Volatility Timing Using ETF Options: Evidence from Hedge Funds*

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Abstract

We find that hedge funds' ETF option positions predict cross-sectional differences in the future volatility of underlying ETFs. The predictive power is strongest for straddle positions and non-equity ETFs. A tracking portfolio of straddles based on funds' straddle positions earns quarterly abnormal returns of 7.35%. Net of fees, funds using ETF straddles deliver lower risk and higher benchmark-adjusted returns than nonusers. We also find that hedge funds' trading in ETF options has a positive impact on ETF option prices and improves price efficiency in individual equity options. We conclude that ETF options are an important venue for informed volatility trading.

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, 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] How investment managers actually use ETFs and ETF options is still largely an open question in the finance literature. 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, the few available empirical studies conclude that investment managers use ETFs to manufacture passive indexing strategies and that institutional investors' 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 asset managers trade on ETFs in the options markets. This is important because options markets are often the preferred venue for informed trading.[3] In this paper, we examine whether asset managers trade on market volatility information by studying the ETF options positions of hedge fund managers over the period of 2007–2021.

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", exploiting superior knowledge about return volatility across several asset markets (e.g., equity,

[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).

fixed income, commodity, currency).

We report several new empirical findings. First, we show that ETF options represent an important part of hedge fund manager portfolios. Over the 2007-2021 period, ETF options represent 7.5% of the number of ETF share positions and have a total notional value of $1.438 trillion. In contrast, option positions on individual equities are only 3.3% of the total number of stock positions with just $1.089 trillion in notional value. In addition, ETF option positions often represent many investment categories, including options on SPY (US Large Cap), GLD (Gold), HYG (High Yield Corporate Bond), TLT (Treasury), and IYR (Real Estate). Therefore, ETF option positions provide a novel window into hedge funds' informed trading across several asset markets.

Next, we undertake a comprehensive investigation into volatility timing ability as revealed by hedge funds' holdings of options. Although the model-free implied volatility of an ETF generally overestimates the ETF's subsequent realized volatility, our results from Fama-MacBeth regressions show that this effect is reduced or even reversed if all hedge funds hold options on the ETF. For example, we estimate that the difference between annualized realized and implied volatility is -6.3% among ETFs for which no advisors hold corresponding option positions. In stark contrast, this difference is 13% when all advisors using the ETF do so as part of a non-directional option strategy. The results are even stronger when hedge funds hold options on non-equity ETFs, including fixed income, commodity, currency, and multi-asset ETFs. In sum, when hedge funds report holding ETF options, systematic volatility tends to increase.

We contrast our findings from ETF option positions with those from individual equity option positions. Aragon and Martin (2012) find that, over the 1999–2006 period, hedge funds' holdings of individual equity options predict both the direction and volatility of underlying equity returns. We confirm these findings over our expanded sample period and decompose a stock's total volatility into its systematic and idiosyncratic parts. Strikingly, the volatility information contained in equity option positions pertains only to idiosyncratic (i.e., firm-specific) volatility, not systematic volatility. This contrasts with our finding of volatility information in ETF options positions that emphasizes systematic over idiosyncratic factors. Furthermore, in contrast to equity options, ETF option positions are not informative about the future direction of the underlying ETF. This indicates that hedge fund managers use ETF options to exploit their skill at volatility timing rather than "market timing" – i.e., information about the direction of aggregate market prices.

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 construct hold-to-maturity straddle returns for each ETF in our sample.[4] We find that greater hedge fund demand for options on ETFs, especially straddle positions, predicts greater straddle returns. This finding is illustrated in Figure 3. The top panel plots the coefficients from quarter-by-quarter regressions of quarter q+1 straddle return for ETF i ($r^{straddle}_{i,q+1}$) on hedge fund demand for straddles on ETF i in quarter q ($STRA_{i,q}$). The average coefficient is positive and significant (t-statistic = 2.41). 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 7.35% (t-statistic = 2.96) after adjusting for the Fama-French 5 factors augmented with the momentum factor. We conclude that the volatility information contained in hedge funds' ETF options positions has significant economic value.

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 quarter (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 the Straddle Users portfolio earns returns with lower after-fee return volatility and higher Sharpe ratio as compared to the portfolio of Non-Straddle Users. Moreover, Straddle Users portfolio earns an annualized alpha 2.88% (t-statistic = 2.24) when benchmarked against the Fung and Hsieh (2004) seven-factor model. Taken together, our findings here suggest that hedge funds use ETF options to profit from volatility information, and these rents are largely passed through to investors in the form of after-fee performance.

Finally, we examine the response of option market makers to volatility demand. In a Kyle (1985)-type framework, the presence of informed traders spurs market makers to adjust price

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

in response to demand. Consistent with this idea, we find that volatility demand has a positive price impact: ETF options on which hedge funds hold straddle positions contemporaneously have greater option-implied volatility. We also show that the volatility information revealed by informed trading in ETF options "spills over" to individual equity options and, in this sense, improves price efficiency in those markets. Specifically, the predictive power of equity option-implied volatility for realized volatility of the underlying equity (i.e., "price efficiency") is greater when there is more informed trading in ETF options, particularly for equities with greater exposure to systematic risk.

We contribute to recent work on how asset managers use ETFs as investment vehicles. These studies focus on managers' holdings of ETFs and find little evidence that ETFs are used to capitalize on information about market fundamentals.[5] Likewise, we find no evidence that hedge funds' positions in ETFs have predictive power for the direction of ETF prices. However, a different picture emerges for ETF options positions in that they strongly predict the volatility of ETF prices.

We also contribute to research on how asset managers use derivatives. Previous studies find that managers use derivatives to manage risk, provide liquidity, and achieve transactional efficiency.[6] Other studies find evidence that derivatives are used to exploit information about the fundamentals of individual stocks. As mentioned above, Aragon and Martin (2012) find that hedge funds' holdings of equity options predict the direction and volatility of underlying equity returns, indicating that hedge funds are informed about individual stock fundamentals. We build on this work by showing that hedge funds are also informed about systematic factors that impact volatility across several asset markets, not just idiosyncratic factors within the equity sector. We achieve this by bringing to bear data on ETF option positions that are typically excluded from empirical work.[7]

Our study is also related to prior work examining the economic benefits from volatility tim-

[5] See, e.g., Ben-David et al. (2018); Cumming and Monteiro (2022); Sun and Teo (2022); Joenväärä and Salehi (2018).

[6] See, e.g., Koski and Pontiff (1999); Deli and Varma (2002); Chen (2011); Aragon et al. (2019a); Kaniel and Wang (2020); Jiang et al. (2021b).

[7] 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.

ing across asset markets and over time.[8] Our evidence highlights ETF options markets as an important device for active fund managers to capitalize on market volatility information, and shows that such volatility timing yields significant investment gains for fund investors. Busse (1999) shows that mutual funds time market volatility in that they reduce their portfolio exposure to the market before market volatility subsequently increases.[9] We show that hedge funds time market volatility by actively holding positions in ETF options, especially straddles. This makes sense because, in contrast to mutual funds, hedge funds face fewer restrictions on derivative securities with nonlinear payoffs that can be used to capitalize on volatility information.

Furthermore, we extend the evidence that option market data are informative about the volatility of future stock prices. Ni et al. (2008) find that non-market maker net demand for volatility in the equity option market is positively related to the subsequent realized volatility of underlying stocks, indicating that investors choose the option market to trade on private information about stocks' idiosyncratic volatility. Our findings that hedge fund demand for straddles on ETFs predict underlying ETF volatility show that ETF options are an important device for trading on systematic volatility information across equity and non-equity markets.

Finally, we contribute to recent work on how financial innovation impacts asset prices and market efficiency. Prior work shows that informed investors' trading in options generates price discovery about the underlying stock (see, e.g., Chakravarty et al., 2004). More recent work highlights the contribution of ETF markets to price discovery in individual stock markets (Huang et al. (2021); Ernst (2020)). We build on this work by showing that ETF options markets improves price discovery in individual stock options markets by attracting traders who are informed about systematic volatility.

2. Data and Sample Construction

In this section, we describe the data sources used in our analysis, the classification of hedge fund option positions, and summary statistics of the sample.

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

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

2.1. *Data Sources*

2.1.1. *Hedge Fund Portfolio Holdings*

Our main database on portfolio holdings contains historical filings of Form 13F. Since 1978, all institutional investment managers (including hedge fund investment advisers) who exercise investment discretion over accounts holding at least $100 million are required by Section 13(f) of the Exchange Act of 1934 to make quarterly disclosures of portfolio holdings to the SEC on Form 13F within 45 days of the quarter-end. The types of securities that are required to be reported on Form 13F include exchange-traded stocks, equity options and warrants, convertible bonds, and shares of closed-end investment companies. Short positions, shares of open-end funds, and private securities are not required to be disclosed. All long positions in such securities with more than ten thousand shares or with market values exceeding $200,000 are required to be reported. Form 13F reporting items include the issuers of the securities, the security type, the Committee on Uniform Securities Identification Procedures (CUSIP) number, the number of shares, and the market value of each security owned. In the case of options positions, advisers must give the entries about CUSIP, fair value, and amount in terms of the securities underlying the options, not the options themselves. Advisers are also required to report whether the options are calls or puts, but they are not required to report an option's striking price or maturity date.[10] Advisers can report aggregated holdings across different funds managed by the same management company.

All filings of Form 13F are available electronically from the SEC Electronic Data Gathering, Analysis, and Retrieval system (EDGAR), but these require considerable further processing due to manual formatting. While most standard commercial databases (e.g., Thomson Reuters) only provide stock holdings, the commercially available WhaleWisdom database offers a complete set of reported 13F positions, including stock, option, and other types of securities. Therefore, we obtain 13F holdings data from WhaleWisdom. Our analysis focuses on Form 13F filings of hedge fund managers. To identify filings of hedge funds, we follow Agarwal et al. (2013) and Agarwal et al. (2017) and use the names of hedge fund company names that appear in four commercial hedge fund databases, namely Eurekahedge, Hedge Fund Research (HFR),

[10] See Aragon and Martin (2012) for additional details on the reporting of equity options in Form 13F.

Morningstar, and Lipper TASS.[11] We then match these hedge fund company names with the reporting names in the 13F filings.

Our sample consists of portfolio holdings disclosed by 855 hedge fund advisers from 2007 to 2021. It starts in 2007 because there were relatively few listed ETF options in the pre-2007 period; for example, options on SPY were first issued on the Chicago Board Options Exchange in 2005. Our post-2007 sample contains a broad cross-section of ETFs, including at least 200 ETFs with implied volatility information and at least 50 ETFs with straddle returns available in each quarter.

2.1.2. Hedge Fund Performance

For empirical tests on the relation between ETF option usage and future hedge fund performance, we obtain the net-of-fees monthly returns of hedge funds reporting to Lipper TASS from 2007 to 2021. Both live and defunct funds are included in the analysis to mitigate any potential survivorship bias. Funds often report return data before their listing date in the database. Since well-performing funds have a stronger incentive to list, for example, after the incubation period, the backfilled returns are usually higher than the non-backfilled returns. To mitigate this backfill and incubation bias, we follow 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 that report in non-U.S. currency.

2.1.3. Exchange-Traded Options

We use OptionMetrics to obtain data on end-of-day bid and ask quotes, expiration dates, and strike prices for options traded on U.S. exchanges. These data are used to construct the model-free implied volatility and option straddle return. Straddles combine a put and a call with the same strike price and expiration date.

The model-free implied volatility is a forward-looking risk-neutral measure of volatility proposed in Bakshi et al. (2003). For a given day t, the implied volatility with τ days to

[11] We thank Vikas Agarwal for providing the list of hedge fund manager names. Joenväärä et al. (2021) show that using multiple hedge fund databases rather than one helps to mitigate data biases.

maturity, denoted by $IV(t,\tau)$, is calculated from the following formula,

$$IV^2(t,\tau) = \frac{2e^{r\tau}}{\tau}\left\{\int_{S_t}^{\infty}\frac{1-\ln(K/S_t)}{K^2}\times C(t,\tau;K)dK + \int_0^{S_t}\frac{1-\ln(K/S_t)}{K^2}\times P(t,\tau;K)dK\right\},$$

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) option at day t. The implied volatility is computed using interpolation and annualized by multiplying $\sqrt{252}$.[12] Hedge funds' positions are disclosed at the end of each quarter, so we focus on the 91-day horizon to calculate the forward-looking risk-neutral volatility over the next quarter. The realized volatility of the 91-day horizon over the same quarter is directly obtained from OptionMetrics.

We follow Heston et al. (2021) to construct straddle returns. First, we discard any options with expiration dates that are outside the regular monthly cycle and beyond 91 days. We then select two matching call/put pairs for each stock or ETF, where all calls and puts are near-the-money with the shortest maturity. From each pair, we form a zero delta straddle. This entails holding the call and put with weights that are proportional to $-\Delta_P S_t C_t$ and $\Delta_C S_t P_t$, respectively, where Δ denotes the option's delta and C_t and P_t are the bid-ask midpoint of the call and put, respectively. The weights are always positive, sum to one, and typically close to 50/50. Straddle returns are the weighted average of the hold-to-maturity returns on the call and the put based on the split-adjusted price of the underlying stock on the expiration date. We take the bid-ask midpoint as the initial price of each option.[13] To ensure that the straddle returns are valid, the options used to construct straddles should be actively traded. However, as emphasized in Heston et al. (2021), the liquidity filters, such as a requirement that open interest is nonzero, substantially reduce the sample size. Therefore, the sample of ETFs with valid option straddle returns is smaller.

[12] We thank Grigory Vilkov for providing efficient Python codes to implement interpolation routine in parallel (Vilkov, 2018).

[13] Although we ignore the possibility of early exercise, we focus on near-the-money options where early exercise is rarely optimal.

2.1.4. US Listed ETFs

We use data from the Center for Research in Security Prices (CRSP) and ETF Global to identify ETFs traded on major U.S. exchanges.ETF Global is a leading provider of ETF data and has been widely used in prior studies (Shim (2019); Hong et al. (2022)). We first draw information from CRSP for all securities with a share code of 73, which exclusively defines ETFs, and merge this sample with the data of ETF Global. We exclude actively managed ETFs, leveraged ETFs, and volatility ETFs in our sample. In total, we identify 2230 ETFs with broad regional coverage including North America, Asia-Pacific, Europe, Emerging Markets, and Developed Markets. Regarding the coverage of asset classes, 1624 ETFs are specialized in equity markets, with the remaining asset classes including commodity (35), currency (22), fixed-income (427), and multi-asset (122). In addition, we find 913 ETFs with option trading volumes in OptionMetrics; the composition of these optionable ETFs is as follows: 751 equity, 18 commodity, 19 currency, 105 fixed-income, 20 multi-asset.

2.2. Classification of Hedge Fund Option Positions

We follow Aragon and Martin (2012) and classify each option position as either nondirectional or directional based on the reported positions in the same underlying asset. For equity options, a call option position is classified as directional if the advisor does not simultaneously report a position in a put option on the same underlying issuer. Likewise, we classify a put option position as directional if the advisor does not simultaneously report a share or call option position in the underlying issuer. This criterion thus classifies straddles and protective put strategies as non-directional option strategies. A protective put is a put option and share position in the same underlying firm, but no call option; a straddle is a put and call option position on the same underlying firm.

We classify hedge fund ETF option positions based on the categories of ETF investment objectives. Our rationale is that the returns of ETFs with the same investment objective tend to be highly correlated as they are focused on the same asset market. Indeed, we find the average pair-wise correlation of ETFs in the same category is 0.82.[14] For example, the pairwise corre-

[14]Figure A.1 in the appendix plots the average correlations of returns of ETFs within a particular investment-

lation of monthly returns between GLD and IAU, two gold ETFs, is nearly 100%. Therefore, when classifying ETF option positions, we first account for a hedge fund's all other ETF positions in the same investment objective. For example, a hedge fund holding a call option on GLD and a put option on IAU indicates two option positions on the gold market, one on GLD and one on IAU, collectively as a straddle. This does not indicate two directional positions, one bullish on GLD and one bearish on IAU.

[Insert Table 1 near here]

Table 1 shows summary statistics of hedge fund positions. The total number of ETF positions (190,653) is about 6.8% of the total number of stock positions (2,782,681). The average size of an ETF position ($31.16 million) is comparable to that of a stock position ($25.44 million). The total number of options on ETFs (14,334 = 2369+4655+2875+4435) is about 7.5% of the total number of ETF positions (190,654). The total number of options on stocks (94505 = 25325+9838+24477+34865) is about 3.3% of the total number of stock positions. The average notional value of ETF options is much larger than that of stock options. For example, the average notional value of nondirectional call options on ETF ($95.07 million) is about nine times the average notional value of nondirectional call options on stocks. In fact, despite being fewer in number, ETF option positions have a greater total notional value than that for stock options ($1.438 trillion vs. $1.089 trillion).

