the average pairwise return correlations of ETFs within the same investment objective, as categorized by the ETFs' investment region and focus provided by ETF Global. ETFs are required to have at least three years of return data to calculate correlations.

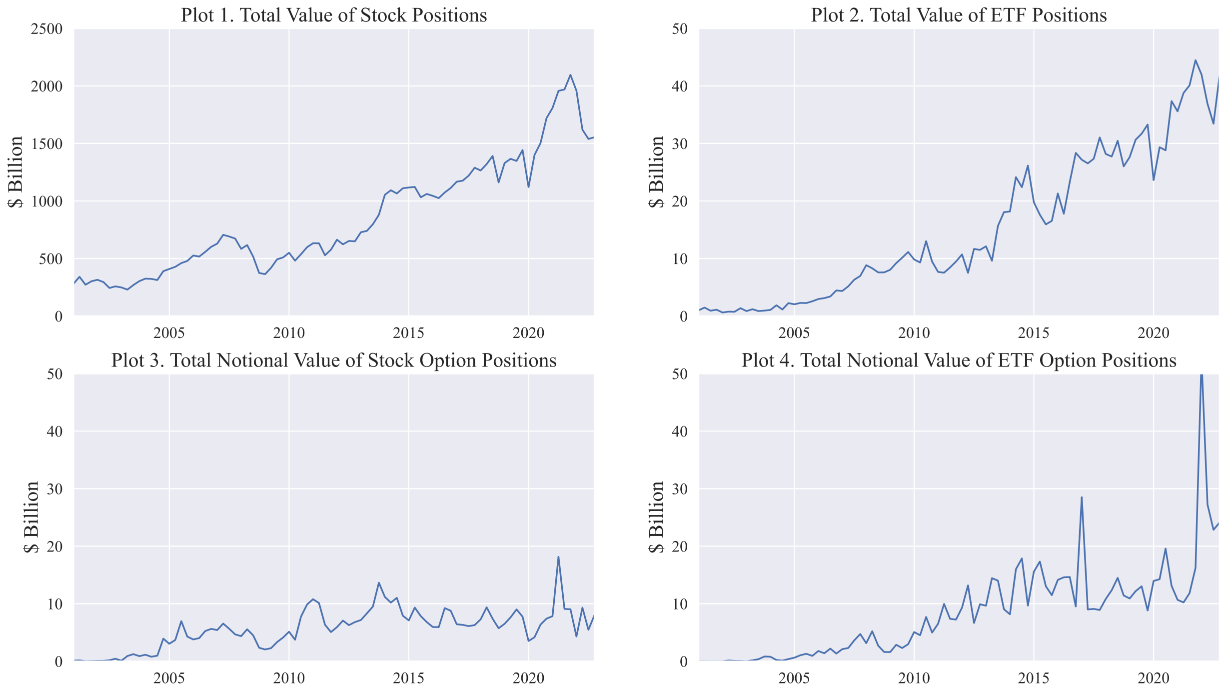

Fig. 2. **Dollar Value of Hedge Fund Positions in Options and Underlying Securities**
This figure presents a time series plot of the aggregate dollar value of hedge funds' holdings in options and underlying securities. Plot 1 and 2 show the total market value of hedge fund positions in stocks and ETFs, respectively. Plot 3 and 4 display the total *notional* value of underlying securities for hedge fund options in stocks and ETFs, respectively.

