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Implied Volatility Dynamics and Predictability

Evidence from Sector SPDR ETF Options

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Abstract

This study provides new evidence on the short-term dynamics and predictability of sectoral implied volatilities, offering insights into how information flow, capital reallocation, and market frictions shape volatility expectations and option pricing. The results reveal that sector IVs tend to underreact to systematic shocks and overreact to idiosyncratic, sector-specific shocks.

Consistent with earlier literature, I document daily reversals in at-the-money IVs and persistent relationships between sector and market volatility premiums. I also confirm asymmetric IV responses to sector returns, as IVs increase more in response to negative returns than decrease in response to positive returns. Unlike prior results, I show that the asymmetry holds for both systematic and idiosyncratic returns.

Further results show that sector IVs respond positively to option demand, underlying ETF volumes, and market-wide volatility (VIX). However, IVs tend to overreact to ETF volumes and sector-specific ETF returns, as evidenced by next-day reversals. In contrast, IVs underreact to systematic signals like VIX and market returns, adjusting with a delay, consistent with theories of slow-moving capital and limits of arbitrage. These over- and underreactions in sector IVs exhibit predictability that results in accurate out-of-sample forecasts and high related option strategy returns.

Keywords Implied Volatility, Option Pricing, Sector ETF options

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Tiivistelmä

Tämä tutkimus tarjoaa uutta näyttöä sektorikohtaisen implisiittisten volatiliteetin (IV) lyhyen aikavälin käyttäytymisestä ja ennustettavuudesta. Löydökset esittävät, kuinka uusi informaatio, pääoman uudelleenallokaatio ja markkinakitkat muovaavat volatiliteettiodotuksia ja optioiden hinnoittelua. Tuloksien mukaan sektoreiden IV:t alireagoivat systemaattisiin tekijöihin ja ylireagoivat sektorikohtaisiin tekijöihin.

Aiemman kirjallisuuden mukaisesti löydän päivittäisiä palautusliikkeitä IV:issä sekä yhteyden sektorikohtaisten ja markkinatason volatiliteettipreemioiden välillä. Vahvistan myös IV:n epäsymmetriset reaktiot sektorituottoihin: IV kasvaa voimakkaammin negatiivisiin tuottoihin kuin mitä se laskee positiivisiin. Vastoin aiempaa näyttöä osoitan, että epäsymmetria koskee sekä systemaattisia että idiosynkraattisia tuottoja.

Tulokset osoittavat myös, että sektorikohtaiset IV:t reagoivat positiivisesti optiokysyntään, kohde-etuutena toimivan ETF:n kaupankäyntivolyymiin sekä markkinatason volatiliteettiin (VIX-indeksi). IV:t ylireagoivat ETF-kaupankäyntivolyymeihin ja sektorikohtaisiin tuottoihin, mikä ilmenee seuraavan päivän korjausliikkeinä. Sen sijaan systemaattisiin signaaleihin, kuten VIX:n ja markkinatuottoihin, sektori-IV:t reagoivat viiveellä, mikä liittyy reaalimaailman arbitraasirajoitteisiin sekä teoriaan hitaista pääomaliikkeistä. Toistuvat yli- ja alireaktiot IV:ssä luovat ennustettavuutta, joka johtaa tarkkoihin ennusteisiin sekä merkittäviin optiostrategioiden tuottoihin.

Avainsanat Implisiittinen volatiliteetti, Optiohinnoittelu, ETF optiot

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Helsinki, 06 July 2025

Akseli E. Kajander

1 Introduction

Market expectations of future return volatility play a fundamental role in asset pricing, risk management, and derivatives trading. Implied volatility (IV), extracted from option prices, offers an established forward-looking measure of this market expected volatility. Higher IV is associated with higher prices of contingent claims, such as options, as it reflects greater uncertainty and higher potential for price movements in the underlying asset. Conversely, lower IV results in lower option prices. The volatility expectations are incorporated into security prices through a trading process.

Implied volatility and volatility premium (VP), measured as the difference between IV and realized past volatility, have received considerable attention in academia. Most earlier studies focus on S&P 500 index options or individual stock options, whereas ETF options, more specifically sector ETF options, are not widely covered. Since their introduction in the late 1990s, ETFs have experienced significant growth through the 2000s and 2010s, and have gained popularity due to their diversification benefits, good liquidity, low-cost structure, and transparency. Sector ETFs, allowing targeted exposure to specific industries and offering alternative tools for risk management, represent an interesting yet rather unexplored area for volatility research. This study addresses that gap, providing new evidence on the sectoral IV dynamics.

Implied volatility is academically interesting as it links market expectations with both asset pricing theory and the real-world constraints of perfectly efficient markets. In frictionless settings, changes in volatility expectations are immediately reflected in asset prices, ensuring efficient option pricing. In practice, however, real-world frictions such as limited investor attention, capital constraints, order imbalances, risk-aversion and slow information diffusion prevent perfect price adjustments.

Consequently, implied volatility dynamics and its short-term predictability relate to theoretical frameworks such as demand-based option pricing, slow-moving capital and limits of arbitrage, with this study offering new evidence that complements and extends this literature. Beyond academic interest, these insights hold practical significance. The predictability stemming from systematic patterns and delayed

responses in IV can be leveraged in risk management, hedging and tactical trading strategies in the option markets.

The research questions guiding this thesis are:

1) Which factors drive the short-term changes in sectoral implied volatilities?
2) Do sectoral implied volatilities exhibit systematic patterns or gradual adjustments that result in short-term predictability?

By addressing these questions, this study contributes to the literature on option pricing under market frictions and extends our understanding of implied volatility dynamics beyond the well-studied S&P 500 and single stock settings.

Aligned with my hypothesis that is based on earlier literature, this study finds the following: I document significant daily reversals in at-the-money implied volatilities and persistent long-term relationships between sector and market volatility premiums. I also confirm asymmetric IV responses to sector returns, as IVs increase more in response to negative returns than decrease in response to positive returns.

Furthermore, this thesis shows that sector IVs respond positively to option demand, underlying ETF volumes, and market-wide volatility (VIX). However, the effects of ETF volumes tend to reverse the following day. The same applies to sector ETF returns, both indicating initial IV overreactions. In contrast, the influence of VIX is transmitted to sector IVs with a one- to two-day delay, indicating underreactions to systematic IV, consistent with theory of slow-moving capital. Overall, sectoral IVs tend to overreact to sector-specific factors and underreact to systematic factors. These over- and underreactions in sectoral IVs exhibit predictability that results in accurate out-of-sample forecasts and significant related trading strategy returns.

The thesis is structured followingly: Chapter 2 reviews the related literature on implied volatility and related theoretical frameworks. Chapter 3 outlines the data and methods used in the analysis and presents the descriptive statistics. Chapter 4 replicates Marks and Simon (2017) with a novel dataset from years 2015-2024. Chapter 5 presents a comprehensive set of IV determinants. Chapter 6 develops a forecasting model and evaluates its out-of-sample performance. Chapter 7 concludes.

2 Literature Review: Theoretical Perspectives on Implied Volatility

2.1 Volatility and Option Pricing

2.1.1 Empirical Dynamics of Volatility

Volatility is commonly measured as the standard deviation of asset returns and serves as a key indicator of market risk. Since riskier assets exhibit greater volatility, investors demand a risk premium, which translates into higher expected returns and lower asset prices. Importantly, volatility is not static but fluctuates over time due to phenomena such as volatility clustering and its sensitivity to market movements. These dynamic properties are central to today's asset pricing models, risk management strategies, and derivative valuation.

Volatility is positively serially correlated. As Mandelbrot (1963) famously notes, "... large changes tend to be followed by large changes — of either sign — and small changes tend to be followed by small changes...." This observation suggests that significant market movements often lead to elevated volatility that tends to persist for some time before eventually fading. Subsequent studies (Fama, 1965; Officer, 1973) corroborate this finding. The persistence of volatility underlies the phenomenon of volatility clustering, which has led to the development of ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized ARCH) models — now fundamental tools for risk forecasting in financial markets. Engle (1982) pioneered the ARCH model framework, which has since been extended by Bollerslev (1986) and numerous other researchers.

Stock market volatility is closely linked to market movements, with volatility generally declining when the market rises and increasing when market falls, a pattern identified by Black (1976). This negative relationship is partially explained by leverage effects: when a firm's value appreciates, equity comprises a larger share of its capital structure, reducing leverage and dampening stock return volatility. Conversely, when a firm's value declines, equity becomes a smaller proportion, increasing leverage and

amplifying stock return fluctuations. Black (1976) and Christie (1982) document this positive association between financial leverage and volatility but find that leverage effects explain only part of volatility fluctuations. Their findings suggest that other factors, such as investor sentiment and behavioral dynamics, also play a role.

Volatility feedback effect (Pindyck, 1984; French, Schwert and Stambaugh, 1987) provides an alternative explanation for the negative relationship between stock returns and volatility. If the market prices in volatility, an anticipated rise in volatility increases time-varying risk premiums, raising the required return for investors. Higher required returns lower the present value of expected future cash flows, causing stock prices to decline before volatility actually rises, independent of leverage effects. As a forward-looking mechanism, the volatility feedback effect influences implied volatility, which captures the market's expectations of future fluctuations and tends to increase before large price moves.

Wu (2001) states that "the leverage effect and the volatility feedback effect both play very important roles in generating asymmetric volatility." Examining the CRSP value-weighted index, Wu finds that while the leverage effect contributes more to the negative return-volatility correlation, the volatility feedback effect becomes more pronounced during high-volatility periods, consistent with Campbell and Hentschel (1992). Similarly, using S&P 500 intraday futures data, Bollerslev, Litvinova and Tauchen (2006) provide stronger evidence for the leverage effect over prolonged periods but also detect an instantaneous volatility feedback effect at short time horizons. In contrast, analysing Japanese markets, Bekaert and Wu (2000) conclude that the volatility feedback effect dominates the leverage effect at the market level.

Beyond market-driven and leverage-related effects, broader macroeconomic conditions also influence volatility patterns. Schwert (1989), in a 130-year historical study of stock market volatility, finds that volatility spikes during economic recessions and periods of macroeconomic instability, such as the Great Depression (1929–1939). He attributes part of this increased volatility to operating leverage, contributing to the literature on leverage effects. Furthermore, Schwert's (1989) findings support the persistence of volatility (volatility clustering) in financial markets.

Volatility, while persistent, does not stay elevated indefinitely; rather, it exhibits mean reversion, gradually returning to a long-term equilibrium level. Vašíček (1977) lays the groundwork by modeling mean reversion in the context of interest rates. In the domain of stock return volatility, Engle (1982) and Bollerslev (1986) introduce ARCH and GARCH models, which account for time-varying volatility while incorporating its tendency to revert over time. Heston (1993) extends this concept by developing a continuous-time stochastic volatility model, structurally similar to the Cox-Ingersoll-Ross (1985) process, where variance follows a mean-reverting square-root diffusion, ensuring it remains strictly positive and avoiding negative variance issues. Further refining this framework, Fouque, Papanicolaou and Sircar (2000) demonstrate that volatility evolves at multiple time scales, with both fast-reverting and slow-reverting components, underscoring the need for multi-factor models to better capture empirical volatility dynamics.