[Insert Figure 1 near here]

Figure 1 plots time series of aggregate hedge fund positions for options and underlying securities. Strikingly, the notional value of ETF options relative to the value of ETFs in the aggregate hedge fund portfolio is an order of magnitude larger than the notional value of stock options to the value of stocks, in particular during the recent periods. This highlights the importance of ETF options in hedge fund investment strategies.

region category. ETFs are required to have at least 3-year return data to calculate correlations.

2.3. *ETF Options and ETF Option Users*

[Insert Table 2 near here]

Table 2 provides a list of the ETFs that are used most frequently by hedge fund advisers. Panel A reports the top 20 ETFs ranked by the aggregate number of positions in ETF shares. Panel B reports the top 20 ETFs ranked by the aggregate number of positions in ETF options. As shown in Panel B, the SPDR S&P ETF Trust, iShares Russell 2000 ETF, Invesco QQQ Trust, SPDR Gold Shares, and Financial Select Sector SPDR Fund rank as the top ETFs held by hedge funds in ETF option positions. Besides equities and gold, several asset markets are represented in commonly held ETF options, including high yield (HYG), silver (SLV), real estate (IYR), and Treasuries (TLT).[15]

[Insert Table 3 near here]

Table 3 shows the hedge fund advisers who most frequently use options on stocks or ETFs. Panel A lists the top 20 ranked by the aggregate number of positions in stock options. Panel B reports the top 20 ranked by the aggregate number of positions in ETF options. As shown in Panel B, the top advisers that hold option positions in ETFs include Polar Asset Management Partners, Mariner Investment Group, Caxton Associates, and Pine River Capital Management. These managers have stated investment profiles that indicate either multi-strategy funds, investment strategies that involve trading across asset classes and geographies, and/or generate returns independent of market direction.[16]

[Insert Table 4 near here]

Table 4 reports the time-series average of the cross-sectional statistics of security characteristics from 2007 through 2021. Panel A shows the summary statistics from the sample of ETFs

[15] Table A.5 in the appendix reports the top 20 ETFs ranked by the four different aggregate hedge fund option positions – directional call, directional put, non-directional call, and non-directional put.

[16] According to Prequin, the profile 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 Street).

and stocks with listed options. Both implied and realized volatilities are lower for ETFs than stocks. This is consistent with ETFs being an index product in which the idiosyncratic factors, cancel each other out, leaving just the systematic factor as the primary source of volatility. The average straddle returns on ETFs and stocks with options are -4.03% and -8.41%, respectively. This negative straddle return is consistent with the negative volatility risk premium found in prior studies (e.g., Coval and Shumway (2001); Bakshi and Kapadia (2003)). The interpretation is that straddles hedge against changes in volatility, and this hedge comes at a cost.

Panel B of Table 4 shows the summary statistics for the sample of securities with hedge fund option positions. Straddle returns are greater (i.e., less negative) as compared to the full sample in Panel A. For example, the average straddle return of hedge fund option positions, including directional and non-directional positions, is -1.06% quarterly and less negative than for the full sample (-4.03%). Likewise, for stock options, the average straddle return is -2.84% when at least one hedge fund manager holds an option on that stock as compared to -8.41% for the full sample. This provides preliminary evidence that hedge fund demand for options is a positive predictor of volatility on the underlying asset.

3. Volatility Timing and ETF Options Use of Hedge Funds

In this section, we analyze the predictive power of hedge funds' ETF option positions for future volatility and compare our findings with those of individual stock options positions.

3.1. *Baseline Results*

Our baseline results are from Fama-MacBeth regressions of future unexpected volatility against aggregate hedge fund demand for options and common shares on a particular ETF. Specifically, for each quarter we estimate the following two models:

Model 1: $\text{UVOL}_{i,q+1} = \gamma\text{NDIR}_{i,q} + \delta\text{DIR}_{i,q} + \beta\text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$

Model 2: $\text{UVOL}_{i,q+1} = \gamma_1\text{STRA}_{i,q} + \gamma_2\text{PPUT}_{i,q} + \delta_1\text{BEAR}_{i,q} + \delta_2\text{BULL}_{i,q} + \beta\text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$

where the dependent variable, $\text{UVOL}_{i,q+1}$, is the unexpected volatility of ETF i in quarter q+1, defined as the difference between $\text{RVOL}_{i,q+1}$ and $\text{IVOL}_{i,q}$, which are the realized volatility of ETF i's daily returns in quarter q+1 and the model-free implied volatility at the end of quarter q, respectively. In Model 1, we construct nondirectional option demand ($\text{NDIR}_{i,q}$) and directional option demand ($\text{DIR}_{i,q}$) based on our classification of hedge fund option positions (see Section 2.2 for details). Specifically, $\text{NDIR}_{i,q}$ is the proportion of hedge fund advisors disclosing a nondirectional option position of underlying ETF i, among all hedge fund advisors that hold at least one share or option position of ETF i at the end of quarter q, and $\text{DIR}_{i,q}$ is defined similarly for directional option positions. In Model 2, we further decompose the nondirectional option demand into straddle position ($\text{STRA}_{i,q}$) and protective put ($\text{PPUT}_{i,q}$), and the directional option demand into directional put ($\text{BEAR}_{i,q}$) and directional call ($\text{BULL}_{i,q}$). In both models, we include the hedge fund demand for shares of underlying ETFs ($\text{COM}_{i,q}$).

[Insert Table 5 near here]

Table 5 summarizes slope coefficient estimates on various hedge fund demands of ETF options and shares, where columns (1) – (4) are from Model 1 and (5) – (8) are from Model 2. t-statistics are computed based on the time-series variability of the slope estimates with the Newey and West (1986) correction. The slope coefficients on NDIR and DIR are both positive and statistically significant in all four specifications. These results suggest that ETFs with options held by a greater proportion of hedge funds are associated with a higher future unexpected volatility. For example, the coefficient on NDIR is 0.134 (t-statistics = 4.00) in column (4), meaning that the unexpected ETF volatility increases by 13.4% (annualized) when the proportion of hedge funds holding non-directional options increases from 0 to 100%. In addition, the coefficient on NDIR (0.134) is about 2.5 times of the coefficient on DIR (0.054), consistent with the intuition that volatility timing is mainly a non-directional bet. Model 2 considers a finer partition of options demand into straddle, protective put, bear, and bull option positions. We find that all option demand variables predict future unexpected ETF volatility; columns (5) – (8) show that the slope coefficients are positive and significant, with the coefficient on straddle being largest.

The results in Table 5 also show that hedge fund demand for ETF shares is negatively associated with future unexpected volatility, as indicated by a negative and significant coefficient on COM across all specifications. This provides further evidence that hedge fund managers have superior information about ETF volatility; they effectively reduce their long positions of ETF shares in anticipation of higher future volatility. However, the coefficient on the ETF share demand (0.014) is an order of magnitude smaller than the coefficient on the ETF option demands. This is not surprising because options, by their nature, are more suited for volatility trading strategies.

Overall, we find strong evidence that ETF option users in the hedge fund industry are more informed of future ETF volatility than the average trader in the ETF options market.

3.2. Volatility Timing by Equity ETF and Non-Equity ETF Options

ETF options markets span several asset classes, not just equities. Our sample of ETF options includes 751 unique equity ETFs, 105 fixed-income ETFs, 20 multi-asset ETFs, 18 commodity ETFs, and 19 currency ETFs. Nevertheless, since most ETF options are equity-based, an interesting question is whether the volatility timing ability of hedge funds extends beyond equity ETFs to other asset classes. We therefore repeat the regression analyses in Section 3.1 for the equity and non-equity ETF subsamples.[17]

[Insert Table 6 near here]

Table 6 reports the results; columns (1) and (2) focus on equity ETFs, and columns (3) and (4) focus on non-equity ETFs. For both equity ETFs and non-equity ETFs, the slope coefficients on NDIR are positive and significant, suggesting that skilled hedge fund managers exploit their volatility information by using both equity and non-equity ETF options. Interestingly, the coefficient on NDIR for non-equity ETF (0.344 in column (3)) is about 2.5 times of the coefficient on NDIR for equity ETF (0.140 in column (1)).

We further decompose hedge fund option demands into the four types in columns (2) and (4). The coefficients are positive and significant for straddle, protective put, and bull option

[17]To ensure the accuracy of statistical inference, we require at least 50 ETFs with traded options each quarter to estimate Fama-MacBeth regressions. Due to this data limitation, we form two subsamples only based on the classification of equity and non-equity ETFs.

positions for both equity and non-equity ETFs; the coefficients are larger for non-equity ETFs than equity ETFs. These findings indicate that ETF options are an important device for hedge fund managers to trade volatility across different asset markets, and managers seem to be more informed of volatility in non-equity markets.

3.3. Idiosyncratic Volatility Timing by Hedge Fund Stock Option Positions

Aragon and Martin (2012) document that hedge funds' stock options positions predict the volatility of underlying stocks over the 1999–2006 period. Unlike ETFs, however, a stock's volatility is mainly driven by idiosyncratic rather than systematic factors. If stock options positions are mainly predictive about a idiosyncratic volatility, then stock and ETF options play different roles in volatility timing. Along these lines, we revisit Aragon and Martin (2012) using our sample of common stocks and stock options positions over the 2007-2021 period. We run Fama-MacBeth regressions of future unexpected volatility on our measures of hedge fund demand of options and common shares. Our models here have the same specifications as those in the analysis of ETF volatility timing in Section 3.1.

[Insert Table 7 near here]

As shown in Table 7, the coefficients on NDIR are positive and significant for all models. In addition, straddle and protective put positions all exhibit strong predictive power for future unexpected stock volatility. Using an extended "out of sample" period, our results confirm the main finding of Aragon and Martin (2012) that hedge funds' stock option positions contain information about the volatility of underlying stock returns.

Next, we test whether hedge funds mainly use stock options to exploit their superior information about *idiosyncratic* volatility of underlying stock returns. We disentangle the systematic and idiosyncratic components of stock volatility using a novel approach that uses the return of a *matched* ETF as the common factor driving the systematic component of returns of an individual stock. An advantage of using ETFs as proxies for common factors is that an ETF's option-implied volatility can be used as a forward-looking measure of the expected volatility of the common factor; the unexpected volatility of a common factor in quarter q+1, denoted by UVOL_{q+1}, is thus the difference between its quarter-q+1 realized volatility $\text{RVOL}_{i,q+1}$ and end-of-quarter-q implied volatility $\text{IVOL}_{i,q}$.

We match a particular stock to an ETF based on sector classifications of this stock. We choose the 11 GICS-based sectors and use the SPDR Sector ETFs as their tradable financial instruments. We assign a stock into a sector portfolio based on its sector classification. For example, a financial stock is matched with the SPDR Financial Sector ETF (ticker: XLF).We then define the systematic component of unexpected volatility of stock i in quarter q+1 as $|\beta_i|\text{UVOL}_{q+1}$, where β_i is stock i's sensitivity to its common factor, estimated from regressions of stock i's daily returns on its matched ETF's daily returns in quarter q. Finally, we define the idiosyncratic component of stock i's unexpected volatility in quarter q+1, denoted by $\text{UIdVOL}_{i,q+1}$, as the difference between its quarter-$q+1$ realized idiosyncratic volatility, $\text{RIdVOL}_{i,q+1}$, and the implied idiosyncratic volatility at the end of quarter q, $\text{IIdVOL}_{i,q}$, which is calculated as $\sqrt{\text{IVOL}_{i,q}^2 - \left(\beta_i \text{IVOL}_q\right)^2}$.

[Insert Table 8 near here]

Table 8 presents results from Fama-MacBeth regressions where the systematic factors are instrumented by the SPDR Sector ETFs.When the dependent variable is the idiosyncratic component of unexpected stock volatility (UIdVOL), the coefficient on NDIR is positive and significant (coefficient = 0.732, t-statistic = 4.28 in column (1)). Column (2) shows that the coefficients on STRA and PPUT are also positive and significant. In contrast, in columns (3) and (4) where the dependent variable is the systematic component of unexpected stock volatility, none of the coefficients on hedge fund option demands are significant. Thus, hedge funds use stock options to trade idiosyncratic volatility, not systematic volatility. This highlights ETF options markets as a special venue for informed trading on systematic volatility.

4. Option Returns and Hedge Fund Option Positions

In the previous section, we demonstrate that hedge funds' demand for ETF options, particularly their straddle positions, have strong predictive power for future ETF volatility. In this section, we examine the economic value of this predictability by studying returns to option straddle strategies formed by tracking hedge funds' option holdings.

4.1. Regressions of Straddle Returns on Hedge Fund Option Demands

We construct straddle returns for each ETF and stock in our sample following the option return literature (i.e., Goyal and Saretto, 2009; Heston et al., 2021). Specifically, at the end of each quarter, we first select a matched pair of the near-at-the-money call and put options with the shortest maturity, and then construct a delta-hedged straddle and hold it to the maturity. We require the maturity to be shorter than 91 days so that the call and put options in straddle will expire before the next 13-F reporting period. We focus on the sample of ETFs and stocks with valid straddle returns. We then test whether hedge fund options demand predict future straddle returns by estimating the following Fama-MacBeth regressions:

$$\textbf{Model 1:}\quad r_{i,q+1}^{straddle} = \gamma \mathrm{NDIR}_{i,q} + \delta \mathrm{DIR}_{i,q} + \beta \mathrm{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

$$\textbf{Model 2:}\quad r_{i,q+1}^{straddle} = \gamma_1 \mathrm{STRA}_{i,q} + \gamma_2 \mathrm{PPUT}_{i,q} + \delta_1 \mathrm{BEAR}_{i,q} + \delta_2 \mathrm{BULL}_{i,q} + \beta \mathrm{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

where aggregate hedge fund demands of options and common shares are the same as those in Section 3.1. We estimate these two models for stock and ETF option straddles.

[Insert Table 9 near here]

The results are reported in Table 9. Columns (1) and (2) show the results for ETF option straddles. Non-directional positions (NDIR) and, in particular, straddle positions (STRA), significantly predict ETF straddle returns. For example, the coefficient on STRA is 0.635 (t-statistic = 2.41), meaning a 63.5% increase in returns to a straddle position when the percentage of hedge funds that hold straddle options increases from 0 to 100%.

[Insert Figure 2 near here]

We provide two concrete examples of hedge funds' volatility timing using ETF options. Figure 2 plots hedge fund straddle positions at the end of each quarter for two popular ETFs, Invesco QQQ Trust (ticker: QQQ) and iShares iBoxx $ High Yield Corporate Bond ETF (ticker:

HYG). We also plot the straddle returns of these two ETFs over the subsequent quarter (i.e, the return plotted at the end of quarter q indicates the straddle return over the quarter q+1). As shown in the figure, hedge fund straddle positions strongly predict future ETF straddle returns; the correlation between the hedge fund straddle demand and the subsequent straddle return is 0.15 for QQQ and 0.45 HYG.

Straddle returns are also predicted by hedge funds' stock options demands, as shown in columns (3) and (4) of Table 9. This is consistent with existing evidence that stock option positions of hedge funds are informative about unexpected volatility on the underlying stock; we show here that this information translates into profitable straddle strategies.

[Insert Figure 3 near here]

Figure 3 summarizes the predictability of hedge fund straddle demand for future unexpected volatility and straddle returns, for both stocks and ETFs. We plot the time-series of coefficients on STRA from Fama-MacBeth regressions, where the dependent variable is either future unexpected volatility or straddle returns. These coefficients are positive and large in most of the quarters in the 2007-2021 period, suggesting that hedge fund managers, in aggregate, are informed of future volatility.

4.2. Straddle Portfolios Formed by Hedge Fund Straddle Demand

Our findings in the previous section indicate the possibility of constructing profitable straddle strategies based on hedge funds' ETF and stock option positions. To test this hypothesis, we construct straddle portfolios based on aggregate hedge fund option positions. Specifically, the straddle of an underlying security i is assigned to the "HF" portfolio if it is held by at least one hedge fund adviser (i.e., $STRA_{i,q}$ is large than zero). Otherwise, it is assigned to the "Other" portfolio. Straddle portfolios are rebalanced at the end of each quarter and the return of a straddle portfolio is calculated as the equal-weighted average return of individual straddles in the portfolio.

[Insert Table 10 near here]

Panel A of Table 10 shows summary statistics of returns to hedge fund straddle portfolios. For ETFs, the average return to the "HF" straddle portfolio is 1.91%; in contrast, the "Other" straddle portfolio generates an average return of -5.69%. The "HF"-minus-"Other" portfolio earns an annualized Sharpe ratio of 0.88. For stocks, we observe a similar pattern: the "HF" stock straddle portfolio earns an average return of 1.53%, which is 13.83% greater than that of the "Other" stock straddle portfolio (-12.30%); the "HF"-minus-"Other" portfolio of stock straddles generates an annualized Sharpe ratio of 2.42.

Panel B of Table 10 reports the results from time-series regressions of returns to the "HF", "Other", and "HF"-minus-"Other" portfolios on the Fama-French 5 factors (see, Fama and French (2015)), augmented with the momentum factor. The HF-minus-Other portfolio of ETF straddles earns a quarterly alpha of 7.35% (t-statistic = 2.96). Similarly, the HF-minus-Other portfolio of stock straddles delivers an alpha of 13.26% (t-statistic = 8.34). In addition, the spread portfolio returns exhibit insignificant exposures to all priced factors, indicating that its performance is unlikely to be driven by a risk-based explanation.