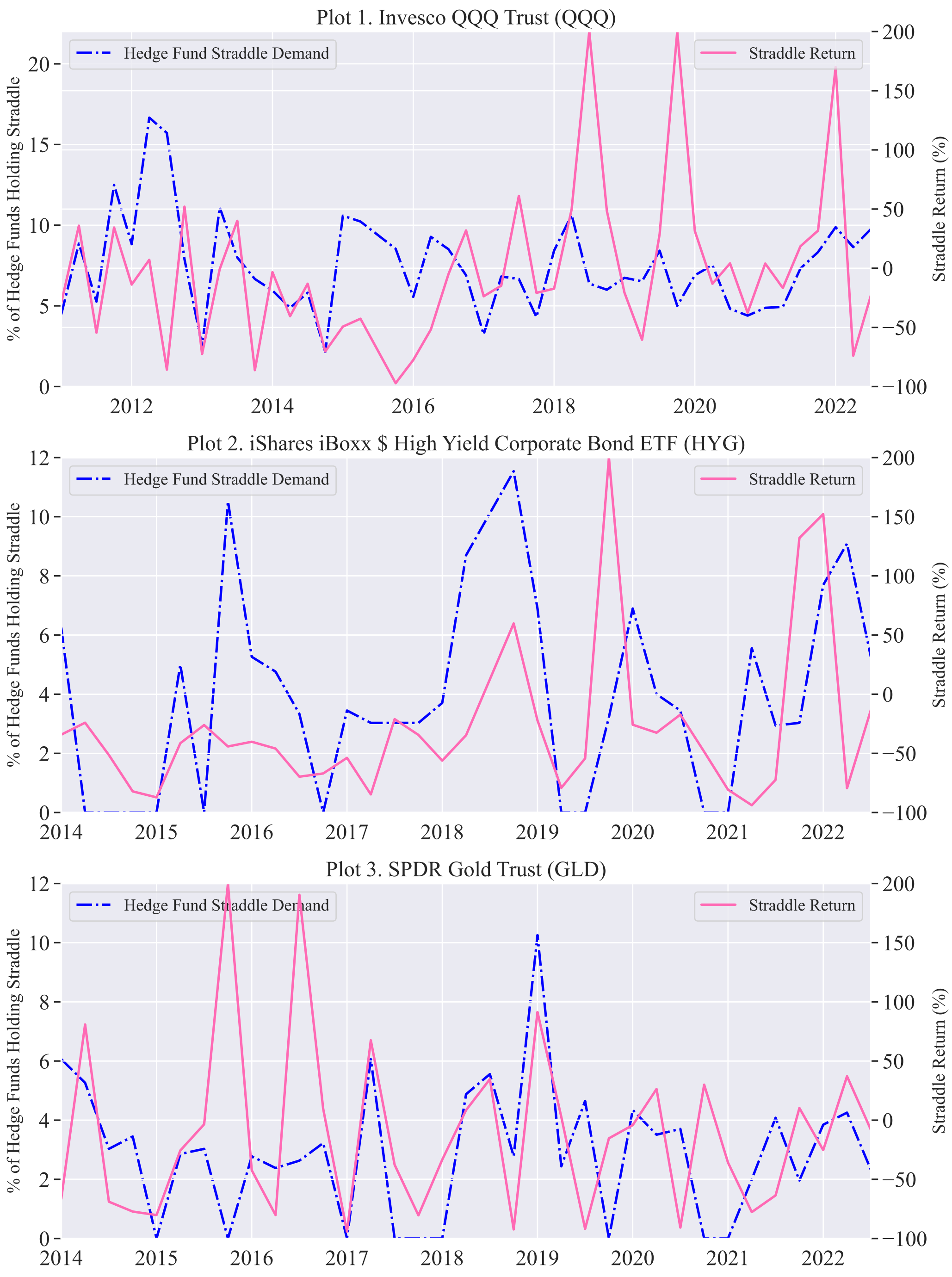

Fig. 3. **Hedge Fund Straddle Demand and Straddle Returns on QQQ, HGY, and GLD**
This figure plots the hedge fund straddle demand on a specific ETF at the end of each quarter, alongside the ETF straddle return over the subsequent quarter. Hedge fund straddle demand is the proportion of ETF straddle users among all hedge funds holding at least one share or option position in an ETF. Straddle returns are constructed following the methodology in the options literature (i.e., Goyal and Saretto, 2009; Heston et al., 2021). Specifically, at the end of each quarter, we select a pair of the near-at-the-money call and put options with a maturity of one quarter, construct a delta-hedged straddle, and hold this straddle to the maturity. We select three popular ETFs: Invesco QQQ Trust (QQQ), iShares iBoxx $ High Yield Corporate Bond ETF (HYG), and SPDR Gold Trust (GLD).

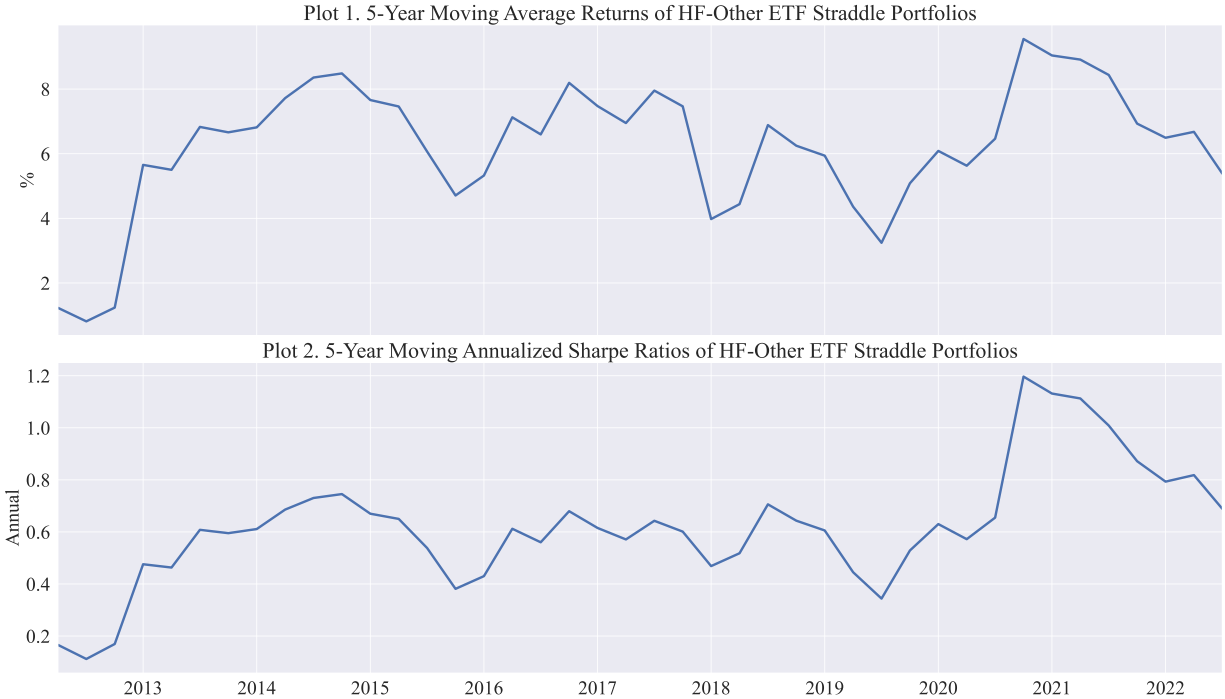

Fig. 4. **Performance of the HF-Other ETF Straddle Portfolio**
Panel A plots the 5-year moving average returns of the HF-Other ETF straddle portfolio, and panel B plots the 5-year moving average Sharpe ratios of the portfolio. The methodology for forming the portfolio is outlined in Table 6.