2.1.2 Implied Volatility and Option Pricing

While historical volatility measures past fluctuations in asset prices, implied volatility represents the market's expectations of future uncertainty. Unlike realized volatility, implied volatility is derived from option prices and is forward-looking, making it a crucial factor in pricing derivatives and forecasting future market conditions. This section explores the theoretical foundations of implied volatility, including its predictive power, the volatility smile and skew, and its connection to risk premiums.

The Black-Scholes model (Black & Scholes, 1973; Merton, 1973) revolutionized derivative pricing by introducing a no-arbitrage framework for option valuation. While the model assumes constant volatility component in determining the theoretical price for an option, in practice market participants extract implied volatility (IV) from option market prices to estimate expected future fluctuations. IV provides a real-time measure of market uncertainty, affecting importantly modern financial models.

Black-Scholes model (1973) relies on various assumptions that often do not hold in real markets. Notably, it assumes constant volatility, whereas empirical evidence suggests that volatility fluctuates over time. Additionally, the model assumes that the log returns of the underlying asset are normally distributed, a premise challenged by non-log-normal empirical observations of price shocks and skewness (e.g. Merton, 1976). Furthermore, the Black-Scholes framework assumes a constant risk-free rate, no dividend payments, no early exercise and continuous hedging in a frictionless market, disregarding real-world constraints such as transaction costs, taxes or liquidity limitations.

Hull & White (1987) extend the Black-Scholes framework by incorporating stochastic volatility into option pricing. They find that Black-Scholes model systematically overprices option, particularly those with longer maturities, highlighting the importance of volatility term structure. Their work bridges the gap between Black-Scholes and later stochastic volatility models, notably Heston (1993), where volatility follows a mean-reverting stochastic process.

Bates (1996) further extends the earlier, integrating both stochastic volatility and price jumps, addressing the presence of fat tails and skewness, and thus challenging both constant volatility and lognormal return assumptions of Black-Scholes. Building on these advances, Rubinstein (1994) and Dupire (1994) introduce model-free volatility structures extracting information directly from market option prices. Through Implied Binomial Trees and local volatility models, they provide a framework that captures the volatility smile and surface, further refining option pricing beyond the constraints of Black-Scholes.

Despite its well-documented theoretical limitations, the Black-Scholes model remains a widely used benchmark in option pricing due to its simplicity, analytical tractability, and effectiveness in extracting market expectations through implied volatility. Dumas, Fleming & Whaley (1998) find that while volatility varies across strikes and maturities, more complex models do not consistently outperform Black-Scholes in predicting and hedging performance, supporting that 'simpler is better'.

Further supporting the practical relevance of Black-Scholes IV, Christensen & Prabhala (1998), in line with Jorion (1995), show that despite its bias, IV predicts future realized volatility more accurately than past volatility. Moreover, Poon & Granger (2003) provide a comprehensive review of 66 studies comparing volatility forecast methods, finding that in 76% of cases, Black-Scholes IV outperforms historical volatility-based models in predicting future volatility, while historical volatility itself beats GARCH-models 56% of the time. The findings suggest that option IV (Black-Scholes) is the most effective predictor, with historical volatility and GARCH models ranking roughly equal.

"Implied volatility (IV), the volatility value that goes into the market's option pricing formula, is a "risk-neutral" value, which impounds both the market's objective estimate of the future realized volatility, and the market's tolerance for volatility risk." (Engle & Figlewski, 2015). In other words, implied volatility not only contains information on the time-varying volatility expectations, but also on the time-varying market risk-aversion, the compensation for the volatility of volatility.

Carr & Wu (2009) compare realized variances to synthetic variance swap rates and find that implied variance systematically overestimates future realized variance, indicating a persistent divergence between market-expected and realized variances. This aligns with Bollerslev, Tauchen and Zhou (2009) who further show that high (low) variance risk premia (VRP = IV – RV) predict high (low) future stock market returns. This suggests that time-variation in both volatility risk and investor risk aversion drives fluctuations in expected returns over time. Moreover, VRP is closely linked to the literature on option-writing returns, where investors systematically capture the premium by selling options — often overpriced due to elevated IV — and dynamically hedging the position in the underlying asset.

2.2 Theoretical Frameworks Explaining Option IV Changes

This study uncovers evidence of implied volatility responses to trading volumes, IV asymmetry, and both over- and underreactions in sectoral ETF options. This chapter outlines the theoretical frameworks that help explain these findings.

2.2.1 Demand in the Options and the Underlying Asset

Traditional option pricing models rely on risk-neutral valuation, yet investor demand significantly influences option prices, leading to deviation from theoretical values. Order imbalances, market frictions, and liquidity constraints affect implied volatility beyond fundamental expectations. This chapter reviews how the demand in options and in the underlying asset influence implied volatility and option pricing.

Non-market maker demand dynamics drive systematic shifts in implied volatility and option prices. Excess buyer-initiated option demand pushes IV and option prices higher, while seller-driven flows cause downward pressure on both. Bollen and Whaley (2004) document this effect, showing buying pressure on index put options contributes to the downward-sloping shape of the implied volatility function for S&P 500 index options. Institutional demand for out-of-the-money (OTM) index puts — primarily for portfolio hedging — leads to option overpricing, creating profitable opportunities for traders who sell these puts and hedge the delta exposure in the underlying. In contrast, stock options exhibit strong supply for OTM calls used for covered call strategy, leading to a downward-sloping right tail in the implied volatility function.

Gârleanu, Pedersen, and Poteshman (2009) recognize that, unlike the Black-Scholes framework, real-world options cannot be perfectly hedged, leading to non-risk-neutral pricing. A model of competitive risk-averse intermediaries shows that option prices increase with end-user demand, proportional to the variance of unhedgeable risk, while demand also impacts other options based on the covariance of their unhedgeable components. Due to a high positive end-user demand, index options appear expensive in the market, contrary to equity options with small and negative end-user demand. A positive relation between expensiveness skew across moneyness is

found with end-user demand skew across moneyness, for both index and equity options, amplified when the market is illiquid. A more recent study by Fournier & Jacobs (2020) complements this by showing that market maker requires higher compensation when incurring losses.

While option demand influences implied volatility and pricing, trading activity in the underlying asset also plays a critical role. Trading volume and return volatility exhibit a strong positive relationship, which Tauchen and Pitts (1983) attribute to the Mixture of Distributions Hypothesis (MDH), where both are jointly driven by the rate of information flow. The Sequential Information Arrival Hypothesis (SIAH), proposed by Copeland (1976), offers an alternative explanation, suggesting that investors receive information at different times, leading to a gradual incorporation of news into prices and sustained trading activity.

Karpoff (1987) further confirms the positive volume-volatility relationship across asset classes and adds that trading volume is positively correlated with price direction in equity markets, a phenomenon linked to short-sale constraints limiting downward price pressure. This asymmetry is not observed in futures markets, where short selling is unrestricted. Lee and Rui (2002) reinforce the volume-volatility relationship but, unlike Karpoff (1987), find no evidence that trading volume predicts stock market returns.

Gallant, Rossi, and Tauchen (1992) show that volume and volatility are positively correlated, but the relationship is nonlinear and depends on past market conditions. Their findings reveal that high lagged volume attenuates the leverage effect, meaning price shocks following periods of high trading activity, lead to smaller future volatility responses. This suggests that past volume absorbs part of the volatility impact by improving price discovery and reducing uncertainty persistence. Since volatility reflects both information flow and market microstructure effects, past trading volume indicates the market's ability to incorporate new information. In high-volume markets, price adjustments are more efficient, dampening future volatility responses, whereas in low-volume markets, large trades lead to greater price fluctuations.

2.2.2 Slow-moving Capital

Slow-moving capital provides an important explanation for market inefficiencies, highlighting how capital constraints and gradual information diffusion contribute to pricing anomalies and return predictability.

Shleifer and Vishny (1997) offer a foundational explanation for why capital moves slowly to correct mispricings, limiting the arbitrage. Contrary to the textbook view of arbitrage, they show that real-world arbitrage is conducted by a small number of specialized investors relying on external capital, making it capital-intensive and inherently risky. As a result, arbitrageurs may be forced to exit positions rather than expand them in extreme circumstances, particularly when short-term losses trigger investor withdrawals.

Brunnermeier and Pedersen (2009) extend Shleifer & Vishny (1997) by showing how traders' funding liquidity and market liquidity interact, creating liquidity spirals. When traders face losses and tighter funding constraints, higher margin requirements force them to reduce positions, further drying up market liquidity. This self-reinforcing cycle deepens mispricings and prolongs price distortions, illustrating how liquidity frictions amplify capital constraints and contribute to persistent pricing anomalies in financial markets.

Mitchell, Pedersen, and Pulvino (2007) document three cases where arbitrageurs, constrained by capital losses, were forced to liquidate rather than correct mispricings. These dislocations were large and persistent, highlighting that capital frictions arise not only from investor withdrawals but also from internal constraints such as risk management policies and information barriers. Duffie (2010) extends this view, showing that supply and demand shocks, initially absorbed by a limited set of investors requiring compensation for liquidity provision, cause sharp price movements followed by gradual reversals as capital reallocates. This delayed correction arises from capital-raising frictions and counterparty search costs associated with unwinding these positions.

Slow information diffusion complements capital frictions in explaining delayed price adjustments. Hong and Stein (1999) explain gradual information diffusion in markets by dividing market participants into two groups of boundedly rational agents: "news-watchers" and "momentum traders". News-watchers receive private signals about fundamentals but fail to extract information from prices, leading to a slow adjustment process and initial underreaction to new information. This delayed response creates an opportunity for momentum traders, who base their strategies on past price trends. As they enter the market, they accelerate price movements, reinforcing short-term momentum. However, because momentum traders rely on simple, trend-following strategies, their trading activity ultimately pushes prices beyond fundamental values, leading to overreaction. Over longer horizons, this mispricing corrects, resulting in mean reversion.

Chen & Lu (2017) provide empirical evidence supporting Hong and Stein's (1999) slow information diffusion model, using options market data to examine price momentum. They find that momentum returns are stronger in stocks with slower information diffusion, particularly when past increases in call option implied volatility signal higher demand for calls and bullish expectations. Conversely, stocks with declining call option IV tend to underperform, consistent with weaker investor sentiment. Their findings refine momentum strategies by identifying information diffusion speed, helping to avoid the pitfalls of simple momentum investing.

Hong, Lim and Stein (2000) show that the slow information diffusion is particularly pronounced in small-cap stocks with low analyst coverage. In chapters 5 and 6 of this thesis, I consider the lagged transmission of VIX in sectoral IVs. Related to Hong, Lim and Stein (2000), I show that the transmission of VIX is particularly slow in less volatile, defensive sectors, such as Utilities and Consumer Staples, which due to their stable nature, are not likely the most followed among investors and analysts. Broadly in line with Hong and Stein (1999), I find evidence on IV-reversals after high underlying ETF volumes, linked to the momentum trading leading to reversals.