The above straddle portfolios and associated abnormal returns would be investable for a hypothetical copycat investor who can gain information on hedge fund option holdings *immediately* at each quarter-end. However, such information is typically unavailable to a real-world investor at the quarter-end due to the 45-day reporting gap between quarter-end and the time when Form 13Fs are filed with the SEC and publicly disseminated via the EDGAR system. Therefore, while our evidence indicates that hedge funds possess private information about market volatility that has not yet reflected in option prices, we cannot reject semi-strong form market efficiency as described by Fama (1970).

4.3. *ETF and Equity Returns*

[Insert Table 11 near here]

Our analyses thus far focus on volatility timing by hedge funds through their use of options. However, it is also interesting to know if hedge fund option positions contain information about the *direction* of future returns. We run Fama-MacBeth regressions of future security returns, in excess of the risk-free rate, on our key variables capturing hedge fund demand for options and shares,

$$\textbf{Model 1:}\ \ r^e_{i,q+1} = \gamma \text{NDIR}_{i,q} + \delta \text{DIR}_{i,q} + \beta \text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

$$\textbf{Model 2:}\ \ r^e_{i,q+1} = \gamma_1 \text{STRA}_{i,q} + \gamma_2 \text{PPUT}_{i,q} + \delta_1 \text{BEAR}_{i,q} + \delta_2 \text{BULL}_{i,q} + \beta \text{COM}_{i,q} + \alpha + \epsilon_{i,q+1}.$$

The results are reported in Table 11. Columns (1) and (2) show that none of the coefficients on NDIR, DIR, STRA, PPUT, BEAR, and BULL are statistically significant, indicating that hedge fund ETF option positions are not informative about the direction of future price movements of the underlying ETFs. In contrast, as shown in columns (3) and (4), DIR, PPUT, and BEAR negatively predict future stock returns, consistent with the previous literature that hedge fund managers are informed of stock-specific news, especially bearish news (see, e.g., Aragon and Martin, 2012; Chen et al., 2019; McLean et al., 2020; Huang et al., 2021)

We conclude that ETFs are mainly used by hedge funds to exploit their superior information about future ETF volatility, not the direction of ETF price movements. Moreover, several recent studies focus on asset managers' holdings on ETFs and find little evidence that ETFs are used to capitalize on information about market fundamentals (see, e.g, Ben-David et al., 2018; Cumming and Monteiro, 2022; Sun and Teo, 2022). Instead, our paper demonstrates that ETF options are an effective volatility-timing vehicle for asset managers.

5. Use of ETF Options and Hedge Fund Performance

Does volatility timing by hedge fund managers translate into investment gains for their investors? We first divide hedge funds into ETF straddle and non-straddle users and then evaluate the net-of-fee performance of hedge funds in each group. Specifically, a hedge fund adviser is classified as an ETF straddle user if it holds at least one ETF straddle in the recent quarter; otherwise, it is classified as a non-straddle user. We then construct two portfolios of hedge funds: one consisting of funds managed by ETF straddle users, and the other consisting of funds managed by non-straddle users. We rebalance these two portfolios at the quarter-end and record monthly fund returns in the subsequent quarter. The portfolio return is calculated as the equal-weighted average of net-of-fee returns of hedge funds in the portfolio. Our sample consists of TASS hedge funds whose advisers are in our sample.

[Insert Table 12 near here]

Panel A of Table 12 reports summary statistics of monthly returns to portfolios of hedge fund ETF straddle users and non-straddle users. Straddle and non-straddle users have an average monthly return of 0.46% and 0.52%, respectively. Even though the portfolio of straddle users earns a slightly lower return, it has a much lower standard deviation (0.16%) compared to the portfolio of non-straddle users (0.24%). Not surprisingly, its annualized Sharpe ratio is 1.03, significantly larger than that of non-straddle users (0.76).

Next, we evaluate the performance of ETF straddle users by running time-series regressions of monthly returns to the straddle-user portfolio against several benchmarks: 1) the portfolio of non-straddle users; 2) the seven 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 Fung and Hsieh (2004) seven factors.

As shown in Panel B of Table 12, ETF straddle users significantly outperform non-straddle users. They also generate positive and significant alphas relative to all benchmarks. For example, the alpha estimated from the Fung and Hsieh (2004) seven-factor model is 2.88% per year (= 0.24% × 12), with a t-statistic of 2.24. For further robustness, we also ran straddle user portfolio returns on a set of five "volatility-managed" benchmarks in the sense of Moreira and Muir (2017), using the returns on dynamic strategies in SPY, EFA, LQD, IEF, and GLD. The results are tabulated in Table A.3 and show that the resulting alphas remain positive, significant, and nearly identical to those in Panel B.1.

In sum, our analysis of net-of-fee returns suggests that hedge fund investors capture at least some of the benefits from their hedge fund managers' volatility timing using ETF options.

6. Price Impact and Efficiency

We now analyze the response of option market makers to hedge fund demand for ETF options. First, we examine how hedge fund demand impacts ETF option prices; second, we examine whether the trading activity in ETF options markets improves price efficiency in individual stock options markets.

6.1. *Price Impact of Hedge Fund Demand on ETF Options*

If hedge funds' order flows are interpreted by options market makers as coming in part from investors with volatility information, then they will increase option prices in response to higher volatility demand, and vice versa. To test, we run Fama-MacBeth regressions of the following form:

Model 1: $\text{IVOL}_{i,q} = \gamma\text{NDIR}_{i,q} + \delta\text{DIR}_{i,q} + \beta\text{COM}_{i,q} + \lambda\text{IVOL}_{i,q-1} + \alpha + \epsilon_{i,q},$

Model 2: $\text{IVOL}_{i,q} = \gamma_1\text{STRA}_{i,q} + \gamma_2\text{PPUT}_{i,q} + \delta_1\text{BEAR}_{i,q} + \delta_2\text{BULL}_{i,q} + \beta\text{COM}_{i,q} + \lambda\text{IVOL}_{i,q-1} + \alpha + \epsilon_{i,q},$

where $\text{IVOL}_{i,q}$ is the model-free implied volatility estimated from options on ETF i at the end of quarter q. The slope coefficient γ captures the average price impact of an increase in volatility demand as measured by hedge funds' non-directional option positions.

[Insert Table 13 near here]

The results are reported in Table 13. Columns (1) and (2) show that γ is positive and significant, indicating that ETF options are more expensive during periods of contemporaneously higher volatility demand. The remaining columns show that the price impact of non-directional option positions is due to straddle demand, not demand for protective puts. Overall, market makers are protecting themselves from volatility information being brought to the ETF option markets when hedge funds report greater long positions in non-directional positions in ETF options.

6.2. *Does ETF Options Trading Improve Price Efficiency of Stock Options?*

Our earlier results show that ETF options are an important venue for informed trading on systematic volatility. Furthermore, the informed trading in ETF option markets reveals volatility information to market makers of ETF options as indicated by a price impact. It is possible that market makers in options markets for stocks, especially those more exposed to systematic risk, incorporate systematic volatility information from the ETF options markets into prices of stock options. In this sense, trading activities in ETF option markets would improve price efficiency in stock options markets.

We follow prior literature and measure option price informativeness in terms of the forecasting power of implied volatility for realized volatility on the underlying asset (see, e.g., Canina and Figlewski, 1993; Lamoureux and Lastrapes, 1993; Jorion, 1995; Fleming, 1998; Christensen and Prabhala, 1998; Jiang and Tian, 2005). We also measure informed trading in the ETF options market using aggregate option volume; the idea is that informed traders would be more active in high-volume markets (see, e.g., Admati and Pfleiderer, 1988; Roll et al., 2009; Blanco and Wehrheim, 2017). Our hypothesis is that the option-implied volatility of a stock is more informative about the stock's future realized volatility when there is more trading activity in the ETF option market, especially for stocks with a greater exposure to the systematic factor driving ETF returns.

Our tests focus on sector-level systematic factors and trading activities in the SPDR Sector ETFs. Specifically, we run the following panel regressions (stock-quarter):

$$\begin{aligned}\mathrm{RVOL}_{i,q+1} &= \gamma \mathrm{IVOL}_{i,q} + \delta \mathrm{IVOL}_{i,q} \times \mathrm{Log}(\mathrm{ETF\ OptVol}_{i,q}) \\ &\quad + \theta \mathrm{IVOL}_{i,q} \times \mathrm{Log}(\mathrm{ETF\ OptVol}_{i,q}) \times \mathrm{Exposure}_{i,q} + \mathrm{X}_{i,q} + FEs + \epsilon_{i,q+1}.\end{aligned}$$

where $\mathrm{RVOL}_{i,q+1}$ is the realized volatility of stock i's daily returns in quarter q+1; ETF $\mathrm{OptVol}_{i,q}$ is the sum of call and put volumes of the SPDR sector ETF associated with a stock; $\mathrm{Exposure}_{i,q}$ is the sensitivity of stock i to its sector index, estimated from daily time-series regressions of stock i's returns on its sector index returns in each quarter. $\mathrm{X}_{i,q}$ represents a variety of stock-level control variables including Log(1+Stock $\mathrm{OptVol}_{i,q}$), Log(Market $\mathrm{Capitalization}_{i,q}$), Log(Book-to-Market$_{i,q}$), Gross Profits-to-Assets$_{i,q}$, Asset Growth$_{i,q}$, and Past 12-Month Return$_{i,q}$, and all other interactions of IVOL$_{i,q}$. All specifications include stock and year-quarter fixed effects.

A finding that $\gamma > 0$ would indicate that stock option prices are informative about future volatility ("price efficiency"); $\delta > 0$ would indicate that price efficiency improves when ETF trading volume is greater, and $\theta > 0$ would indicate that the improvement is greater among stocks with high exposure to the sector-level risk.

[Insert Table 14 near here]

Columns (1) and (2) of Table 14 show that the coefficient on IVOL × Log(1+ETF OptVol) is positive and significant. Therefore, a stock's implied volatility is more informative about its future realized volatility when there is greater trading activity in the ETF option market associated with that stock. Column (3) further shows that the interaction between option-implied volatility and ETF option volume is even stronger among stocks with greater exposure to its associated sector.

Columns (4) – (6) of Table 14 show the results after replacing ETF OptVol$_{i,q}$ with HF ETF Opt$_{i,q}$ – i.e., the sum of notional shares across all hedge funds for a particular ETF option. This is plausibly a more precise measure of informed trading in ETF options markets since it is based on hedge fund activity rather than aggregate trading activity. Again, we find that the informativeness of a stock's options markets is greater when there is greater information trading in the associated ETF options, especially for stocks with a higher sector exposure.

Overall, this evidence supports our hypothesis that ETF options markets improve the price efficiency of individual stock options through the channel of informed trading on systematic volatility.

7. Additional Results and Robustness

7.1. *Controlling for Lagged Realized and Implied Volatility*

To confirm that our main findings are robust, we repeat our analyses in Table 5, Table 7, and Table 9 by controlling for additional variables including lagged realized and implied volatility (Goyal and Saretto, 2009) and the option-to-stock volume ratio (Johnson and So, 2012), which likely contain information about future volatility. As shown in Table A.1, the coefficients on NDIR and STRA remain positive and significant, suggesting that the predictive power of hedge funds' volatility demand is above and beyond other known predictors of volatility.

7.2. *Style-Based Idiosyncratic and Systematic Components of Stock Volatility*

We consider style-based systematic factors and repeat the analyses in Table 8. Specifically, we choose Size and Value sorted portfolios and use the Russell 1000 Value, 1000 Growth, 2000 Value, and 2000 Growth ETFs as their tradable financial instruments. A stock is assigned with a particular style ETF if it is a constituent member of the ETF. For example, a large-cap-growth stock is matched with the Russell 1000 Growth ETF (ticker: IWF). As shown in Table A.2, the coefficients on NDIR and STRA are positive and significant in columns (1) and (2) where the dependent variable is the idiosyncratic component of unexpected stock volatility. In contrast, in columns (3) and (4) where the dependent variable is the systematic component of unexpected stock volatility, none of the coefficients on hedge fund option demands are statistically significant. These results are similar to those in Table 8 where sectors are used as systematic factors, indicating that hedge funds use individual stock options to exploit information about idiosyncratic component of volatility but not the systematic component of the volatility. Thus, our findings are not sensitive to the choice of systematic factors to decompose stock volatility.

7.3. *Source of Hedge Fund Volatility Information: Evidence from Financial News*

We provide additional evidence on the source of hedge fund volatility information by decomposing a stock's return into firm-specific-news-driven and systematic-factor-driven components, using the release dates of financial news articles. Specifically, we first retrieve all news articles from Dow Jones Newswire provided by RavenPack News Analytics. Then, for each firm, we classify its return in a particular 15-minute window (e.g., 10:00 – 10:15 AM) as a firm-specific-news-driven return if an article about the firm is published during this window. Otherwise, the return is classified as a systematic-factor-driven return.[18] This exercise produces two categories of high-frequency, 15-minute returns for all stocks. For an ETF, its firm-specific-news-driven return is defined as the weighted average of firm-specific-news-driven returns of its underlying constituents, and its systematic-factor-driven return is defined similarly using systematic-factor-driven return. Volatility is the standard deviation of 15-minute returns in each quarter for each of the two categories separately.

As shown in columns (1) to (4) of Table A.4 where we examine ETF options, the coefficients on NDIR and STRA are positive and statistically significant for both the aggregated firm-specific-news-driven and systematic-factor-driven volatility. In addition, the magnitude of the coefficients for systematic-factor-driven volatility is more than twice the coefficients for the aggregated firm-specific-news-driven volatility. These results suggest that hedge fund ETF options positions mainly contain information about the systematic-factor-driven volatility, though they also predict the aggregated firm-specific-news-driven volatility. In contrast, in columns (5)-(8) which focus on stock options, the coefficients on NDIR and STRA are positive and significant only for firm-specific-news-driven volatility, but not for systematic-factor-driven volatility. Thus, hedge funds use stock option positions to exploit firm-specific-news-driven volatility of individual stocks. This evidence resonates well with our findings in Table 8 that hedge fund stock option demands predict idiosyncratic volatility only but not systematic volatility.

[18] See, e.g., Boudoukh et al. (2019) and Jiang et al. (2021a) for similar decomposition methods.

7.4. *Informed 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 related to external validity. Our main results show that hedge funds are informed voltaility traders in the ETF option market. If true, then we should find a similar pattern in other markets related to market volatility, like VIX futures. The second objective is related to market clearing. If hedge funds earn abnormal profits from informed volatility trading, then other traders earn abnormal losses from such trading. The futures market data we exploit can help identify which types of traders are losing from 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 related to VIX and other financial futures is updated every Thursday and provides the aggregate long and short positions of investors categorized into four groups: Levered Funds (what are referred to as hedge funds), Asset Managers (pension funds, endowments, insurance companies, mutual funds, and portfolio managers whose clients are predominantly institutional), Non-reportable (small investors), Dealers/Intermediaries (large banks and dealers in securities, swaps, and other derivatives), and Other Reportable (traders who mostly use futures to hedge business risk).

We run 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 to VIX futures from period t to period $t+1$ and computed as the percentage change in the near-maturity futures price.[19] $NP_t^{investor}$ is the net position, defined as $\frac{\text{Long Positions}-\text{Short Positions}}{\text{Open Interest}}$, which captures whether a type of investors are net long or short in aggregate. Observations are sampled weekly (Thursday to Thursday) from 2006 to 2022. t-statistics (in brackets) are computed based on the Newey and West (1986) standard errors and estimated coefficients with a t-statistic larger than 2 are in bold.

[19] 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).

[Insert Table 15 near here]

The results are reported in Table 15. Column (1) shows that the coefficient on $NP^{investor}$ is positive and significant for hedge funds, indicating that a larger net position in VIX futures by hedge funds predicts greater returns on VIX futures over the following period. In contrast, Columns (2) shows a negative and significant coefficient on the net positions of asset managers; thus, the larger long positions in VIX futures of asset managers predict lower returns. Overall, the results provide further evidence that hedge funds are informed traders about market volatility – their net positions in VIX futures can positively predict VIX returns. This helps to validate the conclusions from our main analysis using hedge funds' holdings of ETF options. In addition, the relatively uninformed volatility traders tend to be asset managers, since their net positions are a negative predictor of returns.

8. Conclusion

By their construction as composite securities, ETFs facilitate trading on systematic movements in different asset classes, industries, and geographic regions. 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 asset manager portfolios.

We analyze 15 years of portfolio disclosures of hedge fund managers to provide evidence that ETF option markets are used for informed trading about market volatility. Hedge funds' demand for non-directional positions in ETF options strongly predicts greater volatility on the underlying ETF. The predictive power is particularly strong for simultaneous holdings of calls and puts (i.e., straddles), option positions on non-equity ETFs, and is not subsumed by forward-looking volatility expectations implied by option prices. Hedge funds' positions in equity options predicts underlying stock volatility, too, but only the idiosyncratic (i.e., stock-specific) component of volatility. 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 7.35% 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.