Table 1: **Summary Statistics**

Panel A reports summary statistics for the dollar value (in millions) of hedge fund positions in ETF options and shares by categories. Our sample consists of quarterly portfolio holdings disclosed by 615 hedge fund advisors in 13F filings from 2007 to 2022. The reported dollar values of the ETF options in 13F fillings are in terms of the underlying ETFs rather than the options themselves. Following the method proposed in Aragon and Martin (2012), we assign hedge fund positions in ETF options to one of the four categories: directional calls, directional puts, non-directional calls, and non-directional puts. Because price movements are highly correlated for ETFs in the same investment objective (i.e., large-cap US equity, investment-grade US corporate bond), our classification is based on the categories of ETF investment objectives. Specifically, an ETF call position of a hedge fund advisor is classified as directional if the advisor does not simultaneously report a put option position in any ETF of the same investment objective. Likewise, we classify a put option position as directional if the advisor does not simultaneously report a share or call option position in any ETF of the same investment objective. This criterion defines a straddle position as a pair of nondirectional call and put options on ETFs that are in the same investment objective. Similarly, a protective put position is defined as a pair of ETF shares and nondirectional puts on ETFs of the same investment objective. Panel B reports summary statistics of variables in the ETF-quarter sample from 2007 to 2022. $r^{VS}_{i,t+1}$ $(= \log(RV_{i,t\to t+1}) - \log(IV_{i,t}))$ denotes ETF i's the log return of a (synthetic) variance swap in quarter $t+1$, in which the realized variance ($RV_{i,t\to t+1}$) is defined as the sum of the squared daily returns in quarter $t+1$, and the model-free implied variance ($IV_{i,t}$) is computed by the risk-neutral variance proposed in Bakshi et al. (2003) using a set of out-of-the-money puts and calls with a maturity of 91 days on OptionMetrics Volatility Surface. The expected objective variance ($\mathbb{E}_t(RV_{i,t\to t+1})$) is estimated from the HAR predictive model of future realized variance on current implied variance and past realized variances of 15-minute returns over various horizons following the estimation procedure in Bekaert and Hoerova (2014). $\log(ME_{i,t})$ is the log of market capitalization, $\log(TV_{i,t})$ is the log of share trading volume, and $O/S_{i,t}$ is the ratio of options trading volume to share trading volume (Johnson and So, 2012). $r^{ETF}_{i,t+1}$ denotes ETF i's return in quarter $t+1$. $R^{ETF}_{i,t\to t-4}$ is the cumulative ETF returns over the past year. $r^{Straddle}_{i,t+1}$ denotes the straddle return of ETF i in quarter $t+1$, which is constructed based on the procedure in Heston et al. (2021). At the end of each quarter, we select a pair of the near-at-the-money call and put contracts that expire in the third month of the following quarter and form a delta-hedged straddle. $R^{Straddle}_{i,t\to t-4}$ is the average straddle returns over the past year.

Panel A. Summary Statistics of Hedge Funds' Positions in ETF Options and Shares

	N	Mean	Std. Dev.	Median	P10	P90
Directional Calls	1797	59.96	224.49	8.72	0.12	119.76
Directional Puts	3927	87.50	416.90	15.85	0.22	180.14
Nondirectional Calls	1618	40.28	203.40	4.91	0.07	99.54
Nondirectional Puts	2867	72.01	385.51	5.10	0.07	136.66
Shares	106421	9.55	38.94	1.18	0.12	17.63

Panel B. Summary Statistics of Variables at the ETF-Quarter Sample

	N	Mean	Median	StdDev	25th PCTL	75th PCTL
$r^{VS}_{i,t+1}$	13,109	-0.74	-0.74	1.00	-1.17	-0.25
$RV_{i,t\to t+1}$	13,109	0.05	0.03	0.09	0.01	0.05
$E_t(RV_{i,t\to t+1})$	13,109	0.04	0.02	0.11	0.01	0.04
$IV_{i,t\to t+1}$	13,109	0.08	0.05	0.12	0.03	0.09
$\log(ME_{i,t})$	13,109	7.82	7.84	1.61	6.71	8.92
$\log(TV_{i,t})$	13,109	17.53	17.40	1.85	16.20	18.80
$O/S_{i,t}$	13,109	0.13	0.01	0.39	0.00	0.07
$r^{ETF}_{i,t+1}$	13,109	-0.00	0.00	0.06	-0.02	0.03
$R^{ETF}_{i,t\to t-4}$	13,109	0.09	0.07	0.22	-0.03	0.19
$r^{Straddle}_{i,t+1}$	3,730	-0.02	-0.22	0.94	-0.62	0.31
$R^{Straddle}_{i,t\to t-4}$	3,730	-0.01	-0.10	0.46	-0.32	0.18

Table 2: **Top ETF Options and Hedge Fund ETF Options Users**

This table reports the top 20 ETFs, ranked by the total number of hedge fund positions in ETF options, and the top 20 hedge fund advisors identified as the most frequent users of ETF options.