2.2.3 Behavioural Theories

The negative and asymmetric return-volatility relationship is difficult to explain with purely fundamental effects, such as leverage effect or volatility feedback theory. Black (1976), although presenting leverage effect theory, argues that leverage effect alone is too week to explain the powerful effect of returns to volatility. This suggests that behavioral theories, such as representativeness, affect, extrapolation bias and loss aversion, may play a significant role in shaping market volatility expectations.

Low (2004) links asymmetric and non-linear return-volatility responses to loss aversion, emphasizing that fear triggers sharp volatility spikes whereas optimism builds more gradually. Furthermore, the house money effect suggests that prior gains mitigate loss aversion, leading investors to take greater risks, while prior losses reinforce risk aversion. Dennis, Mayhew and Stivers (2006) find that with single stock IVs, this asymmetry is driven by the systematic component of returns.

Hibbert, Daigler and Dupoyet (2008) and Badshah (2013) further attribute the asymmetric return-volatility patterns to behavioral theories, particularly representativeness, affect and extrapolation. The biases cause option traders to overproject future volatility following market declines, leading to excessive IV levels beyond what is justified by fundamentals. Consequently, this behavior suggests that IV fluctuations reflect investor sentiment shifts more than rational repricing.

Representativeness bias occurs when individuals assess probabilities based on how closely an event resembles a known stereotype rather than considering actual statistical likelihoods. Kahneman and Tversky (1974) demonstrated that this heuristic often leads to systematic errors in judgment, as people rely on surface similarities rather than underlying probabilities. The affect heuristic, first introduced by Zajonc (1980), suggests that emotional reactions often precede and shape cognitive judgments. Later, Finucane, Alhakami, Slovic and Johnson (2000) provided empirical evidence that risk and benefit perceptions are negatively correlated, meaning that when individuals associate an event with positive affect, they tend to perceive lower risk and higher benefit, and vice versa.

Extrapolation bias happens when investors assume that recent trends will persist indefinitely, leading them to overreact to short-term market movements. De Bondt and Thaler (1985) provide empirical evidence showing that stocks that had performed poorly in the past tended to outperform in the future, challenging the efficient market hypothesis. This bias contributes to price momentum and asset mispricing. Loss aversion then, refers to the tendency of individuals to experience the pain of losses more intensely than the pleasure of equivalent gains. Kahneman and Tversky (1979) introduced this concept as a key element of prospect theory, explaining why people tend to avoid risks when facing potential gains but take risks to avoid losses.

Linked to loss aversion, Barberis and Huang (2001) develop a model in which investors assess gains and losses at the individual stock level rather than over total wealth, exhibiting greater sensitivity to losses than gains. This asymmetry helps explain the strong volatility response following negative returns. Consistent with this, Goyal and Huang (2009) document volatility mispricing, leading to abnormal option returns. Moreover, the uncertain information hypothesis of Brown, Harlow, and Tinic (1988) posits that investors react cautiously to new information, resulting in underreaction to positive news and overreaction to negative news. These frameworks help explain the asymmetric volatility response, particularly the muted reaction to positive returns, alongside the well-documented overreaction to negative shocks.

A key implication of linking return-volatility relationship to behavioral biases is that changes in IV often stem from shifts in market sentiment rather than purely rational repricing of options based on new information embedded in asset prices. Lee, Jiang and Indro (2002) show empirical evidence that investor sentiment is a systematic risk that is priced and has a negative (positive) relation with market volatility (excess returns). These results are consistent with De Long, Shleifer, Summers and Waldmann (1990) noise trading model. Similarly, Baker and Wurgler (2006) show that investor sentiment disproportionately affects stocks that are more difficult to value and arbitrage, reinforcing its role in volatility mispricing.

2.3 Sector ETF Options

Sector ETFs and their options are relatively unexplored in academic literature, despite offering a compelling area for research. They exhibit characteristics of both individual stocks and broad indices, making them a unique asset class for studying volatility dynamics and pricing inefficiencies. Marks and Simon (2017) analyse Sector SPDR ETF option IVs, highlighting connections to market (SPY) volatility premiums and sector-specific returns. Using data spanning 2006-2015, their paper identifies both systematic and idiosyncratic drivers of implied volatility changes, finding predictability in IV changes and statistically significant delta-hedged returns when applying a trading strategy based on these factors.

In line with earlier option literature, Marks and Simon (2017) find a negative relationship between today's IV change and tomorrow's IV change, suggesting a daily reversal in implied volatility. During 2006-2015, on average 18-34% of previous day's IV changes were reversed the next day. Historically, this has been explained by implied volatility mean-reversion and investor overreactions. In addition to this, Marks and Simon (2017) add to the earlier research by finding that sector IVs tend to adjust over time to maintain consistent long-term relationships between sector and SPY VPs. Sector-specific deviations from these dynamics significantly influence IV adjustments and exhibit patterns consistent with error-correction.

Volatility premium relationships are not the sole drivers of daily changes in sector implied volatilities; sector returns also play a role (Marks and Simon, 2017). Negative contemporaneous sector returns result in sharper IV increases compared to the decreases associated with positive returns of the same magnitude, a response primarily linked to systematic components. Positive systematic returns tend to cause delayed IV reactions, whereas idiosyncratic sector returns exhibit immediate but short-lived impacts on IV, often leading to reversals. To conclude, Marks and Simon (2017) show that lagged sector returns, and idiosyncratic VPs have predictive power for short-term IV forecasting. This leads to significant delta-hedged option returns in an out-of-sample setting, as IV is an integral part of option prices.

3 Research Material and Methods

This paper studies at-the-money (ATM) call and put options, from January 2015 through September 2024. ATM-options are selected due to their high liquidity and sensitivity to changes in market volatility. The demand for ATM-options should drive the implied volatility of all options, as their prices rapidly incorporate the changes in market volatility expectations (Bollen and Whaley, 2004). The options dataset comprises end-of-day information from FirstRate, covering the best daily bid and ask closing quotes, including annualized Greeks and implied volatilities for both puts and calls.

Throughout this thesis, I focus on eight major SPDR sector ETFs and SPY, the ETF tracking the S&P 500 index. The following major sector ETFs are studied as they mostly comprise the S&P 500: XLE (Energy), XLK (Technology), XLY (Consumer Discretionary), XLB (Materials), XLI (Industrials), XLU (Utilities), XLV (Healthcare) and XLP (Consumer Staples). XLF (Financials) is left out from the study due to data availability issues.

For each date, I find ATM calls and puts using the following criteria: Following the Marks and Simon (2017), I select the closest-to-the-money, nearest to expiration options, with at least 25 days until expiration. Only monthly options expiring on the third Friday of the month are considered. Rather than using interpolated IVs, I calculate the daily implied volatility as the average of call and put mid- Black-Scholes implied volatilities. This approach allows me to avoid results affected by the volatility skew. Mid-implied volatility is calculated as the average of bid- and ask-implied volatilities and according to put-call parity, the IVs should be same for these calls and puts. In my sample, these are indeed very close to each other, with only minor deviations arising from real-world constraints.

Additionally, following the examples from the earlier options literature (Driessen, Maenhout, and Vilkov, 2009; Marks and Simon, 2017), I exclude observations with 1) Zero open interest, 2) Zero bid or ask price, 3) Ask price larger than bid price, 4) Bid price less than 0.8 and bid-ask spread more than 0.8, to avoid unrealistic

observations in the data. There are roughly 2500 trading days in my 10-year sample, which by following the above-mentioned criteria results in approximately 2500 call and put daily observations, for each ETF. Having selected the options, I identify them with an optionid and find the next day observations using the id:s. This approach allows me to find both the change in option prices (strategy return) and in implied volatility (forecasted).

Following the option studies mentioned above and thus ensuring consistency with earlier findings, I analyse implied volatility percent changes using the logarithmic transformation of successive values as log (IV_t/ IV_{t-1}), instead of absolute percentage point differences as (IV_t – IV_{t-1}). This choice reflects documented evidence that kurtosis in absolute implied volatility changes can make percentage point differences less reliable for comparative analysis. My analysis focuses more on the dynamics and predictability of IV, rather than many other studies focusing on the volatility premium, the difference between IV and historical volatility (HV).

However, when volatility premium is used as a variable in regressions, it is calculated as logarithmic percentage spread: log (IV/HV), in line with earlier literature. I follow Bollerslev et al. (2009) in calculating the annualized historical 30-day volatility from 5-minute intraday ETF-data (FirstRate). For a typical month, this means n=22x78=1716 five-minute returns. This more accurate approach for calculating realized volatility is recommended by e.g. Hansen and Lunde (2006).

Tables 3–6 of this study are constructed to replicate the methodology of Marks and Simon (2017), ensuring comparability with their results, as the same topic is examined using a more recent dataset. Consequently, no additional controls are introduced in these tables. However, in regression Tables 8 and 9, I account for weekday effects and the weeks surrounding monthly option expiration by including dummy variables, ensuring that my findings are not driven by intraweek or intramonth patterns. As noted by French and Roll (1986), non-trading days also influence volatility ― Mondays, for instance, tend to exhibit higher volatility as they incorporate information accumulated over the weekend. Furthermore, increased options demand around expiration dates, driven by options rolling, is explicitly controlled for.

Table 1: Descriptive statistics 1, Near-Term ATM-option volatilities

This table reports descriptive statistics for implied volatility (IV), realized volatility (HV30), and the volatility premium (VP) for the S&P 500 SPDR (SPY) and eight Sector SPDR ETFs. Each day, one call and one put are selected for each ETF based on the following criteria: closest-to-money and nearest-to-expiration monthly options with at least 25 days remaining until maturity. All observations are from the midpoint of the bid-ask quotes. Implied volatility (IV) is computed as the average of the daily selected call and put option implied volatilities (Black & Scholes). Realized volatility (HV30) is the annualized past 30-day standard deviation evaluated from 5-minute intraday ETF returns. The volatility premium (VP) is presented both as the percentage point spread between IV and HV30 (IV – HV30) and as the log of their ratio (log (IV/HV30)). The reported statistics include the mean, standard deviation, and top/bottom deciles for each measure. The sample period runs from January 2015 to September 2024. The options and ETF data are obtained from FirstRate.