In contrast to our evidence of volatility timing, neither ETF share nor ETF option positions are informative about the future direction of ETF prices. This is consistent with recent studies that focus on the ETF share positions of institutional investors and conclude that ETFs are not used for informed trading. However, as we show, ETF option positions strongly reveal volatility timing ability because they are followed by significantly higher than normal volatility of ETF prices.

We also show that hedge funds' volatility demand positively impacts ETF option prices, consistent with information trading models such as Kyle (1985). Information revelation via trading in ETF options also improves the price efficiency in the options markets for associated equities. This is because the predictive power of an equity's option-implied volatility is significantly higher during periods of greater ETF trading activity, especially for equities with a greater exposure to systematic risk. Overall, the evidence highlights the ETF option market as a useful tool for allowing managers to exploit information about market volatility and contribute to price efficiency.

REFERENCES

Admati, Anat R, and Paul Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *The review of financial studies* 1, 3–40.

Agarwal, Vikas, Wei Jiang, Yuehua Tang, and Baozhong Yang, 2013, Uncovering hedge fund skill from the portfolio holdings they hide, *The Journal of Finance* 68, 739–783.

Agarwal, Vikas, Stefan Ruenzi, and Florian Weigert, 2017, Tail risk in hedge funds: A unique view from portfolio holdings, *Journal of Financial Economics* 125, 610–636.

Ang, Andrew, 2014, *Asset management: A systematic approach to factor investing* (Oxford University Press).

Aragon, George O, Lei Li, and Jun Qian, 2019a, The use of credit default swaps by bond mutual funds: Liquidity provision and counterparty risk, *Journal of Financial Economics* 131, 168–185.

Aragon, George O, and J Spencer Martin, 2012, A unique view of hedge fund derivatives usage: Safeguard or speculation?, *Journal of Financial Economics* 105, 436–456.

Aragon, George O, J Spencer Martin, and Zhen Shi, 2019b, Who benefits in a crisis? evidence from hedge fund stock and option holdings, *Journal of Financial Economics* 131, 345–361.

Aragon, George O, Rajnish Mehra, and Sunil Wahal, 2020, Do properly anticipated prices fluctuate randomly? evidence from vix futures markets, *The Journal of Portfolio Management* 46, 144–159.

Bakshi, Gurdip, and Nikunj Kapadia, 2003, Delta-hedged gains and the negative market volatility risk premium, *The Review of Financial Studies* 16, 527–566.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock return characteristics, skew laws, and the differential pricing of individual equity options, *The Review of Financial Studies* 16, 101–143.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2017, Exchange-traded funds, *Annual Review of Financial Economics* 9, 169–189.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2018, Do etfs increase volatility?, *The Journal of Finance* 73, 2471–2535.

Black, Fischer, 1975, Fact and fantasy in the use of options, *Financial Analysts Journal* 31, 36–41.

Black, Fischer, and Myron Scholes, 1973, The pricing of options and corporate, *Journal of Political Economy* 81, 637–654.

Blanco, Iván, and David Wehrheim, 2017, The bright side of financial derivatives: Options trading and firm innovation, *Journal of Financial Economics* 125, 99–119.

Boguth, Oliver, Murray Carlson, Adlai Fisher, and Mikhail Simutin, 2011, Conditional risk and performance evaluation: Volatility timing, overconditioning, and new estimates of momentum alphas, *Journal of Financial Economics* 102, 363–389.

Boudoukh, Jacob, Ronen Feldman, Shimon Kogan, and Matthew Richardson, 2019, Information, trading, and volatility: Evidence from firm-specific news, *The Review of Financial Studies* 32, 992–1033.

Busse, Jeffrey A, 1999, Volatility timing in mutual funds: Evidence from daily returns, *The Review of Financial Studies* 12, 1009–1041.

Canina, Linda, and Stephen Figlewski, 1993, The informational content of implied volatility, *The Review of Financial Studies* 6, 659–681.

Cao, Charles, Yong Chen, Bing Liang, and Andrew W Lo, 2013, Can hedge funds time market liquidity?, *Journal of Financial Economics* 109, 493–516.

Cederburg, Scott, Michael S O'Doherty, Feifei Wang, and Xuemin Sterling Yan, 2020, On the performance of volatility-managed portfolios, *Journal of Financial Economics* 138, 95–117.

Chakravarty, Sugato, Huseyin Gulen, and Stewart Mayhew, 2004, Informed trading in stock and option markets, *The Journal of Finance* 59, 1235–1257.

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

Chen, Yong, Zhi Da, and Dayong Huang, 2019, Arbitrage trading: The long and the short of it, *The Review of Financial Studies* 32, 1608–1646.

Chen, Yong, and Bing Liang, 2007, Do market timing hedge funds time the market?, *Journal of Financial and Quantitative Analysis* 42, 827–856.

Cheng, Ing-Haw, 2019, The vix premium, *The Review of Financial Studies* 32, 180–227.

Christensen, Bent J, and Nagpurnanand R Prabhala, 1998, The relation between implied and realized volatility, *Journal of financial economics* 50, 125–150.

Coval, Joshua D, and Tyler Shumway, 2001, Expected option returns, *The journal of Finance* 56, 983–1009.

Cox, John C, and Mark Rubinstein, 1985, *Options markets* (Prentice Hall).

Cumming, Douglas J, and Pedro Monteiro, 2022, Hedge fund investment in etfs, *Available at SSRN 4058765* .

Deli, Daniel N, and Raj Varma, 2002, Contracting in the investment management industry:: evidence from mutual funds, *Journal of Financial Economics* 63, 79–98.

Eraker, Bjørn, and Yue Wu, 2017, Explaining the negative returns to volatility claims: An equilibrium approach, *Journal of Financial Economics* 125, 72–98.

Ernst, Thomas, 2020, Stock-specific price discovery from etfs, Technical report, Working Paper,(October 2017).

Fama, Eugene F, 1970, Efficient capital markets: A review of theory and empirical work, *The journal of Finance* 25, 383–417.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of financial economics* 116, 1–22.

Fleming, Jeff, 1998, The quality of market volatility forecasts implied by s&p 100 index option prices, *Journal of empirical finance* 5, 317–345.

Fleming, Jeff, Chris Kirby, and Barbara Ostdiek, 2001, The economic value of volatility timing, *The Journal of Finance* 56, 329–352.

Fleming, Jeff, Chris Kirby, and Barbara Ostdiek, 2003, The economic value of volatility timing using "realized" volatility, *Journal of Financial Economics* 67, 473–509.

Fung, William, and David A Hsieh, 2001, The risk in hedge fund strategies: Theory and evidence from trend followers, *The review of financial studies* 14, 313–341.

Fung, William, and David A Hsieh, 2004, Hedge fund benchmarks: A risk-based approach, *Financial Analysts Journal* 60, 65–80.

Goyal, Amit, and Alessio Saretto, 2009, Cross-section of option returns and volatility, *Journal of Financial Economics* 94, 310–326.

Heston, Steven L, Christopher S Jones, Mehdi Khorram, Shuaiqi Li, and Haitao Mo, 2021, Option momentum .

Hong, Claire Yurong, Frank Weikai Li, and Avanidhar Subrahmanyam, 2022, Financial intermediaries and contagion in market efficiency: The case of etfs, *Available at SSRN 4062962* .

Huang, Shiyang, Maureen O'Hara, and Zhuo Zhong, 2021, Innovation and informed trading: Evidence from industry etfs, *The Review of Financial Studies* 34, 1280–1316.

Jiang, George J, and Yisong S Tian, 2005, The model-free implied volatility and its information content, *The Review of Financial Studies* 18, 1305–1342.

Jiang, Hao, Sophia Zhengzi Li, and Hao Wang, 2021a, Pervasive underreaction: Evidence from high-frequency data, *Journal of Financial Economics* 141, 573–599.

Jiang, Wei, Jitao Ou, and Zhongyan Zhu, 2021b, Mutual fund holdings of credit default swaps: Liquidity, yield, and risk, *The Journal of Finance* 76, 537–586.

Joenväärä, Juha, Mikko Kaupila, Robert Kosowski, and Pekka Tolonen, 2021, Hedge fund performance: Are stylized facts sensitive to which database one uses?, *Critical Finance Review* 10, 1–70.

Joenväärä, Juha, and Hamed Salehi, 2018, Institutional investors' etf usage and stock selection ability, *Available at SSRN 2817687* .

Johnson, Travis L, and Eric C So, 2012, The option to stock volume ratio and future returns, *Journal of Financial Economics* 106, 262–286.

Jorion, Philippe, 1995, Predicting volatility in the foreign exchange market, *The Journal of Finance* 50, 507–528.

Jorion, Philippe, and Christopher Schwarz, 2019, The fix is in: Properly backing out backfill bias, *The review of financial studies* 32, 5048–5099.

Kaniel, Ron, and Pingle Wang, 2020, Unmasking mutual fund derivative use, *Available at SSRN 3692838* .

Koski, Jennifer Lynch, and Jeffrey Pontiff, 1999, How are derivatives used? evidence from the mutual fund industry, *The journal of finance* 54, 791–816.

Kyle, Albert S, 1985, Continuous auctions and insider trading, *Econometrica: Journal of the Econometric Society* 1315–1335.

Lamoureux, Christopher G, and William D Lastrapes, 1993, Forecasting stock-return variance: Toward an understanding of stochastic implied volatilities, *The Review of Financial Studies* 6, 293–326.

Lettau, Martin, and Ananth Madhavan, 2018, Exchange-traded funds 101 for economists, *Journal of Economic Perspectives* 32, 135–54.

McLean, R David, Jeffrey Pontiff, and Christopher Reilly, 2020, Taking sides on return predictability, *Georgetown McDonough School of Business Research Paper* .

Mencia, Javier, and Enrique Sentana, 2013, Valuation of vix derivatives, *Journal of Financial Economics* 108, 367–391.

Merton, Robert C, 1973, Theory of rational option pricing, *The Bell Journal of economics and management science* 141–183.

Moreira, Alan, and Tyler Muir, 2017, Volatility-managed portfolios, *The Journal of Finance* 72, 1611–1644.

Moreira, Alan, and Tyler Muir, 2019, Should long-term investors time volatility?, *Journal of Financial Economics* 131, 507–527.

Newey, Whitney K, and Kenneth D West, 1986, A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix .

Ni, Sophie X, Jun Pan, and Allen M Poteshman, 2008, Volatility information trading in the option market, *The Journal of Finance* 63, 1059–1091.

Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam, 2009, Options trading activity and firm valuation, *Journal of Financial Economics* 94, 345–360.

Shim, John J, 2019, Arbitrage comovement, *Available at SSRN 3287912* .

Sun, Lin, and Melvyn Teo, 2022, Passive hedge funds, *Available at SSRN 4029354* .

Vilkov, Grigory, 2018, Option-implied data and analysis, *OSF. doi:10.17605/OSF.IO/Z2486.* .

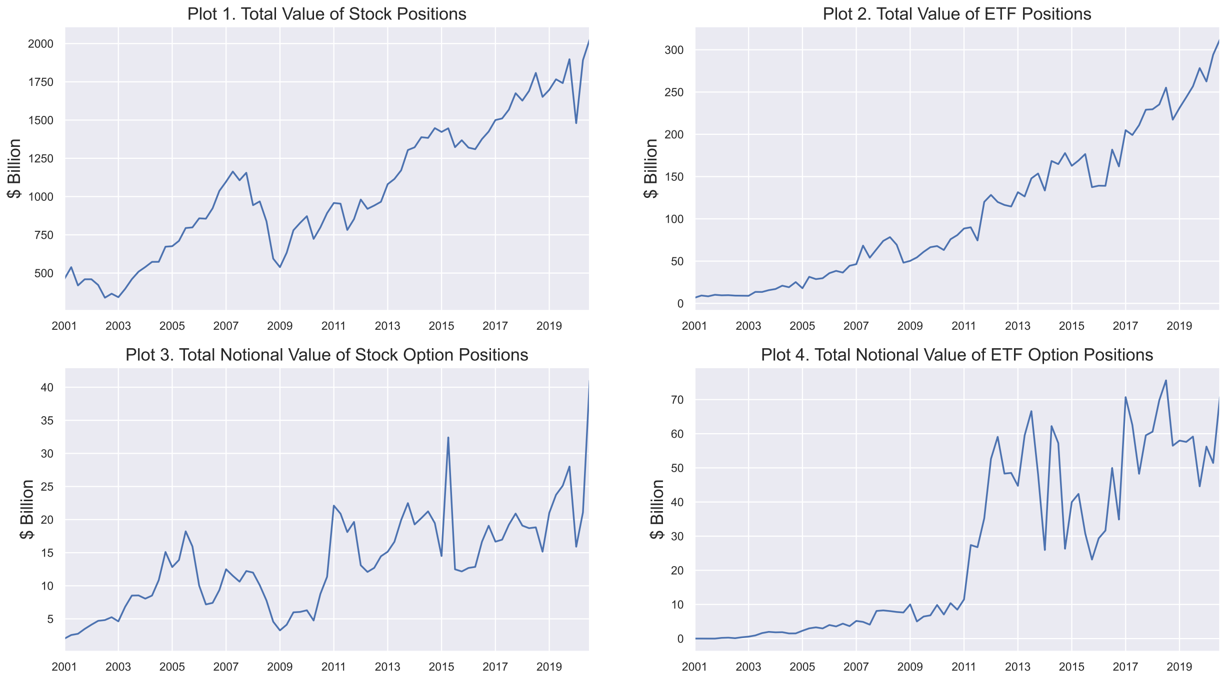

Fig. 1. **Aggregate Hedge Fund Demand for Options and Underlying Securities**
This figure plots the time series of aggregate hedge fund demand for options and underlying securities. Plots 1 and 2 show the total dollar value of hedge fund positions on stocks and ETFs, respectively. Plots 3 and 4 show the total *notional* value of underlying securities of hedge fund positions on stock and ETF options. The data of stocks and ETFs are from CRSP and ETF Global. The data of hedge fund quarterly holdings are from WhaleWisdom.

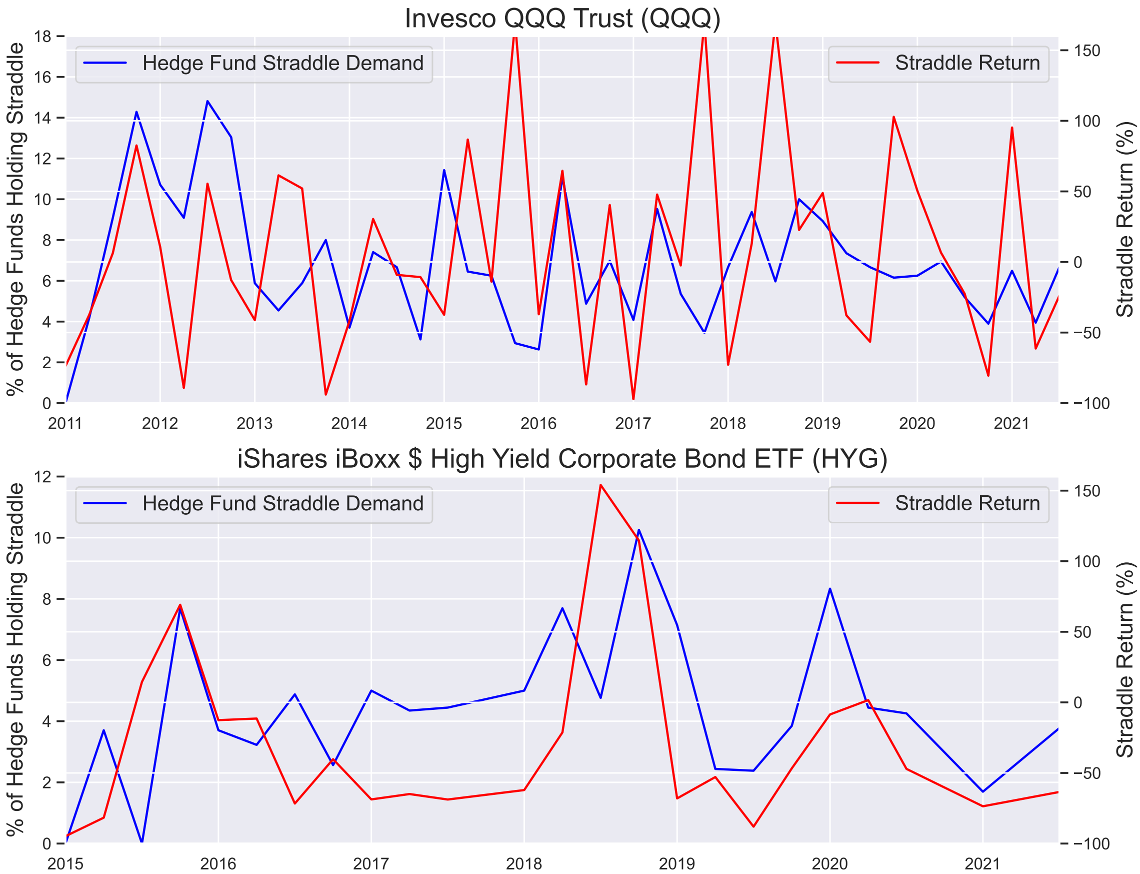

Fig. 2. **Hedge Fund Straddle Demand and Subsequent Straddle Returns: Evidence from QQQ and HGY**

This figure plots the hedge fund straddle demand on a particular ETF at the end of each quarter and the subsequent ETF straddle return. Hedge fund straddle demand is measured as the percentage of ETF straddle users among all hedge funds holding at least one share or option position in ETF. Straddle returns are constructed following the option return 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 the shortest maturity, construct a delta-hedged straddle, and hold this straddle to the nearest maturity. We select two popular ETFs: Invesco QQQ Trust (QQQ) and iShares iBoxx $ High Yield Corporate Bond ETF (HYG). The correlations between straddle demand and subsequent straddle return for QQQ and HYG are 0.15 and 0.45, respectively.