Top ETF Options Used by Hedge Funds		*Top Hedge Funds U sing ETF Options*	
Rank	ETFs	Rank	Hedge Fund Advisors
1	SPDR S&P 500 ETF Trust	1	POLAR ASSET MANAGEMENT PARTNERS INC.
2	iShares Russell 2000 ETF	2	CAXTON ASSOCIATES L.P.
3	Invesco QQQ Trust	3	MARINER INVESTMENT GROUP L.L.C.
4	SPDR Gold Shares	4	PINE RIVER CAPITAL MANAGEMENT L.P.
5	Financial Select Sector SPDR Fund	5	JD CAPITAL MANAGEMENT L.L.C.
6	iShares MSCI Emerging Markets ETF	6	KINGDON CAPITAL MANAGEMENT L.L.C.
7	iShares China Large-Cap ETF	7	CTC FUND MANAGEMENT L.L.C.
8	Energy Select Sector SPDR Fund	8	VICIS CAPITAL L.L.C.
9	iShares iBoxx $ High Yield Corporate Bond ETF	9	THREE ZERO THREE CAPITAL.P.ARTNERS L.L.C.
10	iShares MSCI Brazil ETF	10	INDUS CAPITAL.P.ARTNERS L.L.C.
11	Industrial Select Sector SPDR Fund	11	DIALECTIC CAPITAL MANAGEMENT L.P.
12	iShares Silver Trust	12	SCOPIA CAPITAL MANAGEMENT L.P.
13	SPDR S&P Biotech ETF	13	CLOUGH CAPITAL.P.ARTNERS L.P.
14	Utilities Select Sector SPDR Fund	14	BASSWOOD CAPITAL MANAGEMENT L.L.C.
15	SPDR S&P Oil & Gas Exploration & Production ETF	15	TRELLUS MANAGEMENT COMPANY L.L.C.
16	Health Care Select Sector SPDR Fund	16	LUMINUS MANAGEMENT L.L.C.
17	iShares US Real Estate ETF	17	LUMINA FUND MANAGEMENT L.L.C.
18	iShares Biotechnology ETF	18	NOKOMIS CAPITAL L.L.C.
19	SPDR S&P Retail ETF	19	ZIMMER PARTNERS L.P.
20	SPDR S&P Regional Banking ETF	20	ARCHON CAPITAL MANAGEMENT L.L.C.

Table 3: **ETF Volatility Timing with ETF Option Demand of Hedge Funds**

This table presents the regression results of predicting variance swap returns with hedge fund demands in ETF options. Specifically, we estimate the following pooled OLS regressions at the ETF and year-quarter level:

$$r^{VS}_{i,t+1} = b_1 NDIR_{i,t} + b_2 DIR_{i,t} + \gamma \mathbf{X}_{i,t} + \textbf{FEs} + \varepsilon_{i,t+1},$$
$$\text{or} \quad r^{VS}_{i,t+1} = b_1 STRA_{i,t} + b_2 PPUT_{i,t} + b_3 BEAR_{i,t} + b_4 BULL_{i,t} + \gamma \mathbf{X}_{i,t} + \textbf{FEs} + \varepsilon_{i,t+1},$$

where $r^{VS}_{i,t+1}$ denotes the log return of a (synthetic) variance swap on ETF i in quarter $t+1$, calculated as the logarithmic difference between realized variance and model-free option-implied variance. $NDIR_{i,t}$ is the proportion of hedge fund advisors holding a nondirectional option position on ETF i at the end of quarter t, among all hedge fund advisors holding shares or options of ETF i, and $DIR_{i,t}$ is defined similarly for directional option positions on ETF i. We further decompose the nondirectional option position into straddle ($STRA_{i,t}$) and protective put ($PPUT_{i,t}$), and the directional option position into directional put ($BEAR_{i,t}$) and directional call ($BULL_{i,t}$). $STRA_{i,t}$ is the proportion of hedge fund advisors holding a straddle position on ETF i at quarter t among all hedge fund advisors holding shares or options of ETF i. See Table 1 for details on the classification of hedge fund option positions. $\mathbf{X}_{i,t}$ represents a vector of control variables, including hedge fund demand for ETF shares, the log of market capitalization, the log of share trading volume, the ratio of options trading volume to ETF share trading volume, the lagged one-month ETF return, the cumulative ETF returns over the past year, and log variance risk premium, calculated as the logarithmic difference between expected objective variance and implied variance at the end of quarter t. All regression specifications include the ETF investment objective and year-quarter fixed effects. Standard errors are clustered by year-quarter, and associated t-statistics are reported in brackets, where *, **, and *** denote significance at levels 10%, 5%, and 1%. The sample period is from 2007 to 2022.

	$r^{VS}_{i,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$NDIR_{i,t}$	0.388***		0.389***			
	[3.28]		[3.31]			
$DIR_{i,t}$		0.312***	0.313***			
		[4.47]	[4.55]			
$STRA_{i,t}$				0.449***		0.451***
				[2.87]		[2.94]
$PPUT_{i,t}$				0.286		0.291
				[1.40]		[1.43]
$BEAR_{i,t}$					0.164*	0.165*
					[1.93]	[1.96]
$BULL_{i,t}$					0.605***	0.606***
					[5.61]	[5.67]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investment Obj. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	13,109	13,109	13,109	13,109	13,109	13,109
R-squared	0.693	0.693	0.694	0.693	0.694	0.694

Table 4: **Equity VS Non-equity ETFs**

We estimate the regression models in Table 3 separately for equity ETFs and non-equity ETFs. Columns (1) and (2) report the regression results for the subsample of equity ETFs, and columns (3) and (4) present the regression results for the subsample of non-equity ETFs, including fixed-income, commodity, currency, multi-asset, and real estate ETFs. See Table 3 for details on the dependent variable, hedge fund option demands, control variables, and fixed effects in the regressions. Standard errors are clustered by year-quarter, and associated t-statistics are reported in brackets, where *, **, and *** denote significance at levels 10%, 5%, and 1%. The sample period is from 2007 to 2022.