	SPY	Energy	Tech.	Disc.	Mater.	Industrial	Utilities	Health	Staples
IV, %									
Mean	15.78	26.28	20.51	19.42	19.18	18.05	16.72	15.89	13.65
St.Dev	6.57	10.75	7.50	7.82	6.68	6.98	5.36	5.13	4.49
Top decile	23.93	39.43	30.09	29.63	26.91	25.17	21.37	21.71	18.49
Bottom decile	9.78	16.65	13.07	11.94	13.16	12.33	12.23	11.21	9.94
HV30, %									
Mean	14.86	26.52	19.96	18.84	18.40	17.11	16.66	15.17	13.01
St.Dev	9.76	15.01	11.39	10.83	11.16	10.45	8.83	8.38	7.89
Top decile	24.42	40.46	31.66	30.73	28.20	25.53	21.65	22.30	19.27
Bottom decile	7.39	14.50	10.72	9.24	10.48	9.86	10.73	9.01	8.15
VP, % Point Spread: IV-HV30									
Mean	0.92	-0.24	0.55	0.59	0.78	0.94	0.06	0.72	0.64
St.Dev	5.38	6.99	6.41	5.45	6.64	5.53	4.91	4.97	4.68
Top decile	5.04	4.67	5.37	4.82	5.07	5.01	3.00	4.41	3.66
Bottom decile	-3.37	-6.49	-4.55	-4.62	-3.43	-3.41	-2.76	-3.26	-2.12
VP, % Spread: log (IV/HV30)									
Mean	5.30	1.29	3.38	3.64	3.90	4.51	1.55	4.10	4.21
St.Dev	10.54	7.44	9.42	9.48	8.56	9.15	6.65	9.26	8.67
Top decile	17.85	9.86	14.60	14.86	13.54	14.90	9.07	14.62	14.26
Bottom decile	-7.66	-9.27	-8.26	-8.34	-6.64	-7.02	-6.56	-7.84	-6.14

Tables 1 and 2 provide descriptive statistics for the options dataset. Table 1 presents volatility measures, while Table 2 reports option prices, illustrating that options with higher implied volatility tend to be more expensive, consistent with option pricing

theory. Near-term at-the-money (ATM) implied volatilities range from 13.7% (Consumer Staples) to 26.3% (Energy). Historical 30-day realized volatilities range from 13.0% to 26.5%, yielding positive volatility premiums across all sectors except Energy, where volatility is largely driven by fluctuations in commodity prices. Positive volatility premiums suggest that investors systematically overestimate future volatility, likely due to a risk premium for bearing volatility risk and demand imbalances. Reflecting its diversified composition, the SPY ETF, which tracks the S&P 500, exhibits relatively low implied and realized volatilities, despite being composed primarily of these sectors.

Table 2: Descriptive statistics 2, Near-Term ATM-option prices

This table reports descriptive statistics for call and put option prices on the S&P 500 SPDR (SPY) and eight Sector SPDR ETFs. Each day, one call and one put are selected for each ETF following the same method as in the previous table: we choose the closest-to-money and nearest-to-expiration monthly options, provided there are at least 25 days until maturity. All option prices are calculated from the mid-points of their bid–ask quotes. "Mean ($)" denotes the average option price in U.S. dollars, whereas "Mean (%)" normalizes this amount by the corresponding ETF's share price to facilitate comparability across ETFs with different share-price levels. The standard deviation (St.Dev), top decile, and bottom decile of option prices are also reported for both calls and puts. The sample period runs from January 2015 to September 2024. The options data are obtained from FirstRate.

	SPY	Energy	Tech.	Disc.	Mater.	Indust.	Utilities	Health	Staples
Call price									
Mean ($)	7.05	2.22	3.04	3.47	1.66	1.97	1.29	2.20	1.12
St.Dev	3.72	0.82	2.10	1.97	0.70	0.86	0.54	0.91	0.47
Top decile	12.29	3.40	5.90	6.28	2.68	3.10	1.97	3.43	1.74
Bottom Decile	2.92	1.36	0.77	1.28	0.85	0.92	0.71	1.14	0.60
Mean (%)	2.11%	3.43%	2.77%	2.62%	2.56%	2.41%	2.18%	2.15%	1.80%
Put price									
Mean ($)	6.85	2.27	2.86	3.31	1.63	1.91	1.34	2.10	1.15
St.Dev	3.48	0.77	1.86	1.84	0.65	0.79	0.50	0.84	0.44
Top decile	11.83	3.30	5.40	6.05	2.60	3.01	1.98	3.30	1.72
Bottom decile	3.14	1.47	0.82	1.34	0.91	1.03	0.82	1.20	0.70
Mean (%)	2.09%	3.54%	2.67%	2.53%	2.53%	2.38%	2.29%	2.08%	1.86%

4 Sectoral IV Responses to Past IV, Volatility Premium, and Sector ETF Returns

This chapter presents the empirical findings on changes in implied volatility for Sector SPDR ETFs over the period 2015–2024. Chapter 4 is structured as follows: Section 4.1 examines daily fluctuations in implied volatility, focusing on daily IV-reversals. 4.2 shows evidence of the long-term relationships between sectoral and market-wide volatility premia, resulting in sectoral implied volatility adjustments. 4.3 presents the impact of both contemporaneous and lagged returns on IVs.

4.1 Daily Reversals in Implied Volatility

Volatility's mean-reverting nature is also reflected in implied volatilities. Table 3 examines the daily autocorrelations of sectoral implied volatility changes measured as log (IV_t / IV_{t-1}) and finds significant daily reversals across all sectors. The negative coefficients for lagged sector implied volatility changes (%ΔIV_{t-1}) ranging from -0.07 to -0.15, indicate that 7–15% of daily sector IV movements tend to reverse the following day. In contrast, lagged sector volatility premiums (% VP_{t-1}) do not exhibit statistical significance in explaining subsequent IV changes for any sector.

Technology, Industrials, Utilities and Consumer Staples exhibit the largest daily implied volatility reversals in percentage terms. Higher coefficients appear to be associated with greater predictability, as indicated by adjusted R squared values. Notably, these sectors vary from high-volatility (Technology) to low-volatility (Staples), suggesting that the overall volatility level does not primarily drive the daily IV-reversals.

Findings of Table 3 support the conclusion that implied volatility undergoes daily reversals that are not driven by adjustments toward a sector's long-term typical volatility premium. Marks and Simon (2017) conduct a similar analysis for the 2006–2015 period and document even stronger daily IV reversals (18-34%). However, unlike the results presented here, their findings also suggest that IV reversals partially reflect adjustments toward the typical sector volatility premium levels.

Table 3: Daily Reversals in the Sector SPDR Implied Volatility Changes

This table presents regression results where the dependent variable is the daily log change in implied volatility ($\%\Delta IV_t$) for eight Sector SPDR ETFs. Specifically, $\%\Delta IV_t$ is regressed on an intercept, its one-day lag ($\%\Delta IV_{t-1}$), and the one-day lag of the sector volatility premium ($\%VP_{t-1}$). The volatility premium (%VP) is defined as the log of the ratio of implied volatility (IV) to past 30-day historical volatility (HV30), expressed in percentage terms (log (IV/HV30)). Implied volatilities are derived from monthly, closest-to-maturity, at-the-money (ATM) options with at least 25 days until expiration, using mid-points of their bid–ask quotes. In parentheses are presented the Newey–West standard errors with five lags. Asterisks denote significance levels: * at 10%, ** at 5%, and *** at 1%. The analysis covers the sample period from January 2015 to September 2024, and the data is obtained from FirstRate. The adjusted R-squared values are shown in the bottom row.

$\%\,\Delta IV_t$	Energy	Tech.	Disc.	Materials	Indust.	Utilities	Health	Staples
Intercept	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\%\,\Delta IV_{t-1}$	-0.071*	-0.152***	-0.074***	-0.087***	-0.107***	-0.113***	-0.082***	-0.128***
	(0.030)	(0.023)	(0.028)	(0.026)	(0.026)	(0.027)	(0.027)	(0.026)
$\%\,VP_{t-1}$	-0.003	0.001	0.002	-0.005	-0.002	-0.005	-0.001	-0.005
	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.008)	(0.006)	(0.008)
Adj. R-squared	0.005	0.022	0.004	0.008	0.011	0.013	0.006	0.017

This reduction in the magnitude of IV daily reversals may partly reflect prevailing market conditions during the sample period. However, it also suggests that market participants have become more aware of these reversals and the underlying drivers of the phenomenon. As such insights are increasingly incorporated into analysis, implied volatility — and consequently, option prices — exhibit smaller daily reversals.

4.2 Long-term Relationship with Market Volatility Premium

Table 4 further examines the role of the volatility premium (VP) — defined as the log-percentage spread between implied volatility (IV) and past 30-day historical volatility (HV30) — in explaining subsequent changes in implied volatility. A key finding is that, while total sector VP level does not predict subsequent IV adjustments, idiosyncratic VP shows strong predictive power for next-day IV changes.

Panel A of Table 4 reports the results of a regression examining the relationship between next-day implied volatility changes and both total and idiosyncratic volatility premiums. Panel B removes the total volatility premium, demonstrating that its exclusion has little effect on explanatory power, indicated by the almost unaffected adjusted R-squared values. Both regressions control for one-day lag of the dependent variable, as do all the rest of the regressions in this thesis, too.

For each day, idiosyncratic volatility premium ($\%VP_{t-1}^{ID}$) is equal to the residual from regressing sectoral VPs with a constant and SPY VPs (log % spread). This approach captures the relationship between sector VPs and overall market VP. The coefficient for idiosyncratic volatility premium is negative and significant at 1% level across all sectors, except Energy, indicating a consistent and persistent pattern.

The negative coefficient suggests that when the absolute difference between sector's VP and market VP (SPY) widens, it tends to revert toward zero the following day. Since the volatility premium is composed of implied volatility (IV) and past 30-day historical volatility (HV30), this reversal is primarily driven by changes in IV, as HV30 represents a monthly average and adjusts more gradually. Consequently, if sector VP is high compared to market VP, sector IV decreases, and if sector VP is low relative to market, sector IV increases. This makes sense as VP also reflects the option prices – high sector VP relative to market VP indicates expensive sector ETF options.

As noted by Marks and Simon (2017), the models in Table 4 function as error correction models, where sector IVs adjust based on deviations from their long-term relationship with SPY. The estimates in Table 4 align with this error correction mechanism and are consistent with prior research. Figure 1 illustrates this process, presenting the VP relationship in black and the corresponding IV level in grey.

In black, Figure 1 illustrates the mean-reverting relationship in Sector-SPY volatility premiums, consistent with the negative coefficients for $\%VP_{t-1}^{ID}$ reported in Table 4. This fluctuation around zero (black line) enhances the predictability of IV changes beyond the negative daily autocorrelation of IV movements. The grey lines represent

sector ATM implied volatility levels over the sample period, providing empirical evidence of volatility clustering and long-term mean reversion.

Table 4: Effects of Total and Idiosyncratic Volatility Premiums on the Resulting Changes in Sector SPDR Implied Volatilities

Table 4 introduces an idiosyncratic sector volatility premium, $\%VP_{t-1}^{ID}$, defined as the residual from regressing the total sector volatility premium on a constant and the SPY volatility premium, all measured in log ratio %-spread. In Panel A, the daily log change in implied volatility ($\%\Delta IV_t$) is regressed on a constant, its one-day lag ($\%\Delta IV_{t-1}$), and both the total sector volatility premium ($\%VP_{t-1}$) and the idiosyncratic sector volatility premium ($\%VP_{t-1}^{ID}$). Panel B includes only the constant, the lagged dependent variable, and $\%VP_{t-1}^{ID}$. In parentheses are Newey–West standard errors with five lags. Asterisks denote significance at the *10%, **5%, and ***1% levels. The sample period is from January 2015 to September 2024, and the data are obtained from FirstRate. The adjusted R-squared values are presented in the bottom row.