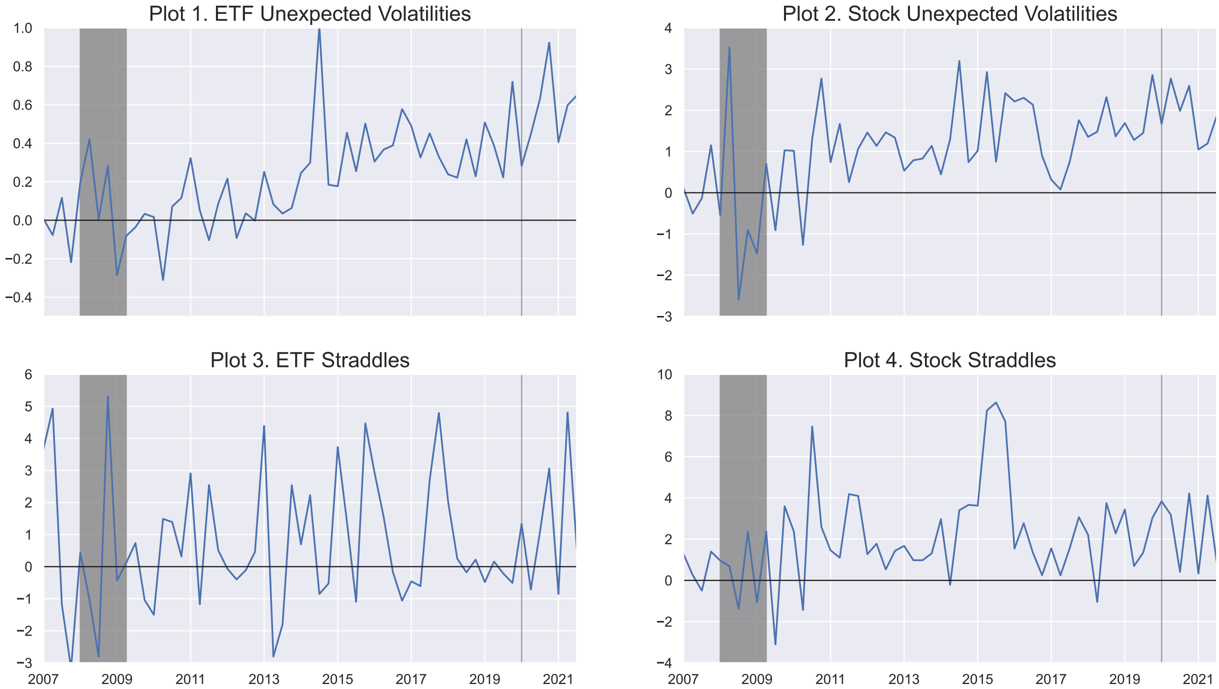

Fig. 3. **Time Series of Coefficients on Hedge Fund Straddle Demand**
This figure plots time series of coefficients on hedge fund straddle demand $STRA_{i,q}$ in quarter q from cross-sectional regressions, where the dependent variable is future unexpected volatility $UVOL_{i,q+1}$ of stocks (Plot 1) or ETFs (Plot 2), and straddle returns $r^{straddle}_{i,q+1}$ of stocks (Plot 3) or ETFs (Plot 4). See Table 5 for details about the definition of expected volatility and aggregate hedge fund straddle demand, and Table 9 for the construction of stock and ETF straddle returns.

Table 1: **Hedge Fund Portfolio Composition**

This table shows summary statistics of hedge fund holdings of shares and options of stocks and ETFs. Our sample consists of portfolio holdings disclosed by 855 hedge fund advisors over the period of 2007–2021. Positions are reported every quarter in 13F filings. The table reports summary statistics for the market value (in millions of dollars) of reported positions aggregated across all sample filings by security type and hedge fund position category. Available market values for options are in terms of the securities underlying the options instead of the options themselves. To compute the dollar values of common shares we multiply the reported shares held times the quarter-end share price. Analogously, for option positions, we obtain dollar notional values held by multiplying the reported notional shares held times quarter-end share prices. Following Aragon and Martin (2012), we classify each option position as non-directional and directional based on the reported positions in other securities of the same issuer. For common stock, a call option position is classified as directional if the advisor does not simultaneously report a put option position in the same underlying firm. Likewise, we classify a put option position as directional if the advisor does not simultaneously report a share or call option position in the underlying firm. This criterion thus classifies option straddle and protective put option as non-directional options strategies. Because of the similar behavior of ETFs with the same investment objective (i.e. large-cap US equity, investment-grade US corporate bond), we classify ETF option positions based on the categories of ETF investment objectives. See Section 2.2 for details about the classification of ETF options.

Securities	Position Types	N	Mean	Std. Dev.	Median	P10	P90
ETF	Shares	190,653	31.16	223.21	1.78	0.13	40.99
	Directional Call Options	2,369	52.32	206.89	7.58	0.13	99.85
	Directional Put Options	4,655	91.30	251.87	19.00	0.28	205.85
	Nondirectional Call Options	2,875	95.07	362.11	10.43	0.31	187.93
	Nondirectional Put Options	4,435	138.95	560.53	10.80	0.21	240.59
Stock	Shares	2,782,681	25.44	162.44	2.37	0.18	41.02
	Directional Call Options	25,325	12.77	84.94	1.97	0.04	28.36
	Directional Put Options	9,838	11.77	35.93	2.67	0.08	24.91
	Nondirectional Call Options	24,477	9.92	36.11	1.53	0.20	21.12
	Nondirectional Put Options	34,865	11.66	60.96	1.51	0.10	21.39

Table 2: **Top ETFs Used by Hedge Fund Advisors**

This table shows the top ETFs that are held by hedge fund advisors. Panel A reports the top 20 ETFs ranked by the total number of hedge fund reported positions in ETF options. Panel B reports the top 20 ETFs ranked by the total number of hedge fund reported positions in ETF shares. Our sample consists of portfolio holdings disclosed by 855 hedge fund advisors over the 2007–2021 period.

Panel A. ETFs Ranked by the Total Number of Hedge Fund Holdings of ETF Options

Rank	Ticker	Names	Category
1	SPY	SPDR S&P 500 ETF Trust	US Large Cap
2	IWM	iShares Russell 2000 ETF	US Small Cap
3	QQQ	Invesco QQQ Trust	US Large Cap
4	GLD	SPDR Gold Shares	Gold
5	XLF	Financial Select Sector SPDR Fund	Financials
6	EEM	iShares MSCI Emerging Markets ETF	Global Equity
7	GDX	VanEck Gold Miners ETF	Materials
8	FXI	iShares China Large-Cap ETF	Global Equity
9	XLE	Energy Select Sector SPDR Fund	Energy
10	HYG	iShares iBoxx $ High Yield Corporate Bond ETF	High Yield
11	EWZ	iShares MSCI Brazil ETF	Global Equity
12	XLU	Utilities Select Sector SPDR Fund	Utilities
13	XOP	SPDR S&P Oil & Gas Exploration & Production ETF	Energy
14	SLV	iShares Silver Trust	Silver
15	IYR	iShares US Real Estate ETF	Real Estate
16	TLT	iShares 20+ Year Treasury Bond ETF	Treasury
17	EFA	iShares MSCI EAFE ETF	Global Equity
18	XLV	Health Care Select Sector SPDR Fund	Health Care
19	IBB	iShares Biotechnology ETF	Health Care
20	XBI	SPDR S&P Biotech ETF	Health Care

Panel B. ETFs Ranked by the Total Number of Hedge Fund Holdings of ETF Shares

Rank	Ticker	Names	Category
1	SPY	SPDR S&P 500 ETF Trust	US Large Cap
2	GLD	SPDR Gold Shares	Gold
3	EFA	iShares MSCI EAFE ETF	Global Equity
4	EEM	iShares MSCI Emerging Markets ETF	Global Equity
5	IWM	iShares Russell 2000 ETF	US Small Cap
6	IVV	iShares S&P 500 ETF	US Large Cap
7	QQQ	Invesco QQQ Trust	US Large Cap
8	VWO	Vanguard FTSE Emerging Markets ETF	Global Equity
9	XLF	Financial Select Sector SPDR Fund	Financials
10	MDY	SPDR S&P MidCap 400 ETF Trust	US Mid Cap
11	IWF	iShares Russell 1000 Growth ETF	US Large Cap
12	EWJ	iShares MSCI Japan ETF	Global Equity
13	XLK	Technology Select Sector SPDR Fund	Technology
14	IJH	iShares S&P 400 MidCap ETF	US Mid Cap
15	IJR	iShares S&P SmallCap 600 ETF	US Small Cap
16	DVY	iShares Select Dividend ETF	Dividend Yield
17	LQD	iShares iBoxx $ Investment Grade Corporate Bond ETF	Investment Grade
18	TIP	iShares TIPS Bond ETF	TIPS
19	XLV	Health Care Select Sector SPDR Fund	Health Care
20	XLE	Energy Select Sector SPDR Fund	Energy

Table 3: **Top Hedge Fund Users of Options**

This table shows the top hedge fund advisors that actively used stock or ETF options. Panel A reports the top 20 advisors ranked by the total number of hedge fund advisors' reported positions in ETF options. Panel B reports the top 20 advisors ranked by the total number of hedge fund advisors' reported positions in stock options. Our sample consists of portfolio holdings disclosed by 855 hedge fund advisors over the 2007–2021 period.

Panel A. Hedge Fund Advisors Ranked by the Number of Positions in ETF Options

Rank	Hedge Fund Advisors	Number of Positions
1	POLAR ASSET MANAGEMENT PARTNERS	355
2	MARINER INVESTMENT GROUP	332
3	CAXTON ASSOCIATES	321
4	PINE RIVER CAPITAL MANAGEMENT	307
5	CONTINENTAL ADVISORS	241
6	KINGDON CAPITAL MANAGEMENT	235
7	VICIS CAPITAL	204
8	CTC FUND MANAGEMENT	201
9	MORGAN STANLEY	192
10	INDUS CAPITAL PARTNERS	170
11	DIALECTIC CAPITAL MANAGEMENT	143
12	SCOPIA CAPITAL MANAGEMENT	100
13	FARALLON CAPITAL MANAGEMENT	90
14	CLOUGH CAPITAL PARTNERS	88
15	BALESTRA CAPITAL	86
16	MASTERS CAPITAL MANAGEMENT	84
17	OWL CREEK ASSET MANAGEMENT	82
18	TRELLUS MANAGEMENT COMPANY	81
19	P SCHOENFELD ASSET MANAGEMENT	80
20	PICTON MAHONEY ASSET MANAGEMENT	79

Panel B. Hedge Fund Advisors Ranked by the Number of Positions in Stock Options

Rank	Hedge Fund Advisors	Number of Positions
1	MORGAN STANLEY	20727
2	VICIS CAPITAL	3855
3	THREE ZERO THREE CAPITAL PARTNERS	2904
4	JD CAPITAL MANAGEMENT	2770
5	PINE RIVER CAPITAL MANAGEMENT	1738
6	TYKHE CAPITAL	1537
7	MARINER INVESTMENT GROUP	1506
8	KINGDON CAPITAL MANAGEMENT	1357
9	MASTERS CAPITAL MANAGEMENT	1284
10	COGHILL CAPITAL MANAGEMENT	1267
11	CTC FUND MANAGEMENT	1014
12	CONTINENTAL ADVISORS	929
13	POLAR ASSET MANAGEMENT PARTNERS	819
14	MM CAPITAL	797
15	DIALECTIC CAPITAL MANAGEMENT	778
16	OTTER CREEK ADVISORS	651
17	CAXTON ASSOCIATES	537
18	ARROWMARK COLORADO HOLDINGS	432
19	ELM RIDGE CAPITAL MANAGEMENT	425
20	ANGELO GORDON & COMPANY	413

Table 4: **Time-Series Average of Cross-Sectional Statistics**

This table reports the time-series average of the cross-sectional statistics of security characteristics from 2007 through 2021. Panel A shows the summary statistics using the sample of optionable securities. Panel B shows the summary statistics using the sample of securities with hedge fund option positions. The model-free implied volatility is computed using prices of out-of-money put and call options following the method in Bakshi et al. (2003). Straddle returns are constructed following the option return literature (e.g., 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 the shortest maturity, construct a delta-hedged straddle, and hold this straddle to the nearest maturity. If the option price is not available at the quarter end, we use the price of a date that is within five days and closest to the quarter end. The implied and realized volatility are annualized and in percent. The returns are quarterly and in percent.

Panel A. The Sample of Securities with Option Trading

Security Types	Variables	N	Mean	Std. Dev.	Median	P10	P90
ETF	Implied Volatility (%)	340	27.28	12.41	25.11	15.09	41.35
	Realized Volatility (%)	340	21.19	10.10	20.19	9.73	32.55
	ETF Return (%)	342	1.70	8.30	1.68	-7.14	10.50
	Straddle Return (%)	127	-4.03	64.03	-9.27	-83.17	76.34
Stock	Implied Volatility (%)	2340	54.13	25.74	47.88	29.22	86.91
	Realized Volatility (%)	2414	46.55	27.08	40.08	23.42	75.49
	Stock Return (%)	2449	3.04	25.30	1.70	-21.87	27.24
	Straddle Return (%)	1379	-8.41	72.86	-19.39	-94.00	88.05

Panel B. The Sample of Securities with Hedge Fund Option Positions

Security Types	Variables	N	Mean	Std. Dev.	Median	P10	P90
ETF	Implied Volatility (%)	50	27.25	10.34	25.70	16.74	39.75
	Realized Volatility (%)	50	23.41	10.93	21.48	12.22	36.69
	ETF Return (%)	51	1.81	8.70	1.79	-7.54	11.32
	Straddle Return (%)	45	-1.06	61.37	-5.22	-75.02	76.20
Stock	Implied Volatility (%)	602	46.35	23.06	40.30	25.79	73.86
	Realized Volatility (%)	605	42.06	25.73	35.77	21.20	68.44
	Stock Return (%)	615	2.85	21.99	2.07	-19.24	24.46
	Straddle Return (%)	546	-2.84	74.27	-14.64	-89.35	96.30

Table 5: **ETF Volatility Timing by Hedge Funds Demand for ETF Options**

The table reports the estimation results from Fama-MacBeth regressions of future unexpected ETF return volatility against various aggregate hedge fund demands of options and common shares of ETFs. Specifically, we estimate the following two models:

$$\text{Model 1: } \text{UVOL}_{i,q+1} = \gamma\text{NDIR}_{i,q} + \delta\text{DIR}_{i,q} + \beta\text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$
$$\text{Model 2: } \text{UVOL}_{i,q+1} = \gamma_1\text{STRA}_{i,q} + \gamma_2\text{PPUT}_{i,q} + \delta_1\text{BEAR}_{i,q} + \delta_2\text{BULL}_{i,q} + \beta\text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

where $\text{UVOL}_{i,q+1}$ denotes the unexpected volatility of ETF i in quarter q+1, defined as the difference between the realized volatility of ETF i's returns over quarter q+1 and the model-free implied volatility of ETF i at the end of quarter q, which is computed from option prices of out-of-money puts and calls using the method proposed in Bakshi et al. (2003). In Model 1, $\text{NDIR}_{i,q}$ ($\text{DIR}_{i,q}$) is the proportion of hedge fund advisors disclosing a non-directional (directional) option position on underlying ETF i at the end of quarter q, among all hedge fund advisors that hold shares or options of ETF i. $\text{COM}_{i,q}$ is defined similarly for hedge fund holdings of ETF shares. In Model 2, $\text{STRA}_{i,q}$, $\text{PPUT}_{i,q}$, $\text{BEAR}_{i,q}$, and $\text{BULL}_{i,q}$ are measures of hedge fund demand for straddles, protective puts, directional puts, and directional calls, respectively. See Table 1 for details on the classification of hedge fund positions on ETF options. Columns (1)–(4) are from Model 1 and (5)–(8) are from Model 2. Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates with a t-statistic larger than 2 are in bold. The sample consists of optionable ETFs from Q1 2007 through Q2 2021.