	$r^{VS}_{i,t+1}$			
	Equity ETFs		Non-equity ETFs	
	(1)	(2)	(3)	(4)
$NDIR_{i,t}$	0.321**		0.826**	
	[2.40]		[2.04]	
$DIR_{i,t}$	0.164**		0.309**	
	[2.25]		[2.10]	
$STRA_{i,t}$		0.436**		0.859***
		[2.61]		[2.86]
$PPUT_{i,t}$		0.094		0.789
		[0.37]		[1.16]
$BEAR_{i,t}$		0.065		0.135
		[0.90]		[0.76]
$BULL_{i,t}$		0.446***		0.506**
		[3.38]		[2.48]
Controls	Yes	Yes	Yes	Yes
Investment Obj. FEs	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes
N	10,534	10,534	2,575	2,575
R-squared	0.735	0.735	0.660	0.660

Table 5: **Predicting ETF Straddle Returns with ETF Option Demand of Hedge Funds**

This table shows the predictability of hedge fund straddle demand for future ETF straddle returns. Specifically, we estimate the following pooled OLS regressions at the ETF and year-quarter level:

$$r^{straddle}_{i,t+1} = b_1 NDIR_{i,t} + b_2 DIR_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1},$$
$$\text{or} \quad r^{straddle}_{i,t+1} = b_1 STRA_{i,t} + b_2 PPUT_{i,t} + b_3 BEAR_{i,t} + b_4 BULL_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1},$$

where $r^{Straddle}_{i,t+1}$ denotes ETF i's straddle return in quarter $t+1$. Following the straddle construction procedure in Heston et al. (2021), at the end of each quarter, we select a pair of near-at-the-money OTM call and put contracts that expire in the third month of the next quarter and then hold a delta-hedged straddle formed by this call-put pair to maturity. See Table 3 for details on hedge fund option demands. In addition to the control variables listed in Table 3, we also include the average straddle return over the past year. All regression specifications include the ETF investment objective and year-quarter fixed effects. Standard errors are clustered by year-quarter and associated t-statistics are reported in brackets, where *, **, and *** denote significance at levels 10%, 5%, and 1%. The sample period is from 2007 to 2022.

	$r^{Straddle}_{i,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$NDIR_{i,t}$	0.339**		0.347**			
	[1.98]		[1.97]			
$DIR_{i,t}$		0.043	0.059			
		[0.31]	[0.42]			
$STRA_{i,t}$				0.588***		0.598***
				[2.80]		[2.76]
$PPUT_{i,t}$				-0.039		-0.032
				[-0.15]		[-0.13]
$BEAR_{i,t}$					0.031	0.054
					[0.19]	[0.32]
$BULL_{i,t}$					0.070	0.087
					[0.38]	[0.47]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investment Obj. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,730	3,730	3,730	3,730	3,730	3,730
R-squared	0.529	0.529	0.529	0.529	0.529	0.529

Table 6: **Performance of Hedge Fund Straddle Strategies**

This table examines the profitability of ETF straddle portfolios based on hedge funds' straddle demand. We create two distinct portfolios of ETF straddles, labeled "HF" and "other". Specifically, we assign the straddle of an ETF to the HF portfolio if this straddle is held by at least one hedge fund advisor (i.e., $STRA_{i,t}$ is greater than zero). Otherwise, it is allocated to the Other portfolio. The straddle portfolios are rebalanced at the end of each quarter, and the portfolio return is calculated as the equal-weighted average return of its straddles. Panel A presents summary statistics of returns to the HF and Other straddle portfolios, and panel B presents the time-series regression results of the "HF–Other" portfolio returns against various factors, including Fama and French (2015) five factors (r^{MKT}, r^{SMB}, r^{HML}, r^{RMW}, r^{CMA}), momentum factor (r^{UMD}), Pástor and Stambaugh (2003) liquidity factor (r^{Liq}), and Agarwal and Naik (2004) option-based factors ($r^{Put,ATM}$, $r^{Call,ATM}$, $r^{Put,OTM}$, $r^{Call,OTM}$). The average returns in panel A and the alphas in panel B are quarterly and in percentage points, and the Sharpe ratios in Panel A are annualized. t-statistics (in brackets) are calculated based on the White heteroskedasticity-robust standard errors, where *, **, and *** denote significance at levels 10%, 5%, and 1%. The sample period is from 2007 to 2022.