Panel A: Both Total and Idiosyncratic VP included

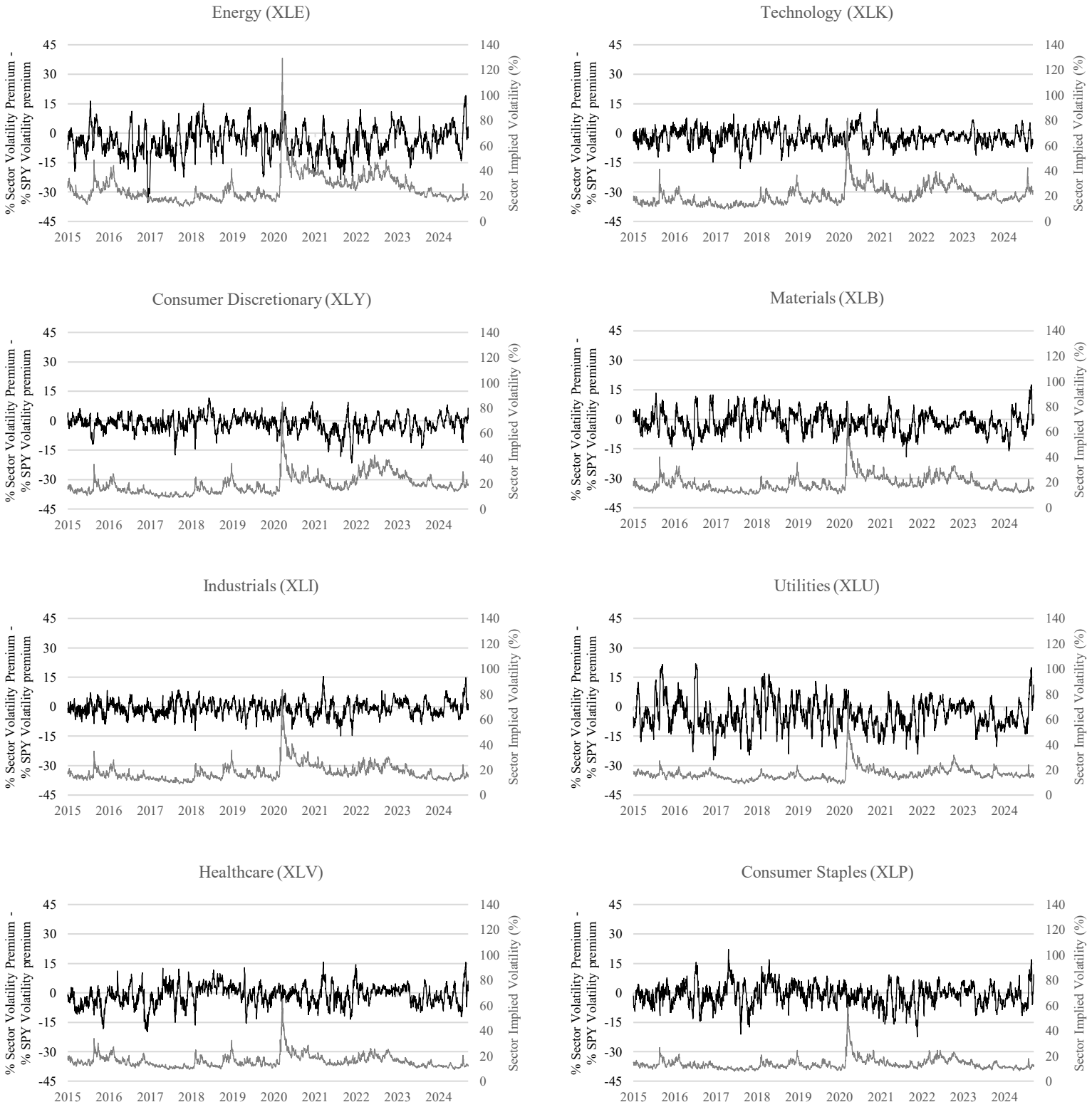
$\%\Delta IV_t$	Energy	Tech.	Disc.	Materials	Indust.	Utilities	Health	Staples
Intercept	0.000	0.000	0.000	-0.001	-0.001	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\%\Delta IV_{t-1}$	-0.073**	-0.149***	-0.078***	-0.091***	-0.108***	-0.114***	-0.085***	-0.127***
	(0.030)	(0.023)	(0.027)	(0.026)	(0.026)	(0.027)	(0.027)	(0.026)
$\%VP_{t-1}$	0.010	0.009	0.009	0.014	0.010	0.024**	0.010	0.017*
	(0.010)	(0.007)	(0.007)	(0.009)	(0.007)	(0.011)	(0.007)	(0.009)
$\%VP_{t-1}^{ID}$	-0.027**	-0.062***	-0.045***	-0.072***	-0.092***	-0.056***	-0.047***	-0.088***
	(0.014)	(0.017)	(0.017)	(0.016)	(0.022)	(0.015)	(0.014)	(0.016)
Adj. R-squared	0.006	0.026	0.007	0.016	0.019	0.019	0.010	0.029

Panel B: Only Idiosyncratic VP included

$\%\Delta IV_t$	Energy	Tech.	Disc.	Materials	Indust.	Utilities	Health	Staples
Intercept	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\%\Delta IV_{t-1}$	-0.068**	-0.144***	-0.071***	-0.082***	-0.101***	-0.104***	-0.078***	-0.117***
	(0.029)	(0.023)	(0.027)	(0.025)	(0.026)	(0.027)	(0.026)	(0.026)
$\%VP_{t-1}$								
$\%VP_{t-1}^{ID}$	-0.018*	-0.054***	-0.036**	-0.058***	-0.082***	-0.033***	-0.038***	-0.071***
	(0.009)	(0.017)	(0.015)	(0.014)	(0.019)	(0.011)	(0.013)	(0.015)
Adj. R-squared	0.006	0.026	0.007	0.015	0.019	0.017	0.009	0.027

Figure 1: Long-Term Volatility Premium Relationship Between Sectors and SPY

Each sector-specific figure presents the difference between the sector volatility premium and the SPY volatility premium (both in percentage terms). This difference is plotted in black, with values corresponding to the left-hand axis. The sector and SPY volatility premiums are both calculated as the log difference between the implied volatility of near-term, at-the-money options and the standard deviation of the past 30-day sector ETF returns. Additionally, each subfigure displays the sector's ATM implied volatility, in grey, with values on the right axis.



4.3 Sector ETF Returns Impacting Sectoral Implied Volatilities

Sector ETF (underlying) returns also have a significant impact on sectoral implied volatilities. Prior research (e.g., Low, 2004; Hibbert et al., 2008) provides evidence of a negative relationship between index implied volatility and contemporaneous index returns, with stronger IV responses to negative returns than to positive returns of the same magnitude.

The findings presented here align with this literature. Table 5 reports regression results on the effect of returns on sector and SPY implied volatilities, controlling for the one-day lagged dependent variable. Across all sectors and SPY, the return-volatility relationship is negative, with more pronounced responses to negative returns. Panel A includes only contemporaneous returns, while Panel B incorporates one-day lagged returns to account for potential delayed IV responses.

In Table 5, positive and negative returns are included as separate variables to analyse the asymmetric response of implied volatility. The dependent variable is the daily implied volatility percent changes, calculated as the log difference: $\log (IV_t / IV_{t-1})$. When considering only contemporaneous returns in Panel A, a 1% positive ETF return is associated with a 0.4% to 1.5% decrease in sector IV and nearly 2.0% decline in SPY IV. Conversely, a 1% negative ETF return leads to an IV increase of 1.1% to 2.3% across sectors, reaching up to 2.6% for SPY. The Wald test (Wald 1) rejects the null hypothesis that the coefficient estimates for positive and negative returns are equal across all regressions, showing further evidence of the asymmetric IV responses.

Including one-day lagged returns in the regression (Table 5, Panel B) allows testing whether the asymmetric volatility response arises from an underreaction to positive returns or an overreaction to negative returns. A significantly negative coefficient for $RET+_{t-1}$ would suggest that implied volatility continues to decline following a positive return, indicating an initial underreaction. Instead, significant positive coefficients for $RET-_{t-1}$ would indicate that the previous day's IV spike was an overreaction, as market participants adjust their expectations and volatility reverts downward.

Table 5: Effects of Contemporaneous and Lagged Sector Returns on the Resulting Changes in Sector SPDR Implied Volatilities

This table reports the daily log change in implied volatilities ($\%\Delta IV_t$), using the same implied volatility (IV) selection method as in previous tables. Panel A shows regressions with contemporaneous sector returns, whereas Panel B adds lagged returns. The returns are simple (daily) percentage changes. Parentheses contain Newey–West standard errors with five lags, and asterisks denote significance at the *10%, **5%, and ***1% levels. Wald 1 displays the p-values from Wald tests evaluating whether the coefficient estimates for positive and negative returns are equal. Wald 2 tests the same hypothesis but allowing for 1-day lagged response in IV. The sample period extends from January 2015 to September 2024, and the data is obtained from FirstRate.

Panel A: Contemporaneous returns only

$\%\ \Delta IV_t$	SPY	Energy	Tech.	Disc.	Materials	Indust.	Utilities	Health	Staples
Intercept	-0.001	-0.004***	-0.001**	-0.002**	-0.003***	-0.003***	-0.003***	-0.002***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\%\ \Delta IV_{t-1}$	-0.056***	-0.073***	-0.120***	-0.066***	-0.082***	-0.098***	-0.098***	-0.067***	-0.119***
	(0.018)	(0.019)	(0.018)	(0.016)	(0.018)	(0.018)	(0.019)	(0.017)	(0.020)
$RET+_t$	-1.957***	-0.416***	-1.158***	-1.176***	-1.009***	-1.179***	-0.655***	-1.469***	-1.209***
	(0.140)	(0.066)	(0.067)	(0.070)	(0.066)	(0.104)	(0.103)	(0.080)	(0.114)
$RET-_t$	-2.629***	-1.073***	-1.669***	-1.670***	-1.784***	-1.948***	-1.370***	-2.220***	-2.266***
	(0.281)	(0.065)	(0.127)	(0.123)	(0.139)	(0.218)	(0.157)	(0.182)	(0.223)
Adj. R-squared	0.581	0.395	0.466	0.480	0.461	0.460	0.305	0.509	0.345
Wald 1	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Panel B: Both Contemporaneous and Lagged returns

$\%\ \Delta IV_t$	SPY	Energy	Tech.	Disc.	Materials	Indust.	Utilities	Health	Staples
Intercept	0.000	-0.004***	-0.001	-0.001	-0.003***	-0.002**	-0.003***	-0.002***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\%\ \Delta IV_{t-1}$	-0.060	-0.017	-0.183***	-0.083***	-0.119***	-0.117***	-0.070**	-0.041	-0.119***
	(0.037)	(0.028)	(0.026)	(0.024)	(0.023)	(0.033)	(0.030)	(0.034)	(0.031)
$RET+_t$	-1.869***	-0.395***	-1.184***	-1.163***	-1.025***	-1.181***	-0.616***	-1.422***	-1.144***
	(0.159)	(0.062)	(0.064)	(0.070)	(0.075)	(0.108)	(0.092)	(0.091)	(0.127)
$RET-_t$	-2.724***	-1.085***	-1.686***	-1.688***	-1.778***	-1.951***	-1.398***	-2.253***	-2.343***
	(0.288)	(0.063)	(0.118)	(0.122)	(0.134)	(0.215)	(0.139)	(0.179)	(0.199)
$RET+_{t-1}$	-0.313*	0.075*	-0.265***	-0.128*	-0.113	-0.082	0.042	-0.011	-0.234**
	(0.174)	(0.041)	(0.076)	(0.077)	(0.074)	(0.156)	(0.086)	(0.104)	(0.118)
$RET-_{t-1}$	0.218	0.146**	-0.151	0.003	-0.123	-0.056	0.156	0.189	0.182
	(0.223)	(0.057)	(0.097)	(0.068)	(0.084)	(0.101)	(0.122)	(0.163)	(0.185)
Adj. R-squared	0.585	0.399	0.471	0.481	0.462	0.460	0.306	0.510	0.346
Wald 2	0.013**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

The results in Panel B of Table 5 provide some evidence of under- and overreactions in implied volatility following returns. The coefficients for $RET+_{t-1}$ are negative across all sectors except Energy, suggesting underreactions to positive returns, though statistical significance remains rather weak. This could be due to investors' cautious responses to positive news, resulting in slow information diffusion. In contrast, $RET-_{t-1}$ generally lacks statistical significance, except in the Energy sector, where IV exhibits reversals after negative return days, supporting the overreaction hypothesis. Slow and cautious responses to positive news, with strong IV reactions to negative news supports the hypothesis of risk-averse market participants.