	Model 1: ETF $\text{UVOL}_{i,q+1}$				Model 2: ETF $\text{UVOL}_{i,q+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{NDIR}_{i,q}$	**0.193**		**0.152**	**0.134**				
	[5.06]		[4.31]	[4.00]				
$\text{DIR}_{i,q}$		**0.116**	**0.071**	**0.054**				
		[4.27]	[3.36]	[2.74]				
$\text{STRA}_{i,q}$					**0.219**		**0.172**	**0.153**
					[3.55]		[4.38]	[4.03]
$\text{PPUT}_{i,q}$					**0.182**		**0.135**	**0.119**
					[4.08]		[3.95]	[3.71]
$\text{BEAR}_{i,q}$						**0.114**	**0.065**	**0.050**
						[4.13]	[2.93]	[2.22]
$\text{BULL}_{i,q}$						**0.167**	**0.119**	**0.101**
						[3.64]	[2.93]	[2.56]
$\text{COM}_{i,q}$				**-0.014**				**-0.014**
				[-2.71]				[-2.73]
CONST	**-0.063**	**-0.062**	**-0.063**	**-0.051**	**-0.063**	**-0.062**	**-0.063**	**-0.051**
	[-4.94]	[-4.87]	[-4.96]	[-3.49]	[-5.03]	[-4.90]	[-4.96]	[-3.49]

Table 6: **ETF Volatility Timing: Equity and Non-Equity ETFs**

This table repeats the Fama-MacBeth regressions in Table 5 for subsamples of equity ETFs and non-equity ETFs. Non-equity ETFs include fixed-income, commodity, currency, and multi-asset ETFs. The table reports the estimated results from the following two models:

$$\text{Model 1: } \mathrm{UVOL}_{i,q+1} = \gamma \mathrm{NDIR}_{i,q} + \delta \mathrm{DIR}_{i,q} + \beta \mathrm{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$
$$\text{Model 2: } \mathrm{UVOL}_{i,q+1} = \gamma_1 \mathrm{STRA}_{i,q} + \gamma_2 \mathrm{PPUT}_{i,q} + \delta_1 \mathrm{BEAR}_{i,q} + \delta_2 \mathrm{BULL}_{i,q} + \beta \mathrm{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

where $\mathrm{UVOL}_{i,q+1}$ denotes the unexpected volatility of ETF i in quarter q+1, defined as the difference between the realized volatility of ETF i's returns over quarter q+1 and the model-free implied volatility of ETF i at the end of quarter q, which is computed from option prices of out-of-money puts and calls using the method proposed in Bakshi et al. (2003). See Table 5 for details about the measures of various aggregate hedge fund demands of options and common shares. Columns (1)–(4) focus on equity ETFs and (5)–(8) focus on non-equity ETFs. We require at least 50 ETFs in each quarter to estimate cross-sectional regressions. Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates with a t-statistic larger than 2 are in bold. The sample consists of optionable ETFs from Q1 2007 through Q2 2021.

	Equity ETF $\mathrm{UVOL}_{i,q+1}$		Non-Equity ETF $\mathrm{UVOL}_{i,q+1}$	
	(1)	(2)	(3)	(4)
$\mathrm{NDIR}_{i,q}$	**0.140**		**0.344**	
	[4.44]		[2.59]	
$\mathrm{DIR}_{i,q}$	**0.063**		0.042	
	[2.56]		[1.36]	
$\mathrm{STRA}_{i,q}$		**0.161**		**0.464**
		[4.16]		[2.04]
$\mathrm{PPUT}_{i,q}$		**0.119**		**0.339**
		[3.93]		[2.03]
$\mathrm{BEAR}_{i,q}$		0.044		-0.146
		[1.53]		[-1.11]
$\mathrm{BULL}_{i,q}$		**0.141**		**0.203**
		[4.19]		[2.83]
$\mathrm{COM}_{i,q}$	-0.010	-0.010	**-0.033**	**-0.032**
	[-1.78]	[-1.70]	[-2.26]	[-2.29]
CONST	**-0.054**	**-0.054**	**-0.052**	**-0.055**
	[-3.45]	[-3.48]	[-2.98]	[-3.09]

Table 7: **Stock Volatility Timing by Hedge Funds' Demand for Stock Options**

The table reports the estimation results from Fama-MacBeth regressions of future unexpected stock return volatility against various aggregate hedge fund demands of stock options and common shares. Specifically, we estimate the following two models:

$$\text{Model 1:} \quad \text{UVOL}_{i,q+1} = \gamma\text{NDIR}_{i,q} + \delta\text{DIR}_{i,q} + \beta\text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$
$$\text{Model 2:} \quad \text{UVOL}_{i,q+1} = \gamma_1\text{STRA}_{i,q} + \gamma_2\text{PPUT}_{i,q} + \delta_1\text{BEAR}_{i,q} + \delta_2\text{BULL}_{i,q} + \beta\text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

where $\text{UVOL}_{i,q+1}$ denotes the unexpected volatility of stock i in quarter q+1, defined as the difference between the realized volatility of stock i's returns over quarter q+1 and the model-free implied volatility of stock i at the end of quarter q, which is computed from option prices of out-of-money puts and calls using the method proposed in Bakshi et al. (2003). See Table 5 for details about the measures of various aggregate hedge fund demands of options and common shares. Columns (1)–(4) are from Model 1 and (5)–(8) are from Model 2. Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates with a t-statistic larger than 2 are in bold. The sample consists of optionable stocks from Q1 2007 through Q2 2021.

	Model 1: Stock $\text{UVOL}_{i,q+1}$				Model 2: Stock $\text{UVOL}_{i,q+1}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{NDIR}_{i,q}$	**0.813**		**0.783**	**0.796**				
	[5.54]		[5.41]	[5.43]				
$\text{DIR}_{i,q}$		**0.198**	0.079	**0.095**				
		[4.13]	[1.82]	[2.29]				
$\text{STRA}_{i,q}$					**1.092**		**1.056**	**1.068**
					[5.07]		[6.01]	[6.06]
$\text{PPUT}_{i,q}$					**0.436**		**0.425**	**0.439**
					[3.02]		[3.52]	[3.51]
$\text{BEAR}_{i,q}$						**0.182**	0.042	0.056
						[2.70]	[0.58]	[0.82]
$\text{BULL}_{i,q}$						**0.220**	0.102	0.117
						[3.30]	[1.71]	[1.93]
$\text{COM}_{i,q}$				0.018				0.017
				[1.80]				[1.69]
CONST	**-0.099**	**-0.094**	**-0.099**	**-0.113**	**-0.099**	**-0.094**	**-0.100**	**-0.113**
	[-5.20]	[-5.09]	[-5.24]	[-5.31]	[-4.87]	[-5.09]	[-5.26]	[-5.28]

Table 8: **Volatility Information of Hedge Funds' Stock Option Positions: Idiosyncratic or Systematic?**

This table examines the predictive power of hedge funds' stock options positions for systematic and idiosyncratic components of stock return volatility. For each stock, we assign a systematic factor as one of the 11 SPDR Sector ETFs (i.e., XLF for Financial Sector). A stock is assigned with a sector ETF if it is the ETF's constituent. The table reports results from the following models:

$$\text{Model 1:}\ \ \text{DepVar}_{i,q+1} = \gamma \text{NDIR}_{i,q} + \delta \text{DIR}_{i,q} + \beta \text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

$$\text{Model 2:}\ \ \text{DepVar}_{i,q+1} = \gamma_1 \text{STRA}_{i,q} + \gamma_2 \text{PPUT}_{i,q} + \delta_1 \text{BEAR}_{i,q} + \delta_2 \text{BULL}_{i,q} + \beta \text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

$$\text{where DepVar}_{i,q+1} = \text{UIdVOL}_{i,q+1} \text{ or } |\beta_i|\text{UVOL}_{q+1}.$$

$\text{UIdVOL}_{i,q+1}$ denotes the idiosyncratic component of unexpected volatility of stock i in quarter q+1, defined as the difference between the quarter-q+1 realized idiosyncratic volatility ($\text{RIdVOL}_{i,q+1}$) and the option-implied idiosyncratic volatility at the end of quarter q ($\text{IIdVOL}_{i,q}$), which is computed as $\sqrt{\text{IVOL}_{i,q}^2 - \left(\beta_{i,q}\text{IVOL}_q\right)^2}$ where $\text{IVOL}_{i,q}$ (IVOL_q) is the model-free implied volatility of stock i (the ETF of stock i's systematic factor) and β_i is stock i's beta on the systematic factor, estimated from regressions of daily returns of stock i on daily returns of the ETF in quarter q. $|\beta_{i,q}|\text{UVOL}_{i,q+1}$ is defined as the systematic component of unexpected volatility of stock i in quarter q+1, where $\text{UVOL}_{i,q+1}$ is the difference between the quarter-$q+1$ realized volatility and quarter-q-end implied volatility of the ETF of stock i's systematic factor. The model-free implied volatility of a stock or an ETF is computed from option prices of out-of-money puts and calls using the method proposed in Bakshi et al. (2003). See Table 5 for details about the measures of various aggregate hedge fund demands of options and common shares. Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates with a t-statistic larger than 2 are in bold. The sample consists of optionable stocks from Q1 2007 through Q2 2021.

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	Idiosyncratic: $\text{UIdVOL}_{i,q+1}$		Systematic: $|\beta_{i,q}|\text{UVOL}_{q+1}$	
	(1)	(2)	(3)	(4)
$\text{NDIR}_{i,q}$	**0.732**		0.016	
	[4.28]		[0.53]	
$\text{DIR}_{i,q}$	**0.240**		-0.001	
	[4.39]		[-0.02]	
$\text{STRA}_{i,q}$		**0.952**		0.039
		[4.08]		[0.87]
$\text{PPUT}_{i,q}$		**0.481**		-0.014
		[3.37]		[-0.59]
$\text{BEAR}_{i,q}$		**0.224**		-0.014
		[3.07]		[-0.47]
$\text{BULL}_{i,q}$		**0.255**		0.007
		[3.11]		[0.16]
$\text{COM}_{i,q}$	**-0.030**	**-0.031**	0.011	0.011
	[-3.31]	[-3.35]	[1.84]	[1.78]
CONST	0.014	0.014	**-0.052**	**-0.052**
	[0.87]	[0.87]	[-3.20]	[-3.19]

Table 9: **Straddle Returns Following Hedge Funds' Option Demands**

This table reports the results from Fama-MacBeth regressions of future straddle returns against various aggregate hedge fund demands. Specifically, we estimate the following two models:

$$\text{Model 1: } r_{i,q+1}^{straddle} = \gamma \text{NDIR}_{i,q} + \delta \text{DIR}_{i,q} + \beta \text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$
$$\text{Model 2: } r_{i,q+1}^{straddle} = \gamma_1 \text{STRA}_{i,q} + \gamma_2 \text{PPUT}_{i,q} + \delta_1 \text{BEAR}_{i,q} + \delta_2 \text{BULL}_{i,q} + \beta \text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

where $\text{r}_{i,q+1}^{straddle}$ is the return to an option straddle of underlying security i from quarter-q-end to its nearest expiration date in quarter $q+1$. Straddle returns are constructed following the option return literature (e.g., 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 the shortest maturity, construct a delta-hedged straddle, and hold this straddle to the nearest maturity. If the option price is not available at the quarter end, we use the price of a date that is within five days and closest to the quarter end. See Table 5 for details about the measures of various aggregate hedge fund demands of options and common shares. Columns (1)–(2) report results for ETF straddles and (3)–(4) report results for stock straddles. Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates with a t-statistic larger than 2 are in bold. The sample consists of stocks and ETFs with valid straddle returns from Q1 2007 through Q2 2021.

	ETF Straddle Return $r_{i,q+1}^{straddle}$		Stock Straddle Return $r_{i,q+1}^{straddle}$	
	(1)	(2)	(3)	(4)
$\text{NDIR}_{i,q}$	**0.471**		**1.277**	
	[2.66]		[5.16]	
$\text{DIR}_{i,q}$	-0.016		**0.399**	
	[-0.14]		[2.94]	
$\text{STRA}_{i,q}$		**0.635**		**1.976**
		[2.41]		[5.67]
$\text{PPUT}_{i,q}$		0.125		**0.591**
		[0.36]		[2.49]
$\text{BEAR}_{i,q}$		0.208		0.326
		[1.42]		[1.38]
$\text{BULL}_{i,q}$		-0.142		**0.434**
		[-0.56]		[3.11]
$\text{COM}_{i,q}$	-0.066	-0.072	0.050	0.046
	[-1.26]	[-1.39]	[1.51]	[1.38]
CONST	0.000	0.003	**-0.145**	**-0.143**
	[0.00]	[0.04]	[-5.13]	[-5.00]

Table 10: **Performance of Hedge Fund Straddle Strategies**

This table reports the performance of portfolios of straddle formed by aggregate hedge funds' straddle positions. A straddle on a security i is assigned to the "HF" portfolio if it is held by at least one hedge fund advisor (i.g., $STRA_{i,q}$ is large than zero), otherwise it is assigned to the "other" portfolio. Portfolios are rebalanced at the end of each quarter. The return to the straddle portfolio is calculated as the equal-weighted average return of individual straddles in the portfolio. Panel A reports summary statistics of returns to hedge fund straddle strategies for ETFs and stocks separately. Panel B reports the results from time-series regressions of quarterly portfolio returns to straddle strategies on Fama-French 5 factors augmented with the momentum factor. Returns and alphas are quarterly and in percent. Sharpe ratios are annualized. The sample consists of ETFs and stocks with valid straddle returns from Q1 2007 through Q2 2021.

Panel A. Returns to Hedge Fund Straddle Strategies

		Mean	Std. Dev.	Skewness	Kurtosis	SR (annual)
ETF Straddle	HF	1.91	45.19	1.85	3.96	0.08
	Other	-5.69	40.86	1.85	3.79	-0.28
	HF – Other	7.60	17.34	0.58	0.78	0.88
Stock Straddle	HF	1.53	29.34	1.69	3.56	0.10
	Other	-12.30	25.11	2.36	6.79	-0.98
	HF – Other	13.83	11.45	1.08	1.55	2.42

Panel B. Performance Evaluation of Hedge Fund Straddle Strategies

	ETF Straddle Portfolios			Stock Straddle Portfolios		
	HF	Other	HF – Other	HF	Other	HF – Other
	(1)	(2)	(3)	(4)	(5)	(6)
α	2.12	-5.42	**7.35**	2.88	**-10.57**	**13.26**
	[0.32]	[-1.08]	[2.96]	[0.85]	[-3.74]	[8.34]
β_{MKT}	**-1.44**	**-1.49**	0.05	**-1.24**	**-1.35**	0.11
	[-2.36]	[-2.79]	[0.18]	[-3.55]	[-4.04]	[0.71]
β_{SMB}	0.63	0.68	-0.05	1.07	0.86	0.22
	[0.52]	[0.58]	[-0.10]	[1.30]	[1.32]	[0.58]
β_{HML}	-1.62	-1.86	0.23	-1.25	-1.04	-0.21
	[-1.19]	[-1.46]	[0.42]	[-1.43]	[-1.35]	[-0.55]
β_{RMW}	2.28	2.17	0.12	0.85	1.01	-0.16
	[1.36]	[1.53]	[0.19]	[0.77]	[0.96]	[-0.46]
β_{CMA}	3.76	4.31	-0.53	3.63	2.79	0.85
	[1.06]	[1.47]	[-0.37]	[1.72]	[1.59]	[1.03]
β_{UMD}	-0.99	-0.95	-0.04	-0.45	**-0.79**	0.33
	[-1.29]	[-1.54]	[-0.13]	[-0.98]	[-2.09]	[1.88]

Table 11: **Security Returns Following Hedge Funds' Option Demands**

This table reports the results from Fama-MacBeth regressions of future security returns against various aggregate hedge fund demands of options and common shares on a particular security. Specifically, we estimate the following two models:

$$\text{Model 1: } r^e_{i,q+1} = \gamma \text{NDIR}_{i,q} + \delta \text{DIR}_{i,q} + \beta \text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$
$$\text{Model 2: } r^e_{i,q+1} = \gamma_1 \text{STRA}_{i,q} + \gamma_2 \text{PPUT}_{i,q} + \delta_1 \text{BEAR}_{i,q} + \delta_2 \text{BULL}_{i,q} + \beta \text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$

where $r_{i,q+1}$ is the return of security i in excess of the risk-free rate in quarter $q+1$. See Table 5 for details about the measures of various aggregate hedge fund demands of options and common shares. Columns (1)–(2) focus on ETFs and (3)–(4) focus on stocks. Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates with a t-statistic larger than 2 are in bold. The sample consists of optionable ETFs from Q1 2007 through Q2 2021.