Panel A. Returns to ETF Straddle Portfolios by Hedge Fund Straddle Demand

Straddle Portfolios	Mean	Std. Dev.	SR (Annual)
HF	1.46	74.15	0.04
Other	-3.43	69.05	-0.10
HF – Other	4.89	18.48	0.54

Panel B. Performance Evaluation of the HF–Other ETF Straddle Strategy

	$r_t^{HF-Other}$		
	(1)	(2)	(3)
α	7.05***	7.48***	7.95**
	[2.59]	[2.75]	[2.40]
r_t^{MKT}	0.02	-0.13	-0.11
	[0.08]	[-0.50]	[-0.39]
r_t^{SMB}	-0.10	-0.36	-0.36
	[-0.20]	[-0.61]	[-0.58]
r_t^{HML}	-0.16	0.01	0.14
	[-0.31]	[0.01]	[0.27]
r_t^{RMW}	-1.94***	-1.93***	-1.88***
	[-3.32]	[-3.21]	[-2.94]
r_t^{CMA}	0.04	0.25	0.18
	[0.06]	[0.28]	[0.19]
r_t^{UMD}		-0.11	-0.12
		[-0.33]	[-0.37]
r_t^{LIQ}		0.45	0.48
		[1.56]	[1.50]
$r_t^{Put,ATM}$			-0.78
			[-1.64]
$r_t^{Call,ATM}$			0.30
			[0.63]
$r_t^{Put,OTM}$			0.67
			[1.44]
$r_t^{Call,OTM}$			-0.41
			[-0.97]

Table 7: **Do Hedge Fund Managers Anticipate Volatility Related to Macro-News?**

This table examines whether hedge fund demand for ETF straddles can predict unexpected volatility on days with scheduled macro news announcements. We estimate the following pooled OLS regression at the ETF and year-quarter level:

$$r_{i,t+1}^{VS,news} = bSTRA_{i,t} + \gamma \mathbf{X}_{i,t} + FEs + \varepsilon_{i,t+1},$$
$$news = \textit{Non-Macro, Macro, FOMC, NFP, CSI, INC, CPI, GDP, HST, IP, ISM}$$

where $r_{i,t+1}^{VS,news}$ is the log difference between the macro-news driven realized variance in quarter $t+1$ ($RV_{i,t\to t+1}^{news}$) and the model-free option-implied variance at the end of quarter t. $RV_{i,t\to t+1}^{news}$ is computed as the (annualized) sum of squared daily returns on the day of a macro-news announcement and the following day in the quarter $t+1$. We focus on the nine releases of macroeconomic news that occur periodically and are important to the economy and financial markets: Federal Open Market Committee Statements (FOMC), Nonfarm Payroll Employment (NFP), Initial Claims for Unemployment Insurance (INC), the Preliminary Release of the Consumer Sentiment Index (CSI), Consumer Price Index (CPI), the Institute for Supply Management's Manufacturing Index (ISM), Gross Domestic Production (GDP), Industrial Production (IP), and Housing Starts (HST). $r_{i,t+1}^{VS,Macro}$ is computed over days (and the following day) with one of the nine macro-news announcements, and $r_{i,t+1}^{VS,Non-Macro}$ is computed over all other trading days. $\mathbf{X}_{i,t}$ includes the control variables listed in Table 3 and measures of other hedge fund option demand. Standard errors are clustered by year-quarter and associated t-statistics are reported in brackets, where *, **, and *** denote significance at levels 10%, 5%, and 1%.

	$r_{i,t+1}^{VS,Non-Macro}$	$r_{i,t+1}^{VS,Macro}$	$r_{i,t+1}^{VS,FOMC}$	$r_{i,t+1}^{VS,NFP}$	$r_{i,t+1}^{VS,CSI}$	$r_{i,t+1}^{VS,INC}$
	(1)	(2)	(3)	(4)	(5)	(6)
$STRA_{i,t}$	0.257	0.364**	0.440**	0.477**	0.453**	0.348**
	[1.52]	[2.38]	[2.05]	[2.57]	[2.50]	[2.13]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investment Obj. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	9,834	9,834	9,834	9,834	9,834	9,834
R-squared	0.691	0.720	0.625	0.625	0.697	0.691

	$r_{i,t+1}^{VS,CPI}$	$r_{i,t+1}^{VS,GDP}$	$r_{i,t+1}^{VS,HST}$	$r_{i,t+1}^{VS,IP}$	$r_{i,t+1}^{VS,ISM}$
	(7)	(8)	(9)	(10)	(11)
$STRA_{i,t}$	0.318*	0.312*	0.275	0.257	0.232
	[1.76]	[1.87]	[1.55]	[1.05]	[1.04]
Controls	Yes	Yes	Yes	Yes	Yes
Investment Obj. FEs	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes
N	9,834	9,834	9,834	9,834	9,834
R-squared	0.673	0.631	0.624	0.630	0.562

Table 8: **Hedge Fund Performance of ETF Straddle Users**

This table compares the net-of-fees performance of hedge fund ETF straddle users and non-straddle users. A hedge fund advisor is classified as an ETF straddle user if it holds at least one ETF straddle in the recent quarter. We construct two portfolios of hedge funds: one consisting of funds managed by ETF straddle users, and the other by non-straddle users. These portfolios are rebalanced quarterly and the monthly returns of the funds are recorded in the following quarter. The return of each portfolio is calculated as the equal-weighted average of the net-of-fees returns of the funds in the portfolio. Panel A presents summary statistics of monthly net-of-fee returns of ETF straddle user and non-straddle user portfolios. Panel B reports the performance evaluation of the ETF straddle-nonstraddle portfolio against various benchmarks: 1) Fung and Hsieh (2004) seven factors; 2) the average hedge fund returns by the TASS primary categories: Global Macro (GM), Emerging Market (EM), Long/Short Equity (LS), Equity Market Neutral (EMN), Fixed Income Arbitrage (FIA), Multi-Asset Strategy (MS), Options Strategy (OS); and 3) the CRSP value-weighted market return in excess of the risk-free rate and Agarwal and Naik (2004) option-based factors. Panel C repeats the performance evaluation for the ETF straddle user portfolio. The average returns in panel A and the alphas in panel B and panel C are monthly and in percentage points, and the Sharpe ratios in panel A are annualized. t-statistics are calculated based on the White heteroskedasticity-robust standard errors, where *, **, and *** denote significance at levels 10%, 5%, and 1%. The sample consists of TASS hedge firms that are in our pool of hedge fund advisors from 2007 to 2022.