The coefficients for contemporaneous returns remain largely consistent with those in Panel A, while the one-day lagged dependent variable ($\%\Delta IV_{t-1}$) loses explanatory power in some sectors but remains significant in most after incorporating lagged returns into the regression. Wald Test 2 evaluates whether accounting for lagged responses eliminates the asymmetric IV reaction to ETF returns. The null hypothesis ($RET+_t + RET+_{t-1} = RET-_t + RET-_{t-1}$) is rejected across all sectors and SPY, indicating that the asymmetry in IV responses to positive and negative returns persists, even when controlling for lagged adjustments.

Including lagged returns in the regressions provides little additional explanatory power, as reflected in the adjusted R-squared values. The coefficients for one-day lagged positive returns show some evidence of underreaction to positive news, though statistical significance remains weak. All findings in Table 5 are consistent with those reported by Marks and Simon (2017) for the 2006–2015 period. During their sample period, both contemporaneous $RET+_t$ and $RET-_t$ coefficients were significantly negative across all sectors and SPY. Similarly, in line with the present results, lagged (t-1) positive returns exhibited negative coefficients but with limited statistical significance, while the impact of lagged (t-1) negative returns on IV changes at t was near zero and statistically insignificant.

Next, I assess whether systematic or idiosyncratic sector returns drive sectoral implied volatility changes. Engle and Figlewski (2015) find that large-cap stock IVs are primarily driven by VIX (systematic), while Cao and Han (2013) argue that

idiosyncratic volatility, being harder to hedge, has a greater impact on option prices and IVs. Table 6 presents regressions decomposing sector returns into systematic and idiosyncratic components to compare their relative influence on IV fluctuations. Systematic returns are the fitted component from regressing daily sector returns on SPY returns, whereas idiosyncratic returns are the corresponding residuals.

Table 6, Panel A examines the impact of contemporaneous returns on sectoral implied volatilities, distinguishing between positive and negative, systematic and sector-specific returns. The regression controls for the lagged dependent variable, which, consistent with prior findings, exhibits daily reversals. The significant and negative coefficients for systematic returns indicate that the negative return-volatility relationship is largely driven by market-wide (SPY) returns. In contrast, negative idiosyncratic returns lead to rapid and significant IV spikes, while positive sector-specific returns elicit weak and mostly insignificant responses.

These findings further support the notion that risk-averse investors react more strongly to negative news while treating positive developments with caution. Wald 3 and 4 evaluate the null hypotheses $RET^{SY+}{}_t = RET^{SY-}{}_t$ and $RET^{ID+}{}_t = RET^{ID-}{}_t$, respectively, and are largely rejected across all sectors. This shows that the asymmetric IV response to positive and negative returns remains robust, even when returns are decomposed into systematic and idiosyncratic components.

Table 6, Panel B extends the analysis by incorporating lagged systematic and idiosyncratic returns into the regression. Notably, lagged positive systematic returns ($RET^{SY+}{}_{t-1}$) exhibit negative coefficients across all sectors, mostly with high significance. This suggests that information from positive systematic returns is incorporated gradually, leading to delayed declines in IV (initial underreaction).

Lagged negative systematic returns ($RET^{SY-}{}_{t-1}$) show some signs of slow IV increases, but with little statistical significance. Still, this is evidence that the asymmetric IV response is not likely due to overreactions to systematic negative returns, as they do not systematically reverse the next day. For both positive and negative lagged idiosyncratic returns ($RET^{ID+}{}_{t-1}$, $RET^{ID-}{}_{t-1}$) the coefficients are generally positive but statistically significant in only a few sectors. This provides some evidence

of IV overreactions to idiosyncratic shocks, contributing to subsequent sector IV reversals.

Interestingly, Wald test 5, which accounts for lagged responses to systematic returns, rejects the null hypothesis $RET^{SY+}{}_t + RET^{SY+}{}_{t-1} = RET^{SY-}{}_t + RET^{SY-}{}_{t-1}$ at the 5% significance level only in the Consumer Discretionary sector. This suggests that, when allowing for one-day lagged adjustments, the IV response to positive and negative systematic returns becomes symmetric across most sectors.

Table 6: Effects of Systematic and Idiosyncratic Returns on the Resulting Changes in Sector SPDR Implied Volatilities

Table 6 reports daily log change in implied volatilities ($\%\Delta IV_t$), using the same implied volatility (IV) selection method as earlier. Systematic returns are the fitted component from regressing daily sector returns on SPY returns, whereas idiosyncratic returns are the corresponding residuals. Panel A shows regressions with contemporaneous sector returns, and Panel B expands the models to include one-day lagged returns. The returns are simple (daily) percentage changes. Parentheses contain Newey–West standard errors with five lags, and asterisks denote significance at the *10%, **5%, and ***1% levels. The sample period runs from January 2015 to September 2024, and the data is from FirstRate. Wald tests 3-6 are explained in the body text.

Panel A: Contemporaneous returns only

$\%\Delta IV_t$	Energy	Tech.	Disc.	Materials	Industrials	Utilities	Health	Staples
Intercept	-0.003***	-0.002**	-0.002**	-0.003***	-0.002***	-0.004***	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\%\Delta IV_{t-1}$	-0.049**	-0.122***	-0.062***	-0.072***	-0.083***	-0.078***	-0.055***	-0.116***
	(0.022)	(0.019)	(0.018)	(0.020)	(0.019)	(0.022)	(0.018)	(0.021)
$RET^{SY+}{}_t$	-1.221***	-1.379***	-1.434***	-1.434***	-1.668***	-1.697***	-2.044***	-2.177***
	(0.067)	(0.093)	(0.083)	(0.085)	(0.109)	(0.131)	(0.120)	(0.142)
$RET^{SY-}{}_t$	-1.331***	-1.643***	-1.857***	-1.905***	-2.031***	-2.104***	-2.430***	-2.919***
	(0.108)	(0.161)	(0.173)	(0.182)	(0.210)	(0.151)	(0.224)	(0.243)
$RET^{ID+}{}_t$	-0.122	-0.289	-0.275	-0.292**	-0.066	-0.141	-0.342**	-0.058
	(0.076)	(0.185)	(0.237)	(0.120)	(0.152)	(0.090)	(0.136)	(0.163)
$RET^{ID-}{}_t$	-0.715***	-1.218***	-0.665***	-1.129***	-1.004***	-0.992***	-1.695***	-1.409***
	(0.064)	(0.147)	(0.179)	(0.134)	(0.175)	(0.171)	(0.156)	(0.255)
Adj. R-squared	0.494	0.479	0.526	0.497	0.505	0.412	0.556	0.430
Wald 3	0.167	0.004***	0.000***	0.000***	0.000***	0.006***	0.001***	0.000***
Wald 4	0.000***	0.000***	0.056*	0.000***	0.000***	0.000***	0.000***	0.000***

Panel B: Both Contemporaneous and Lagged returns

$\% \Delta IV_t$	Energy	Tech.	Disc.	Materials	Industrials	Utilities	Health	Staples
Intercept	-0.003***	-0.001	0.000	-0.003***	-0.002**	-0.003***	-0.003***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\% \Delta IV_{t-1}$	-0.056	-0.191***	-0.097***	-0.151***	-0.159***	-0.123***	-0.087**	-0.175***
	(0.035)	(0.029)	(0.031)	(0.024)	(0.035)	(0.032)	(0.036)	(0.029)
$RET^{SY+}{}_t$	-1.201***	-1.398***	-1.402***	-1.468***	-1.707***	-1.721***	-2.033***	-2.176***
	(0.075)	(0.091)	(0.097)	(0.090)	(0.112)	(0.127)	(0.132)	(0.169)
$RET^{SY-}{}_t$	-1.356***	-1.675***	-1.923***	-1.939***	-2.061***	-2.119***	-2.464***	-3.007***
	(0.107)	(0.156)	(0.157)	(0.164)	(0.198)	(0.137)	(0.217)	(0.202)
$RET^{ID+}{}_t$	-0.111	-0.307	-0.217	-0.260**	-0.073	-0.122	-0.331**	-0.042
	(0.069)	(0.189)	(0.233)	(0.126)	(0.140)	(0.087)	(0.134)	(0.147)
$RET^{ID-}{}_t$	-0.729***	-1.272***	-0.697***	-1.131***	-0.988***	-1.011***	-1.708***	-1.449***
	(0.060)	(0.156)	(0.171)	(0.130)	(0.180)	(0.168)	(0.165)	(0.245)
$RET^{SY+}{}_{t-1}$	-0.134	-0.361***	-0.280***	-0.445***	-0.405***	-0.473***	-0.357**	-0.742***
	(0.102)	(0.094)	(0.111)	(0.093)	(0.129)	(0.165)	(0.155)	(0.180)
$RET^{SY-}{}_{t-1}$	-0.014	-0.137	0.002	-0.206**	-0.222	-0.267**	-0.051	-0.209
	(0.074)	(0.129)	(0.112)	(0.094)	(0.156)	(0.123)	(0.191)	(0.147)
$RET^{ID+}{}_{t-1}$	0.052	0.037	-0.137	0.168	0.287	0.167**	0.327**	0.060
	(0.067)	(0.180)	(0.225)	(0.143)	(0.235)	(0.066)	(0.130)	(0.182)
$RET^{ID-}{}_{t-1}$	0.122*	-0.084	0.277**	-0.010	0.016	0.140	0.113	0.154
	(0.069)	(0.142)	(0.141)	(0.105)	(0.153)	(0.154)	(0.172)	(0.285)
Adj. R-squared	0.498	0.486	0.530	0.507	0.513	0.425	0.562	0.440
Wald 5	0.728	0.648	0.032**	0.053*	0.184	0.304	0.385	0.184
Wald 6	0.000***	0.001***	0.810	0.000***	0.000***	0.000***	0.000***	0.000***

Thus, the previously observed asymmetric IV responses to systematic returns stem from the slow incorporation of positive systematic returns into IV, as seen in the negative and significant coefficients for $RET^{SY+}{}_{t-1}$. In contrast, IV adjusts faster to negative systematic shocks with less significant lagged effects. A similar Wald Test (6) examines IV asymmetry to idiosyncratic sector returns. Unlike systematic returns, the asymmetry persists, even after accounting for lagged effects.