	ETF Excess Return $r^e_{i,q+1}$		Stock Excess Return $r^e_{i,q+1}$	
	(1)	(2)	(3)	(4)
$\text{NDIR}_{i,q}$	-0.003		-0.163	
	[-0.13]		[-1.59]	
$\text{DIR}_{i,q}$	-0.012		**-0.134**	
	[-0.53]		[-2.13]	
$\text{STRA}_{i,q}$		-0.008		-0.151
		[-0.20]		[-0.90]
$\text{PPUT}_{i,q}$		0.020		**-0.205**
		[0.40]		[-2.11]
$\text{BEAR}_{i,q}$		0.022		**-0.350**
		[0.97]		[-3.40]
$\text{BULL}_{i,q}$		-0.013		-0.041
		[-0.24]		[-0.64]
$\text{COM}_{i,q}$	-0.007	-0.006	-0.007	-0.006
	[-1.42]	[-1.19]	[-0.63]	[-0.61]
CONST	0.022	0.021	0.038	0.038
	[1.91]	[1.84]	[1.80]	[1.78]

Table 12: **Performance of Hedge Fund ETF Straddle Users**

This table evaluates the performance of hedge funds using ETF straddles. A hedge fund advisor is classified as an ETF straddle user if it holds at least one ETF straddle; otherwise, it is classified as a non-straddle user. We form portfolios of straddle users and non-straddle users at the end of each quarter and record returns of hedge funds over the subsequent three months. Monthly portfolio returns are calculated as the equal-weighted average of net returns of funds in the portfolio. Panel A reports summary statistics of returns to portfolios of hedge fund ETF straddle users and non-straddle users. Panel B reports the results from time-series regressions of monthly returns to ETF straddle users against four different benchmarks: 1) the portfolio of non-straddle users; 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), Options Strategy (OS); and 3) the Fung and Hsieh (2004) seven hedge fund risk factors. Returns and alphas are monthly and in percent. Sharpe ratios are annualized. The sample consists of TASS hedge funds whose advisor is in our sample of hedge fund advisors from 2007 to 2021.

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

	Equal-Weighted Monthly Return (%)					
Hedge Fund Portfolios	Mean	Std. Dev.	Skewness	Kurtosis	Sharpe Ratio	AUM ($Million)
ETF Straddle User	0.46	0.16	-1.96	10.20	1.03	659.27
Non-Straddle User	0.52	0.24	-1.05	5.70	0.76	381.48

Panel B. Performance Evaluation of Hedge Fund ETF Straddle Users

Panel B.1. Performance Evaluation Against Non-straddle Users

α	$\beta_{non-straddle}$
0.17	**0.53**
[2.11]	[10.50]

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

α	β_{GM}	β_{EM}	β_{LS}	β_{EMN}	β_{FIA}	β_{MS}	β_{OS}
0.19	**-0.08**	0.05	**0.21**	0.01	0.13	**0.21**	0.00
[2.16]	[-2.81]	[1.34]	[3.28]	[0.09]	[1.73]	[2.47]	[0.25]

Panel B.3. Performance Evaluation Against the Fung and Hsieh (2001) Risk Factors

α	β_{S5RF}	β_{R2S5}	β_{PTFSBD}	β_{PTFSFX}	$\beta_{PTFSCOM}$	β_{PTFSIR}	$\beta_{PTFSSTK}$
0.24	**0.15**	0.07	-0.01	-0.00	-0.01	-0.00	-0.01
[2.24]	[4.69]	[1.41]	[-0.95]	[-0.54]	[-0.93]	[-0.16]	[-1.17]

Table 13: **Price Impact of Hedge Fund ETF Option Demand**

This table shows the impact of hedge fund ETF option demand on the contemporaneous implied volatility of ETF options. We estimate the following Fama-MacBeth regressions of the contemporaneous implied volatility of ETF options against various aggregate hedge fund demands of options and common shares of ETFs.

Model 1: $\text{IVOL}_{i,q} = \gamma\text{NDIR}_{i,q} + \delta\text{DIR}_{i,q} + \beta\text{COM}_{i,q} + \lambda\text{IVOL}_{i,q-1} + \alpha + \epsilon_{i,q},$

Model 2: $\text{IVOL}_{i,q} = \gamma_1\text{STRA}_{i,q} + \gamma_2\text{PPUT}_{i,q} + \delta_1\text{BEAR}_{i,q} + \delta_2\text{BULL}_{i,q} + \beta\text{COM}_{i,q} + \lambda\text{IVOL}_{i,q-1} + \alpha + \epsilon_{i,q},$

Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates with a t-statistic larger than 2 are in bold. The sample consists of optionable ETFs from Q1 2007 through Q2 2021.

	$\text{IVOL}_{i,q}$			
	(1)	(2)	(3)	(4)
$\text{NDIR}_{i,q}$	**0.076**	**0.033**		
	[2.11]	[2.17]		
$\text{DIR}_{i,q}$	**0.124**	0.022		
	[3.95]	[1.98]		
$\text{STRA}_{i,q}$			**0.164**	**0.051**
			[3.51]	[2.38]
$\text{PPUT}_{i,q}$			-0.059	-0.005
			[-1.33]	[-0.22]
$\text{BEAR}_{i,q}$			0.011	-0.007
			[0.45]	[-0.83]
$\text{BULL}_{i,q}$			**0.243**	**0.049**
			[3.76]	[2.06]
$\text{COM}_{i,q}$	**-0.022**	**-0.009**	**-0.020**	-0.009
	[-2.98]	[-2.01]	[-2.76]	[-1.96]
$\text{IVOL}_{i,q-1}$		**0.834**		**0.832**
		[35.12]		[34.86]

Table 14: **ETF Options Trading and Price Efficiency of Stock Options**

The table examines the predictive power of stock option implied volatility for future volatility on the underlying stock, and its interactions with ETF options trading activity and the stock's exposure to the systematic factor driving ETF returns. We focus on sector-level systematic factors and trading activities in the SPDR Sector ETFs. The table reports the results from the following panel regressions:

$$\begin{aligned} \text{RVOL}_{i,q+1} &= \gamma \text{IVOL}_{i,q} + \delta \text{IVOL}_{i,q} \times \text{Log(ETF OptVol}_{i,q}) \\ &\quad + \theta \text{IVOL}_{i,q} \times \text{Log(ETF OptVol}_{i,q}) \times \text{Exposure}_{i,q} + \text{X}_{i,q} + FEs + \epsilon_{i,q+1}, \end{aligned}$$

where $\text{RVOL}_{i,q+1}$ is the realized volatility of stock i's daily returns in quarter q+1; $\text{IVOL}_{i,q}$ is the model-free option-implied volatility of stock i at the end of quarter q; ETF $\text{OptVol}_{i,q}$ is the sum of call and put volumes of the SPDR sector ETF associated with a stock; $\text{Exposure}_{i,q}$ is the sensitivity of stock i to its sector index, estimated from daily time-series regressions of stock i's returns on its sector index returns in each quarter. $\text{X}_{i,q}$ represents a variety of stock-level control variables including Log(1+Stock OptVol), Log(Market Capitalization), Log(Book-to-Market), Gross Profits-to-Assets, Asset Growth, and Past 12-Month Return, and all other interactions of IVOL (IV), ETF option volume, and the stock's systematic exposure. All specifications include stock and year-quarter fixed effects. t-statistics are computed based on robust standard errors double-clustered by stock and year-quarter. The ETF option trading activities are measured by the aggregate ETF option trading volumes in columns (1) – (3) and by the aggregate hedge fund ETF option positions in columns (4) – (6). We focus on sector-level systematic factors and trading activities in the SPDR Sector ETFs. The sample consists of optionable stocks from Q1 2007 to Q2 2021.

	$\text{RVOL}_{i,q+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{IVOL}_{i,q} \times \text{Log(ETF OptVol}_{i,q})$	0.020	0.020	-0.001			
	[2.05]	[2.10]	[-0.08]			
$\text{IVOL}_{i,q} \times \text{Log(ETF OptVol}_{i,q}) \times \text{Exposure}_{i,q}$			0.018			
			[2.08]			
$\text{IVOL}_{i,q} \times \text{Log(HF ETF Opt}_{i,q})$				0.006	0.005	0.009
				[4.81]	[4.65]	[3.79]
$\text{IVOL}_{i,q} \times \text{Log(HF ETF Opt}_{i,q}) \times \text{Exposure}_{i,q}$						0.003
						[2.10]
$\text{Log(ETF OptVol}_{i,q})$	0.009	0.013	0.021			
	[1.45]	[2.28]	[2.90]			
$\text{Log(ETF OptVol}_{i,q}) \times \text{Exposure}_{i,q}$			-0.006			
			[-1.31]			
$\text{Log(HF ETF Opt}_{i,q})$				0.001	0.001	0.001
				[1.57]	[1.73]	[1.76]
$\text{Log(HF ETF Opt}_{i,q}) \times \text{Exposure}_{i,q}$						-0.004
						[-3.87]
$\text{IVOL}_{i,q}$	0.153	0.067	0.352	0.434	0.357	0.346
	[1.24]	[0.54]	[1.68]	[16.89]	[13.21]	[13.49]
$\text{IVOL}_{i,q} \times \text{Exposure}_{i,q}$			-0.241			0.005
			[-2.00]			[0.49]
$\text{Log(1+Stock Opt}_{i,q})$		0.015	0.015		0.014	0.014
		[12.60]	[13.02]		[12.73]	[12.83]
$\text{Exposure}_{i,q}$		0.031	0.114		0.029	0.027
		[8.71]	[1.69]		[8.25]	[3.90]
$\text{Log(Market Capitalization}_{i,q})$		-0.051	-0.051		-0.050	-0.049
		[-8.83]	[-8.90]		[-8.67]	[-8.64]
$\text{Log(Book-to-Market}_{i,q})$		-0.005	-0.005		-0.006	-0.006
		[-2.42]	[-2.39]		[-2.75]	[-2.77]
$\text{Gross Profits-to-Asset}_{i,q}$		-0.024	-0.024		-0.019	-0.020
		[-2.73]	[-2.72]		[-2.33]	[-2.44]
$\text{Asset Growth}_{i,q}$		0.000	0.000		0.000	0.000
		[0.26]	[0.28]		[0.29]	[0.21]
$\text{Past 12-Month Return}_{i,q}$		0.003	0.003		0.003	0.003
		[1.19]	[1.22]		[1.12]	[1.03]
Stock FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,041	116,041	116,041	116,041	116,041	116,041
R-squared	0.659	0.668	0.669	0.659	0.667	0.668

Table 15: **VIX Futures Return Predictability of Investor Net Futures Positions**

This table reports results from 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} is the return to VIX futures from period t to period $t+1$ and $NP_t^{investor}$ is the net position in aggregate of a type of investors, which is 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 categorized into four groups: Levered Funds (what are referred to as 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 Non-reportable (small investors). Observations are sampled weekly (Thursday to Thursday) from 2006 to 2022. VIX futures returns are computed using daily settlement prices for the nearest-to-expiration futures contract and are scaled in percentage points in these regressions. t-statistics (in brackets) are computed based on the Newey and West (1986) standard errors and coefficients with a t-statistic larger than 2 are in bold.

	r_{t+1}^{VIX} (%)				
	(1)	(2)	(3)	(4)	(5)
$NP_t^{HedgeFund}$	**1.16**				
	[2.80]				
$NP_t^{AssetManager}$		**-3.00**			
		[-2.65]			
NP_t^{Dealer}			-0.53		
			[-1.36]		
$NP_t^{Other-reportable}$				-1.98	
				[-1.41]	
$NP_t^{Non-reportable}$					7.13
					[1.79]
$r_{t-i}^{VIX}, i = 0, \ldots 9$	Yes	Yes	Yes	Yes	Yes
Adj-R^2 (%)	0.251	0.427	-0.228	-0.266	0.097
N	810	810	810	810	810

Appendix

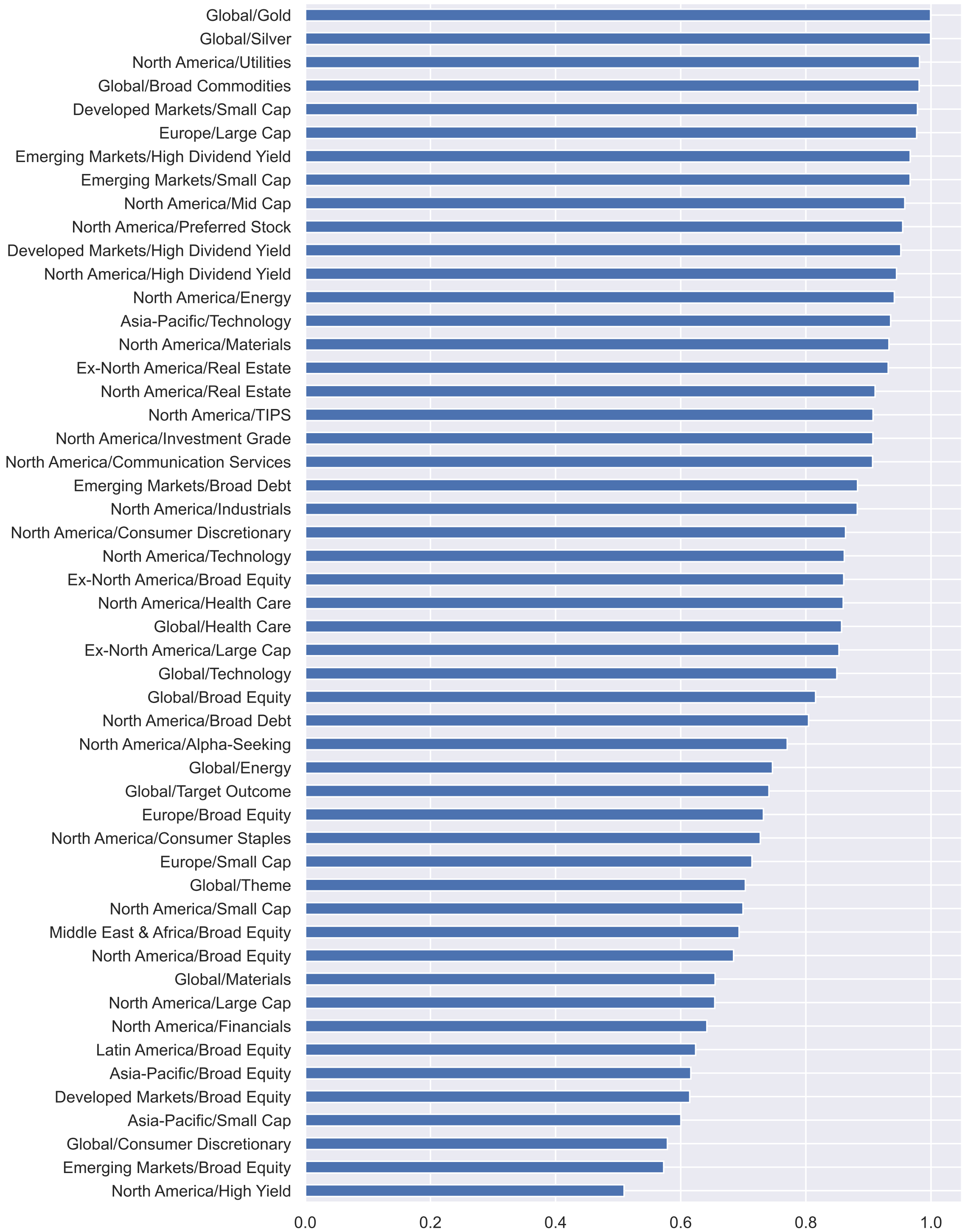

Fig. A.1. **Average Correlations of Returns of ETFs in different Investment-Region Categories**
This figure plots average pairwise correlations of returns to ETFs within a particular investment-region category. ETFs are required to have at least 3 year return data to calculate correlations. All correlations in the figure are above 0.5, and the average correlation across categories is 0.82.

Table A.1: **Robustness: Control Variables**

This table repeats the regression analyses in Table 5, Table 7, and Table 9 with the following additinal control variables: the option-to-stock volume ratio (O/S) (Johnson and So (2012)), the lagged realized volatility (RV), and lagged implied volatility (IV) (Goyal and Saretto (2009)). See Table 5 for details about the measures of various aggregate hedge fund demands of options and common shares. Columns (1)–(4) report results for ETFs and (5)–(8) report results for stocks. Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates that are significant at the 5% confidence level are in bold. The sample consists of optionable stocks or ETFs from Q1 2007 through Q2 2021.