Panel A. Summary Statistics of Hedge Fund ETF Straddle Users and Non-Straddle Users

	Mean	Std. Dev.	Sharpe Ratio (Annual)
Straddle User	0.51	0.17	1.03
Non-Straddle User	0.45	0.24	0.65

Panel B. Performance Evaluation of ETF Straddle-Nonstraddle User Portfolio

Panel B.1. Evaluation Against the Fung and Hsieh (2004) Seven Factors

α	β_{S5RF}	β_{R2S5}	β_{T10Y}	β_{CS}	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$
0.38***	-0.26***	-0.17**	-0.05	-0.07	-0.01	0.01	-0.00
[3.29]	[-3.34]	[-2.40]	[-0.61]	[-0.85]	[-1.47]	[1.06]	[-0.34]

Panel B.2. Evaluation Against the TASS Primary Category Returns

α	β_{GM}	β_{EM}	β_{LS}	β_{EMN}	β_{FIA}	β_{MS}	β_{OS}
0.32***	-0.02	0.04	-0.62***	0.22	-0.17	0.02	-0.05
[2.67]	[-0.70]	[0.63]	[-5.15]	[1.39]	[-1.36]	[0.08]	[-1.81]

Panel B.3. Evaluation Against the Market Factor and Agarwal and Naik (2004) Option-Based Factors

α	β_{MKT}	$\beta_{Put,ATM}$	$\beta_{Call,ATM}$	$\beta_{Put,OTM}$	$\beta_{Call,OTM}$
0.29**	-0.16**	0.01	0.00	-0.00	-0.00
[2.00]	[-2.01]	[1.40]	[0.35]	[-0.14]	[-0.32]

Panel C. Performance Evaluation of ETF Straddle User Portfolio

Panel C.1. Evaluation Against the Fung and Hsieh (2004) Seven Factors

α	β_{S5RF}	β_{R2S5}	β_{T10Y}	β_{CS}	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$
0.38***	0.11*	-0.03	-0.12	0.16*	-0.01	0.01	-0.01
[2.72]	[1.73]	[-0.44]	[-1.52]	[1.80]	[-0.95]	[0.77]	[-0.51]

Panel B.2. Evaluation Against the TASS Primary Category Returns

α	β_{GM}	β_{EM}	β_{LS}	β_{EMN}	β_{FIA}	β_{MS}	β_{OS}
0.34***	-0.01	0.13*	0.01	0.25	-0.13	0.15	-0.04
[2.86]	[-0.29]	[1.88]	[0.06]	[1.61]	[-1.05]	[0.75]	[-1.26]

Panel C.3. Evaluation Against the Market Factor and Agarwal and Naik (2004) Option-Based Factors

α	β_{MKT}	$\beta_{Put,ATM}$	$\beta_{Call,ATM}$	$\beta_{Put,OTM}$	$\beta_{Call,OTM}$
0.35***	0.04	-0.00	-0.00	0.00	0.01
[2.52]	[0.58]	[-0.77]	[-0.36]	[0.30]	[1.25]

Table 9: **Net Positions of Various Investors in VIX Futures**

This table presents the results of the following time-series regressions,

$$r_{t+1}^{VIX} = a + bNP_t^{Investor} + \sum_{i=0}^{9} c_i r_{t-i}^{VIX} + \varepsilon_{t+1},$$

where r_{t+1}^{VIX} denotes the return to VIX futures in $t+1$ and $NP_t^{investor}$ is the net position of a type of investors, calculated as $\frac{\text{Long Positions}-\text{Short Positions}}{\text{Open Interest}}$. CFTC publishes the Traders and Financial Futures (TFF) report every Thursday for financial futures, which provides the aggregate long and short positions of investors, which are categorized into five groups: Levered Funds (hedge funds), Asset Managers (pension funds, endowments, insurance companies, mutual funds, and portfolio managers whose clients are predominantly institutional), Dealers/Intermediaries (large banks and dealers in securities, swaps, and other derivatives), Other Reportable (traders who mostly use futures to hedge business risk), and Nonreportable (small investors). VIX futures returns are computed using daily settlement prices of the nearest-to-expiration futures contract and are scaled in percentage points in these regressions. t-statistics (in brackets) are calculated based on the White heteroskedasticity-robust standard errors, where *, **, and *** denote significance at levels 10%, 5%, and 1%. Observations are weekly (Thursday to Thursday) from 2007 to 2022.