The findings in Table 6 are largely consistent with those from the 2006–2015 sample period reported by Marks and Simon (2017). The conclusions align, as sector IVs exhibit a lagged adjustment to positive systematic returns, explaining the asymmetric

IV response at the daily level. However, unlike the present results, their study finds symmetric IV responses to positive and negative idiosyncratic returns. During the sample period 2015-2024, I find asymmetric IV responses to positive and negative idiosyncratic returns, even when allowing for lagged responses. Moreover, the difference in contemporaneous IV-responses is very significant, as coefficients for $RET^{ID-}{}_t$ are highly negative and statistically significant, and the coefficients for $RET^{ID+}{}_t$ are mostly insignificant and close to zero.

Despite these differences, also the findings by Marks and Simon (2017) indicate sectoral IV overreactions to idiosyncratic returns, leading to IV reversals, with even stronger significance compared to the novel results. During my sample period from 2015 to 2024, the coefficients for lagged idiosyncratic returns are positive only for some sectors, whereas during 2006-2015, all sectors except Financials show statistically significant coefficients for $RET^{ID}{}_{t-1}$, at the 1% significance level.

Strengthening the robustness of the results of Tables 5 and 6, the responses to all return-variables are well-aligned across all sectors. Findings reveal that the changes in sectoral IVs are mostly explained by systematic return shocks and negative sector-specific shocks. Interestingly, the coefficients for the less volatile, defensive sectors are largest. This can be explained by the low baseline IV-level, often resulting in higher percentage changes, when markets absorb new information. Nevertheless, the absolute IV level of these defensive sectors still likely remains below other sectors.

In addition, and to conclude, the strong and immediate volatility responses to negative returns with the slow and cautious responses to positive returns, are also in line with the existing behavioural finance theories such as loss-aversion, affect and representativeness. E.g. Low (2004), Hibbert (2008) and Badshah (2013) attribute the asymmetric return-volatility relation to these behavioural theories. Next, chapter 5 introduces new explanatory variables to regressions, to deepen the understanding on the IV over- and underreactions beyond those explained by sector ETF returns.

5 Determinants of Sector Implied Volatility Changes

Chapter 5 introduces a comprehensive explanatory regression that provides evidence of demand-driven option pricing and underlying demand pressures, as these trading volumes play a key role in driving sectoral implied volatilities. In addition to this, changes in market wide IV (VIX), affect strongly the sectoral IVs, partly with a lag.

Beyond past implied volatility, volatility premiums, and returns, IV changes are also influenced by options demand, liquidity conditions, shifts in market sentiment, and constraints on arbitrage that prevent efficient price correction. This chapter presents a set of IV determinants and shows their effect on implied volatility changes. Variables "Option Volume", "ETF volume", and "VIX-return" are introduced and their effect on sectoral implied volatility changes is examined. These effects are consistent with demand-based option pricing and limits of arbitrage.

Table 7 reports descriptive statistics for the variables used in Table 8 and 9 regressions, covering the sample period 2015–2024. Panel A defines the variables and Panel B present summary statistics, including means and standard deviations.

All regressions in Tables 8 and 9 include controls for weekday effects, the monthly option expiration week, and the post-expiration week, implemented through dummy variables. Regression coefficients of these controls are reported in the appendices, documenting the observed intraweek and intramonth patterns. The control variables are generally statistically significant and ensure that the main results are not confounded by regular calendar effects.

On average, implied volatilities are higher on Mondays, suggesting that non-trading days contribute to volatility expectations. During the expiration week, near-term at-the-money options ― defined as those with at least 25 days to expiration ― tend to exhibit a decline in implied volatility, followed by a rebound in the post-expiration week. This pattern reflects expiration-driven repositioning and a maturity shift effect, as implied volatilities vary systematically with time-to-expiration.

Table 7: Descriptive Statistics 3

The options data is the end-of-the-day data of Sector SPDR ETF monthly options expiring the third Friday of the month. The sample period runs from January 2015 through September 2024 and the data is from FirstRate. The ETF data is also sourced from FirstRate, covering the same sample period. VIX-data is obtained from WSJ.

Panel A: Data Description

$\% \Delta IV_{t-1}$	1-day lagged dependent variable, log change in ATM-option implied volatility. Always expressed as bid-ask quotes' mid-point.
$\% VP_{t-1}^{ID}$	1-day lagged residual from regressing Sector SPDR volatility premia with SPY volatility premia. In this, regressed VP:s expressed as %-spread, log(IV/HV30).
RET	Sector returns. Systematic returns are the fitted component from regressing daily sector returns on SPY returns, whereas idiosyncratic returns are the corresponding residuals. T means contemporaneous, t-1 lagged returns. In addition to this, positive and negative returns are presented separately to capture the asymmetric IV responses.
Option Volume	Total Sector SPDR ETF options' daily trading volume in terms of contracts in all outstanding options expiring the third Friday of the month. The Option Volume is scaled with 10^{-6}.
ETF Volume	Total Sector SPDR ETF daily trading volume in terms of contracts during market opening hours, calculated from 1-minute intraday data. The raw ETF Volume is scaled with 10^{-9}. Δ ETF Volume used in Table 8 means the difference between the ETF trading volumes on day t and t-1. Table 9 uses simply the previous day's (t-1) level of ETF trading volume, instead of a change.
VIX return	The daily percentage change in The Cboe Volatility Index (VIX). Contemporaneous, 1-day lagged, and 2-day lagged VIX-returns are introduced in the models.
Controls:	
Weekdays	Weekday dummies to control for the intraweek dynamics in IV changes.
Option-expiration variables	TTM -4-0 means the option expiration week, -4 days to expiry until the day 0, the third Friday of the month. TTM 1-5 means the week after the option expiration day. Dummy variables: If true, 1, if false 0. These are used as control variables.

Panel B: Data Summary

	Energy	Tech.	Disc.	Mater.	Indust.	Utilities	Health	Staples
% ΔIV								
Mean	-0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
St.Dev.	0.024	0.032	0.028	0.028	0.030	0.024	0.028	0.029
% VP^{ID}								
Mean	0.000	0.000	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
St.Dev.	0.050	0.035	0.037	0.043	0.032	0.047	0.044	0.044
RET								
Mean	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000
St.Dev.	0.019	0.015	0.013	0.013	0.013	0.012	0.011	0.009
Option Volume								
Mean	0.077	0.018	0.015	0.013	0.025	0.029	0.019	0.019
St.Dev.	0.068	0.014	0.015	0.016	0.028	0.024	0.017	0.020
ETF Volume								
Mean	0.023	0.009	0.005	0.006	0.011	0.016	0.009	0.012
St.Dev.	0.012	0.006	0.003	0.003	0.006	0.007	0.005	0.006
VIX-return*	*not sector-specific							
Mean	0.003							
St.Dev.	0.086							

To ensure robustness, all regressions apply Newey–West (1987) standard errors with a lag of five to correct for potential autocorrelation and heteroscedasticity. Additionally, Variance Inflation Factor (VIF) values are reported in the appendices to confirm that the results are not driven by multicollinearity among the explanatory variables.

Table 8 reports the regression results on the determinants of daily implied volatility changes across sectors. Even after controlling for ETF-returns, trading volumes, and the market-wide volatility index (VIX), the mean-reverting behaviour in both lagged implied volatility (% ΔIV_{t-1}) and the lagged idiosyncratic volatility premium (% VP_{t-1}^{ID}) remains highly significant, indicating that these dynamics are persistent features of daily IV fluctuations.

The coefficient estimates on both positive ($RET+_t$) and negative ($RET-_t$) returns remain negative and statistically significant across every sector. Once trading

volume and the VIX are added to the regression specifications, however, the earlier asymmetry in IV responses to returns vanishes, and the coefficients on positive and negative returns are roughly equal in magnitude. This is explained by the fact that VIX and trading volume — both of which tend to rise on negative return days and market-wide stress — absorb part of the explanatory power previously attributed to negative returns, thereby reducing their direct effect on IV. Although offsetting partly the effect of returns, low variance-inflation factors (see Appendix C) confirm that the result is not an artifact of multicollinearity.

High option demand, measured by the total daily trading volume of all outstanding traditional monthly Sector SPDR ETF option contracts, is associated with contemporaneous increases in implied volatility across most sectors. Every sector displays positive coefficients, and although statistical significance varies, the evidence is strongly supporting a consistent and persistent pattern. The effect is particularly strong and significant for the Energy, Industrials and Consumer Staples sectors. The evidence aligns with demand-driven option-pricing theory (Bollen & Whaley 2004; Gârleanu et al. 2009), which posits that elevated option demand pushes up option premiums and, in turn, implied volatility.

Having established the relationship between option demand and implied volatility, I next examine the role of ETF trading volume, which primarily reflects trading activity in the underlying asset while also capturing aspects of market liquidity. ETF volume is measured as the total daily trading volume (in contracts) of each Sector ETF during market opening hours and then scaled with 10^{-9}. Δ ETF Volume $_t$ used in Table 8 regressions, is the difference between todays and yesterday's ETF volumes (ETF volume $_t$ - ETF volume $_{t-1}$).

Increases in ETF volumes are positively and significantly associated with increases in implied volatility across all sectors. In other words, during the days of high underlying ETF trading activity, the IV tends to rise. Decreases in trading volumes, however, are linked with declining IVs. All coefficient estimates for Δ ETF Volume $_t$ are statistically significant at 1% level, indicating a persistent relation between underlying trading volumes and implied volatilities.

Table 8: Determinants of Sector Implied Volatility Changes

This table reports the daily log change in implied volatilities ($\%\Delta IV_t$), using the same implied volatility (IV) selection method as in previous tables. Regression variables are described in Table 7. Parentheses contain Newey–West standard errors with five lags, and asterisks denote significance at the *10%, **5%, and ***1% levels. The sample period extends from January 2015 to September 2024, and the data is obtained from FirstRate. All regressions further control for weekday and monthly option expiration-related effects.