	ETF				Stock			
	UVOL$_{i,q+1}$		$r^{straddle}_{i,q+1}$		UVOL$_{i,q+1}$		$r^{straddle}_{i,q+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NDIR$_{i,q}$	**0.063**		**0.462**		**0.367**		**0.801**	
	[2.36]		[2.43]		[3.91]		[3.39]	
DIR$_{i,q}$	**0.044**		0.013		**0.140**		**0.269**	
	[2.34]		[0.10]		[4.15]		[2.15]	
STRA$_{i,q}$		**0.070**		**0.651**		**0.552**		**1.384**
		[2.15]		[2.38]		[4.76]		[3.99]
PPUT$_{i,q}$		**0.050**		0.244		0.126		0.260
		[2.04]		[0.65]		[1.64]		[1.14]
BEAR$_{i,q}$		0.038		0.328		**0.127**		0.164
		[1.45]		[1.64]		[2.16]		[0.72]
BULL$_{i,q}$		**0.084**		-0.072		**0.146**		**0.321**
		[3.03]		[-0.31]		[2.80]		[2.32]
COM$_{i,q}$	**-0.013**	**-0.013**	-0.084	-0.083	**-0.043**	**-0.044**	0.004	0.003
	[-2.41]	[-2.40]	[-1.37]	[-1.37]	[-4.16]	[-4.21]	[0.13]	[0.10]
RVOL$_{i,q}$	**0.311**	**0.309**	0.257	-0.048	**0.110**	**0.110**	0.014	0.012
	[7.58]	[7.59]	[0.94]	[-0.92]	[9.74]	[9.79]	[0.57]	[0.50]
IVOL$_{i,q-1}$	**-0.401**	**-0.401**	0.086	0.325	**-0.304**	**-0.303**	**-0.140**	**-0.137**
	[-11.50]	[-11.47]	[0.33]	[1.31]	[-19.15]	[-19.13]	[-3.85]	[-3.72]
O/S$_{i,q}$	-0.000	0.000	-0.027	0.069	0.007	0.005	**0.152**	**0.149**
	[-0.01]	[0.00]	[-0.54]	[0.29]	[0.47]	[0.34]	[6.83]	[6.72]

Table A.2: **Style-Based Decomposition of Stock Volatility**

This table repeats the analysis in Table 8, where we consider style-based systematic factors and use the 4 Russell Size/Value ETFs as their financial instruments (i.e., IWF for Russell 1000 Growth). A stock is assigned with a particular style ETF if it is a constituent member of the ETF. The table reports the estimation results from the following models:

$$\text{Model 1:}\;\; \text{DepVar}_{i,q+1} = \gamma\text{NDIR}_{i,q} + \delta\text{DIR}_{i,q} + \beta\text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$
$$\text{Model 2:}\;\; \text{DepVar}_{i,q+1} = \gamma_1\text{STRA}_{i,q} + \gamma_2\text{PPUT}_{i,q} + \delta_1\text{BEAR}_{i,q} + \delta_2\text{BULL}_{i,q} + \beta\text{COM}_{i,q} + \alpha + \epsilon_{i,q+1},$$
$$\text{where DepVar}_{i,q+1} = \text{UIdVOL}_{i,q+1} \text{ or } |\beta_i|\text{UVOL}_{q+1}.$$

$\text{UIdVOL}_{i,q+1}$ denotes the idiosyncratic component of unexpected volatility of stock i in quarter q+1, defined as the difference between the quarter-q+1 realized idiosyncratic volatility ($\text{RIdVOL}_{i,q+1}$) and the option-implied idiosyncratic volatility at the end of quarter q ($\text{IIdVOL}_{i,q}$), which is computed as $\sqrt{\text{IVOL}_{i,q}^2 - \left(\beta_i\text{IVOL}_q\right)^2}$ where $\text{IVOL}_{i,q}$ (IVOL_q) is the model-free implied volatility of stock i (the ETF of stock i's systematic factor) and β_i is stock i's beta on the systematic factor, estimated from regressions of daily returns of stock i on daily returns of the ETF in quarter q. $|\beta_i|\text{UVOL}_{i,q+1}$ is defined as the systematic component of unexpected volatility of stock i in quarter q+1, where $\text{UVOL}_{i,q+1}$ is the difference between the quarter-$q+1$ realized volatility and quarter-q-end implied volatility of the ETF of stock i's systematic factor. The model-free implied volatility of a stock or an ETF is computed from option prices of out-of-money puts and calls using the method proposed in Bakshi et al. (2003). See Table 5 for details about the measures of various aggregate hedge fund demands of options and common shares. Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates with a t-statistic larger than 2 are in bold. The sample consists of optionable stocks from Q1 2007 through Q2 2021.

Style-based Idiosyncratic and Systematic Components of Stock Volatility

	Idiosyncratic: $\text{UIdVOL}_{i,q+1}$		Systematic: $\lvert\beta_{i,q}\rvert\text{UVOL}_{q+1}$	
	(1)	(2)	(3)	(4)
$\text{NDIR}_{i,q}$	**0.876**		0.016	
	[5.17]		[0.39]	
$\text{DIR}_{i,q}$	0.054		0.011	
	[1.14]		[0.29]	
$\text{STRA}_{i,q}$		**1.150**		0.014
		[5.43]		[0.31]
$\text{PPUT}_{i,q}$		**0.502**		0.026
		[3.42]		[0.71]
$\text{BEAR}_{i,q}$		0.014		0.003
		[0.19]		[0.09]
$\text{BULL}_{i,q}$		0.084		0.017
		[1.11]		[0.38]
$\text{COM}_{i,q}$	**0.023**	**0.022**	**0.014**	**0.014**
	[2.51]	[2.40]	[2.13]	[2.13]
CONST	**-0.094**	**-0.093**	**-0.054**	**-0.054**
	[-5.61]	[-5.59]	[-3.01]	[-3.01]

Table A.3: **Do Volatility-Managed Portfolios (Moreira and Muir, 2017) Explain the Outperformance of Hedge Fund ETF Straddle Users?**

Panel A reports the result from the following time-series regression,

$$r_t^{e,straddle} = \alpha + \beta_{non-straddle} r_t^{e,non-straddle} + \beta_{SPY} r_t^{e,SPY} + \beta_{EFA} r_t^{e,EFA} + \beta_{LQD} r_t^{e,LQD} + \beta_{IEF} r_t^{e,IEF} + \beta_{GLD} r_t^{e,GLD} + \epsilon_t$$

where $r_t^{e,straddle}$ is the monthly return to the portfolio of hedge fund ETF Straddle Users in excess of the risk-free rate; $r_t^{e,non-straddle}$ is the excess return to the portfolio of hedge fund ETF Non-straddle Users; $r_t^{e,j}$, j = SPY, EFA, LQD, IEF, GLD, denote the excess returns to five popular ETFs, each of which represents a particular asset market: 1) SPY: SPDR S&P 500 ETF (US equity), 2) EFA: iShares MSCI EAFE ETF (global equity), 3) LQD: iShares iBoxx $ Investment Grade Corporate Bond ETF (US corporate bond), 4) IEF: iShares Barclays 7-10 Year Treasury Bond ETF (US Treasury), and 5) GLD: SPDR Gold (precious metal). Panel B reports the result from the time-series regression of the same form, where an ETF is replaced with its volatility-managed portfolio (see., Moreira and Muir, 2017), which is constructed as $r_t^{\sigma} = \frac{c}{\hat{\sigma}_t^2(r_t)} r_t$, where $\hat{\sigma}_t^2(r_t)$ is the previous month's realized variance of daily ETF returns and c is a constant which is chosen to make the managed portfolio have the same unconditional variance as the original ETF. The sample consists of TASS hedge funds whose advisor is in our sample of hedge fund advisors from 2007 to 2021.

Panel A. Performance Evaluation Using ETFs

α	$\beta_{non-straddle}$	β_{SPY}	β_{EFA}	β_{LQD}	β_{IEF}	β_{GLD}
0.25	**0.61**	**-0.11**	0.01	0.10	**-0.16**	-0.02
[3.45]	[7.71]	[-2.31]	[0.42]	[1.58]	[-2.76]	[-1.40]

Panel B. Performance Evaluation Using Volatility-Managed ETFs

α	$\beta_{non-straddle}$	β_{SPY}	β_{EFA}	β_{LQD}	β_{TLT}	β_{GLD}
0.17	**0.47**	0.00	0.01	0.04	-0.08	-0.00
[2.13]	[7.76]	[0.16]	[0.79]	[1.16]	[-1.62]	[-0.52]

Table A.4: **Evidence from Firm-Specific News Driven Volatilities**

This table examines the predictability of hedge funds' ETF and stock options positions for financial news-driven measures of systematic and firm-specific volatility. We decompose stock returns into firm-specific news-driven and systematic-factor-driven components using release times of financial news articles. Specifically, we first retrieve all news articles from Dow Jones Newswire provided by RavenPack News Analytics. Then we classify stock return in a particular 15-minute window (i.e., 10:00 – 10:15 AM) as a firm-specific-news-driven return if an article is published during this window; otherwise, the stock returns is a systematic-factor-driven return. This exercise produces two categories of 15-minute, high-frequency returns for all stocks. For an ETF, its firm-specific-news-driven return is the weighted average of firm-specific-news-driven returns of its underlying constituents; its systematic-factor-driven return is defined similarly. The volatility is computed as the standard deviation of 15-minute returns for two categories separately. See Table 5 for details about the measures of various aggregate hedge fund demands of options and common shares. Newey and West (1986) t-statistics (in brackets) are computed based on the time-series variability of coefficients estimated from cross-sectional regressions. Estimates with a t-statistic larger than 2 are in bold. The sample consists of optionable stocks and ETFs from Q1 2012 through Q2 2021, during which the daily weights of underlying constituents of ETFs are available in ETF Global.

	ETF				Stock			
	$\text{RVOL}_{i,q+1}^{firm-specific-news}$		$\text{RVOL}_{i,q+1}^{systematic-factor-news}$		$\text{RVOL}_{i,q+1}^{firm-specific-news}$		$\text{RVOL}_{i,q+1}^{systematic-factor-news}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\text{NDIR}_{i,q}$	**0.070**		**0.156**		**0.547**		-0.088	
	[3.06]		[3.21]		[5.68]		[-0.39]	
$\text{DIR}_{i,q}$	-0.002		**0.119**		**0.324**		0.070	
	[-0.17]		[3.35]		[3.86]		[0.41]	
$\text{STRA}_{i,q}$		**0.127**		**0.291**		**0.703**		-0.036
		[2.44]		[2.69]		[5.55]		[-0.12]
$\text{PPUT}_{i,q}$		0.014		-0.025		**0.326**		-0.013
		[0.26]		[-0.57]		[2.49]		[-0.06]
$\text{BEAR}_{i,q}$		**0.030**		0.068		**0.207**		-0.324
		[2.70]		[1.61]		[2.10]		[-1.37]
$\text{BULL}_{i,q}$		-0.062		**0.205**		**0.382**		0.271
		[-1.87]		[2.38]		[4.06]		[1.37]
$\text{IVOL}_{i,q}$	**-0.026**	**-0.026**	**0.347**	**0.344**	**0.033**	**0.033**	-0.037	-0.036
	[-3.91]	[-4.08]	[13.24]	[13.23]	[2.04]	[2.06]	[-0.91]	[-0.89]
$\text{RVOL}_{i,q}^{firm-news}$	**-0.138**	**-0.145**	**-0.411**	**-0.418**	**0.209**	**0.209**	-0.002	-0.003
	[-11.86]	[-12.55]	[-4.55]	[-4.55]	[3.48]	[3.49]	[-0.01]	[-0.02]
$\text{RVOL}_{i,q}^{syst-news}$	**0.021**	**0.022**	**0.288**	**0.286**	**0.168**	**0.168**	**1.046**	**1.046**
	[3.55]	[3.71]	[6.17]	[6.19]	[4.83]	[4.83]	[11.65]	[11.65]

Table A.5: **Top ETFs by Various Hedge Fund Options Demand**

This table reports the top 20 ETFs ranked by the four different aggregate hedge fund option positions – directional call, directional put, nondirectional call, and nondirectional put.

Panel A. Rank by the Total Number of Positions in Nondirectional Call Options

Rank	Ticker	Names	Category
1	SPY	SPDR S&P 500 ETF Trust	US Large Cap
2	IWM	iShares Russell 2000 ETF	US Small Cap
3	QQQ	Invesco QQQ Trust	US Large Cap
4	GLD	SPDR Gold Shares	Gold
5	GDX	VanEck Gold Miners ETF	Materials
6	XLF	Financial Select Sector SPDR Fund	Financials
7	FXI	iShares China Large-Cap ETF	Global Equity
8	EWZ	iShares MSCI Brazil ETF	Global Equity
9	XLE	Energy Select Sector SPDR Fund	Energy
10	XLU	Utilities Select Sector SPDR Fund	Utilities
11	XOP	SPDR S&P Oil & Gas Exploration & Production ETF	Energy
12	DIA	SPDR Dow Jones Industrial Average ETF Trust	US Large Cap
13	EFA	iShares MSCI EAFE ETF	Global Equity
14	SLV	iShares Silver Trust	Silver
15	IYR	iShares US Real Estate ETF	Real Estate
16	HYG	iShares iBoxx $ High Yield Corporate Bond ETF	High Yield
17	XLI	Industrial Select Sector SPDR Fund	Industrials
18	XLV	Health Care Select Sector SPDR Fund	Health Care
19	XLB	Materials Select Sector SPDR Fund	Materials
20	XLP	Consumer Staples Select Sector SPDR Fund	Consumer Staples

Panel B. Rank by the Total Number of Positions in Nondirectional Put Options

Rank	Ticker	Names	Category
1	SPY	SPDR S&P 500 ETF Trust	US Large Cap
2	QQQ	Invesco QQQ Trust	US Large Cap
3	IWM	iShares Russell 2000 ETF	US Small Cap
4	GLD	SPDR Gold Shares	Gold
5	EEM	iShares MSCI Emerging Markets ETF	Global Equity
6	XLF	Financial Select Sector SPDR Fund	Financials
7	GDX	VanEck Gold Miners ETF	Materials
8	XLE	Energy Select Sector SPDR Fund	Energy
9	FXI	iShares China Large-Cap ETF	Global Equity
10	EWZ	iShares MSCI Brazil ETF	Global Equity
11	EFA	iShares MSCI EAFE ETF	Global Equity
12	XLU	Utilities Select Sector SPDR Fund	Utilities
13	HYG	iShares iBoxx $ High Yield Corporate Bond ETF	High Yield
14	XOP	SPDR S&P Oil & Gas Exploration & Production ETF	Energy
15	XLI	Industrial Select Sector SPDR Fund	Industrials
16	TLT	iShares 20+ Year Treasury Bond ETF	Treasury
17	IYR	iShares US Real Estate ETF	Real Estate
18	SLV	iShares Silver Trust	Silver
19	XLV	Health Care Select Sector SPDR Fund	Health Care
20	XRT	SPDR S&P Retail ETF	Consumer Discretionary

Panel C. Rank by the Total Number of Positions in Directional Call Options

Rank	Ticker	Names	Category
1	GLD	SPDR Gold Shares	Gold
2	GDX	VanEck Gold Miners ETF	Materials
3	SPY	SPDR S&P 500 ETF Trust	US Large Cap
4	XLF	Financial Select Sector SPDR Fund	Financials
5	SLV	iShares Silver Trust	Silver
6	IWM	iShares Russell 2000 ETF	US Small Cap
7	EEM	iShares MSCI Emerging Markets ETF	Global Equity
8	FXI	iShares China Large-Cap ETF	Global Equity
9	XLE	Energy Select Sector SPDR Fund	Energy
10	QQQ	Invesco QQQ Trust	US Large Cap
11	XOP	SPDR S&P Oil & Gas Exploration & Production ETF	Energy
12	TLT	iShares 20+ Year Treasury Bond ETF	Treasury
13	XLI	Industrial Select Sector SPDR Fund	Industrials
14	UUP	Invesco DB US Dollar Index Bullish Fund	Currency
15	XLU	Utilities Select Sector SPDR Fund	Utilities
16	EFA	iShares MSCI EAFE ETF	Global Equity
17	DXJ	WisdomTree Japan Hedged Equity Fund	Global Equity
18	XME	SPDR S&P Metals & Mining ETF	Materials
19	XLV	Health Care Select Sector SPDR Fund	Health Care
20	GDXJ	VanEck Junior Gold Miners ETF	Materials

Panel D. Rank by the Total Number of Positions in Directional Put Options

Rank	Ticker	Names	Category
1	SPY	SPDR S&P 500 ETF Trust	US Large Cap
2	IWM	iShares Russell 2000 ETF	US Small Cap
3	QQQ	Invesco QQQ Trust	US Large Cap
4	EEM	iShares MSCI Emerging Markets ETF	Global Equity
5	XLF	Financial Select Sector SPDR Fund	Financials
6	HYG	iShares iBoxx $ High Yield Corporate Bond ETF	High Yield
7	IYR	iShares US Real Estate ETF	Real Estate
8	XLI	Industrial Select Sector SPDR Fund	Industrials
9	FXI	iShares China Large-Cap ETF	Global Equity
10	IBB	iShares Biotechnology ETF	Health Care
11	XBI	SPDR S&P Biotech ETF	Health Care
12	TLT	iShares 20+ Year Treasury Bond ETF	Treasury
13	XOP	SPDR S&P Oil & Gas Exploration & Production ETF	Energy
14	XRT	SPDR S&P Retail ETF	Consumer Discretionary
15	XLU	Utilities Select Sector SPDR Fund	Utilities
16	XLV	Health Care Select Sector SPDR Fund	Health Care
17	KRE	SPDR S&P Regional Banking ETF	Financials
18	XLB	Materials Select Sector SPDR Fund	Materials
19	EWZ	iShares MSCI Brazil ETF	Global Equity
20	XME	SPDR S&P Metals & Mining ETF	Materials