	r_{t+1}^{VIX} (%)				
	(1)	(2)	(3)	(4)	(5)
$NP_t^{HedgeFund}$	1.18**				
	[2.41]				
$NP_t^{AssetManager}$		-3.07**			
		[-2.55]			
NP_t^{Dealer}			-0.54		
			[-1.19]		
$NP_t^{Other-reportable}$				-2.14	
				[-1.28]	
$NP_t^{Non-reportable}$					7.41*
					[1.86]
$r_{t-i}^{VIX}, i = 0, \ldots 9$	Yes	Yes	Yes	Yes	Yes
N	805	805	805	805	805
R-squared (%)	0.252	0.447	-0.235	-0.261	0.115

Table 10: **ETF Returns and ETF Option Demands of Hedge Funds**

This table reports the results of the following pooled OLS regression at the ETF and year-quarter level:

$$r^{ETF}_{i,t+1} = b_1 NDIR_{i,t} + b_2 DIR_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1},$$

$$\text{or} \quad r^{ETF}_{i,t+1} = b_1 STRA_{i,t} + b_2 PPUT_{i,t} + b_3 BEAR_{i,t} + b_4 BULL_{i,t} + \gamma \mathbf{X}_{i,t} + \mathbf{FEs} + \varepsilon_{i,t+1},$$

where $r^{ETF}_{i,t+1}$ denotes ETF i's return in quarter t+1. See Table 3 for details on hedge fund option demands, control variables, and fixed effects in the regressions. Standard errors are clustered by year-quarter and associated t-statistics are reported in brackets, where *, **, and *** denote significance at levels 10%, 5%, and 1%. The sample period is from 2007 to 2022.

	$r^{ETF}_{i,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$NDIR_{i,t}$	0.003		0.003			
	[0.15]		[0.14]			
$DIR_{i,t}$		-0.018	-0.018			
		[-0.94]	[-0.94]			
$STRA_{i,t}$				0.013		0.013
				[0.35]		[0.36]
$PPUT_{i,t}$				-0.012		-0.014
				[-0.37]		[-0.43]
$BEAR_{i,t}$					0.013	0.013
					[0.95]	[0.96]
$BULL_{i,t}$					-0.077*	-0.077*
					[-1.80]	[-1.80]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Investment Obj. FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
N	13,109	13,109	13,109	13,109	13,109	13,109
R-squared	0.514	0.514	0.514	0.514	0.515	0.515

Table 11: **Do Hedge Funds Use Stock Options to Time Market or Sector-Level Volatilities? Evidence from Idiosyncratic and Systematic Components of Stock Volatility**

This table reports the results of the pooled OLS regressions at the stock and year-quarter level, where future log variance swap return, and its idiosyncratic and systematic components, are regressed on various hedge fund demands in stock options. We use the *matched* ETF as a proxy for the common factor driving returns of a given stock. Specifically, we match a stock to an ETF based on the sector or style classifications of this stock. For sector matching, we choose the 11 GICS-based sectors and use SPDR Sector ETFs as their financial instruments. For example, a financial stock is matched with the SPDR Financial Sector ETF (ticker: XLF), and a large-cap-growth stock is matched with the Russell 1000 Growth ETF (ticker: IWF). Likewise, for style matching, we use the Russell 1000 Value, 1000 Growth, 2000 Value, and 2000 Growth ETFs for the size and value factors. We define the systematic component of stock j's realized variance in the quarter $t+1$ as $\beta_{j,t}^2 \mathrm{RV}_{t\to t+1}^{etf}$, where $\beta_{j,t}$ is the sensitivity of stock j to its matched ETF, estimated using the daily returns of stock j and its matched ETF in the quarter t. The systematic component of stock j's implied variance at the end of quarter t is $\beta_{j,t}^2 \mathrm{IV}_t^{etf}$. The idiosyncratic component of stock j's RV (IV) is then calculated as its RV (IV) minus the systematic component. Column (1) shows the regression result in which the dependent variable is the log return of variance swap ($\log(RV_{j,t\to t+1}) - \log(IV_{j,t})$). Columns (2) and (3) show the results in which the dependent variables are the log difference of RV and IV for the sector-based systematic and idiosyncratic components, respectively. Similarly, columns (4) and (5) show the results for the style-based systematic and idiosyncratic components. Standard errors are clustered by year-quarter and associated t-statistics are reported in brackets, where *, **, and *** denote significance at levels 10%, 5%, and 1%. The sample period is from 2007 to 2022.

	Stock-Level Variance Swap Return and Its Systematic/Idiosyncratic Components				
	$r_{j,t+1}^{VS}$	$r_{j,t+1}^{VS,sector}$	$r_{j,t+1}^{VS,idio}$	$r_{j,t+1}^{VS,style}$	$r_{j,t+1}^{VS,idio}$
	(1)	(2)	(3)	(4)	(5)
$STRA_{j,t}$	1.423***	0.133	1.550***	-0.044	1.707***
	[3.48]	[1.18]	[3.41]	[-0.43]	[4.20]
$PPUT_{j,t}$	-0.074	-0.175*	0.028	0.033	0.319
	[-0.33]	[-1.91]	[0.08]	[0.31]	[0.91]
$BEAR_{j,t}$	0.352**	0.007	0.102	-0.015	0.114
	[2.29]	[0.09]	[0.47]	[-0.24]	[0.53]
$BULL_{j,t}$	-0.054	-0.123**	0.142	0.040	-0.082
	[-0.49]	[-2.35]	[0.89]	[0.93]	[-0.60]
Controls	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes
N	118,205	85,544	77,644	105,246	97,474
R-squared	0.345	0.917	0.176	0.937	0.173