$\%\,\Delta IV_t$	Energy	Tech.	Disc.	Materials	Industrials	Utilities	Health	Staples
Intercept	0.000	0.001	0.001	0.002**	0.000	0.002*	0.002**	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\%\,\Delta IV_{t-1}$	-0.139***	-0.248***	-0.212***	-0.223***	-0.238***	-0.163***	-0.165***	-0.245***
	(0.021)	(0.029)	(0.027)	(0.021)	(0.024)	(0.020)	(0.020)	(0.023)
$\%\,VP_{t-1}^{ID}$	-0.016**	-0.049***	-0.019**	-0.043***	-0.062***	-0.028***	-0.028***	-0.057***
	(0.006)	(0.010)	(0.008)	(0.008)	(0.011)	(0.008)	(0.008)	(0.009)
$RET+_t$	-0.350***	-0.678***	-0.658***	-0.655***	-0.711***	-0.537***	-1.018***	-0.784***
	(0.060)	(0.069)	(0.071)	(0.062)	(0.065)	(0.112)	(0.068)	(0.094)
$RET-_t$	-0.600***	-0.542***	-0.574***	-0.801***	-0.645***	-0.897***	-1.004***	-1.117***
	(0.058)	(0.087)	(0.069)	(0.084)	(0.094)	(0.108)	(0.107)	(0.142)
Option Volume $_t$	0.019***	0.054**	0.000	0.045**	0.038***	0.055**	0.046*	0.063***
	(0.005)	(0.026)	(0.017)	(0.022)	(0.011)	(0.016)	(0.024)	(0.019)
Δ ETF Volume $_t$	0.310***	0.545***	0.964***	0.765***	0.553***	0.401***	0.530***	0.410***
	(0.058)	(0.141)	(0.232)	(0.184)	(0.108)	(0.072)	(0.145)	(0.113)
VIX return $_t$	0.137***	0.202***	0.197***	0.166***	0.201***	0.116***	0.166***	0.164***
	(0.010)	(0.017)	(0.013)	(0.010)	(0.013)	(0.010)	(0.010)	(0.010)
VIX return $_{t-1}$	0.032***	0.065***	0.064***	0.068***	0.073***	0.043***	0.049***	0.071***
	(0.007)	(0.015)	(0.012)	(0.009)	(0.012)	(0.007)	(0.008)	(0.010)
VIX return $_{t-2}$	-0.000	-0.012**	0.007	0.002	0.001	0.020***	0.005	0.018***
	(0.005)	(0.005)	(0.006)	(0.008)	(0.006)	(0.005)	(0.006)	(0.005)
Adj. R-squared	0.627	0.669	0.713	0.658	0.698	0.517	0.694	0.566

Controls: Weekdays, Monthly option expiration.

This finding on ETF volumes is consistent with prior literature (e.g. Karpoff, 1987; Gallant et al., 1992), which documents a positive relationship between trading activity and volatility. Elevated ETF trading volume likely reflects market reactions to new information, with increased investor attention, speculative flows, and hedging activity contributing to heightened uncertainty and, consequently, higher implied volatilities.

Interestingly, presented more detailed in Table 9, previous day's ETF trading volume (t-1) is negatively associated with today's IV changes. This relationship holds across sectors, with mostly significant negative coefficients for one-day lagged ETF volume. This suggests that while trading activity has a strong positive relation with sectoral IVs, days with high ETF volume are often followed by reversals in implied volatility.

These findings may reflect market overreactions during periods of elevated trading activity, with implied volatility adjusting downward the following day as uncertainty subsides. Alternatively, they may indicate that the informational value of trading volume decays quickly, as markets rapidly price in the underlying event. Once the information has been absorbed and the event fades in relevance, investor attention and capital flows diminish, leading to a subsequent normalization in IV.

Elevated past volume may enhance price discovery and the markets' ability to process new information, thereby reducing the uncertainty and dampening the volatility impact of future market events. In contrast, in less prepared markets with low prior volume, large trades lead to greater price fluctuations, amplifying volatility. This is related to Gallant et al. (1992), who find that conditioning on past volume attenuates the leverage effect.

In addition to returns and trading volumes, VIX plays a central role in explaining sectoral implied volatility changes. The VIX index, often referred to as the "fear gauge," reflects the market's expectation of 30-day forward-looking volatility in the S&P 500, derived from the prices of near-term SPX index options. In this study, I use VIX return, defined as the daily percentage change in the VIX index, to capture shifts in market-wide volatility expectations. A positive VIX return signals an increase in market implied volatility, while a negative VIX return reflects a decrease.

As expected, contemporaneous VIX return is positively and significantly associated with changes in sectoral implied volatilities, reinforcing earlier findings that systematic market components are key drivers of sector IVs. Somewhat surprisingly, the effect of VIX returns is transmitted to the sectoral level partially with a lag. While the contemporaneous coefficient is the largest and most significant, the coefficients

on lagged VIX returns are also positive and statistically significant across all sectors at the 1% level, with magnitudes approximately one-third of the contemporaneous effect.

Moreover, two-day lagged VIX returns are positive and significant at the 1% level for Utilities and Consumer Staples, suggesting a more gradual adjustment in these traditionally defensive sectors. For most other sectors, the two-day lagged effect is statistically insignificant. For Technology, however, the effect is negative and significant at the 5% level, potentially reflecting high investor attention and fast information absorption, aligned with Technology sector's fast-paced nature.

The positive and significant effect of lagged VIX returns on sectoral IVs suggests that market-wide volatility shocks are not incorporated instantaneously into sector option prices. This finding is consistent with the concepts of limits to arbitrage and slow-moving capital, which propose that real-world frictions — such as capital constraints, funding liquidity, or segmented investor bases — can delay price adjustments across markets.

For instance, exploiting such delays may require capital-intensive trades between sector and index options. These mechanisms help explain the gradual diffusion of market-wide volatility expectations into sector-level option pricing, aligning my results with the literature on market frictions (e.g., Shleifer and Vishny, 1997; Brunnermeier and Pedersen, 2009). Slow sector IV responses are also related to Hong and Stein (1999) slow information diffusion model.

In conclusion, Option Volume, ETF Volume and VIX-return show a consistent, positive and statistically significant effect on contemporaneous implied volatility changes. Volumes posit initial overreactions, partially followed by reversals, whereas changes in VIX are transmitted to sectoral IVs with a lag, suggesting an underreaction. This relates to the earlier evidence on underreactions to systematic shocks. Table 8 shows higher explanatory power as measured with adjusted R-squared, to those models presented earlier. Not only do these factors explain the IV changes, but also have predictive power on the short term, as presented next.

6 Forecasting changes in Sector ETF Implied Volatility

Chapter 6 is structured followingly: Section 6.1 focuses on the short-term predictability of IV changes, exploiting the predictable patterns in IV changes and the delayed sectoral responses to market-wide information. Section 6.2 validates these findings through out-of-sample tests, linking forecasted volatility changes to associated straddle returns and emphasizing the economic significance.

6.1 Short-term Predictability in Sectoral Implied Volatilities

Table 9 shows evidence on the short-term predictability of implied volatility changes. All variables in Table 9 regressions are lagged and the regression specifications are controlled with weekdays and expiration-related effects.

Consistent with previous results, Table 9 indicates that both the one-day lagged implied volatility change ($\%\Delta IV_{t-1}$) and one-day lagged idiosyncratic volatility premium ($\%VP_{t-1}^{ID}$) exhibit negative and statistically significant coefficients in forecasting regressions. This confirms earlier findings of daily implied volatility reversals and the long-term relations with the market (SPY) volatility premium.

Interestingly, both positive and negative one-day lagged sector returns display positive coefficients across all sectors, with a varying degree of statistical significance. At first, this positive relation appears counterintuitive given the earlier results. However, Tables 5 and 6 account also for contemporaneous returns, which predominantly drive changes in IV, thereby explaining the discrepancy.

Sector ETFs exhibit strong evidence of daily return reversals, as indicated by consistently negative daily autocorrelations ranging from -0.04 to -0.14 (see appendix E for details). These reversals suggest that positive (negative) returns today are typically followed by negative (positive) returns tomorrow, implying short-term overreactions in underlying ETF prices. Given the documented inverse relationship between ETF returns and implied volatility, this return reversal pattern helps explain

the positive coefficients on lagged returns in the IV forecasting regressions. Importantly, as the regressions include VIX-return to control for systematic effects, $RET+_{t-1}$ and $RET-_{t-1}$ predominantly capture the effect of idiosyncratic return components. In result, positive coefficients provide additional support for the earlier evidence on short-term IV overreactions to idiosyncratic shocks, which appeared rather weak in regressions of Table 6.

Table 9: Forecasting Regressions for Short-term Sector IV Changes

This table reports the forecasting regression estimates for the daily log change in implied volatilities ($\%\Delta IV_t$) across eight sectors, using the same implied volatility (IV) selection method as in previous tables. Regression variables are described in Table 7. Parentheses contain Newey–West standard errors with five lags, and asterisks denote significance at the *10%, **5%, and ***1% levels. The sample period spans January 2015 to September 2024, with data obtained from the FirstRate. All regressions control for weekday and monthly option expiration-related effects.

$\%\Delta IV_t$	Energy	Tech.	Disc.	Materials	Industrials	Utilities	Health	Staples
Intercept	0.007***	0.007***	0.007***	0.009***	0.008***	0.006***	0.009***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\%\Delta IV_{t-1}$	-0.070*	-0.231***	-0.140***	-0.205***	-0.224***	-0.181***	-0.094**	-0.214***
	(0.041)	(0.043)	(0.047)	(0.037)	(0.046)	(0.031)	(0.041)	(0.038)
$\%\ VP_{t-1}^{ID}$	-0.013	-0.039**	-0.029*	-0.043***	-0.055***	-0.016	-0.031**	-0.046***
	(0.009)	(0.016)	(0.015)	(0.013)	(0.019)	(0.012)	(0.013)	(0.016)
$RET+_{t-1}$	0.196***	0.170	0.162	0.125	0.205	0.249**	0.372**	0.322*
	(0.052)	(0.131)	(0.114)	(0.116)	(0.127)	(0.112)	(0.118)	(0.191)
$RET-_{t-1}$	0.064	0.132	0.090	-0.059	0.063	-0.011	0.330**	0.064
	(0.088)	(0.104)	(0.100)	(0.145)	(0.138)	(0.114)	(0.149)	(0.156)
ETF Volume $_{t-1}$	-0.117**	-0.253*	-0.654***	-0.554**	-0.376**	-0.023	-0.321**	-0.301**
	(0.053)	(0.141)	(0.241)	(0.263)	(0.176)	(0.088)	(0.147)	(0.150)
VIX return $_{t-1}$	0.027***	0.067***	0.051***	0.060***	0.077***	0.045***	0.052***	0.069***
	(0.010)	(0.021)	(0.017)	(0.015)	(0.018)	(0.009)	(0.015)	(0.014)
VIX return $_{t-2}$	0.006	-0.015	0.005	0.005	0.003	0.022***	0.005	0.018**
	(0.008)	(0.009)	(0.010)	(0.011)	(0.011)	(0.007)	(0.010)	(0.009)
Adj. R-squared	0.031	0.052	0.026	0.042	0.046	0.060	0.045	0.063

Controls: Weekdays, Monthly option expiration.

This evidence on short-term ETF return reversals is consistent with findings of e.g. Petäjistö (2017) and Da and Shive (2018), who document negative daily ETF return autocorrelations evidencing for reversals. Moreover, Da and Shive (2018) show that such autocorrelations become even more negative when ETF volumes are higher. My findings extend this by demonstrating similar reversals in IVs, suggesting that option-market reversals are partially driven by underlying ETF returns and volumes.

Presented in Table 8, contemporaneous increases (decreases) in the ETF volumes result in higher (lower) sectoral implied volatilities. Table 9, however, shows that high ETF trading volume days are typically followed by a decline in IV the next day. Plausible explanations for this include potential initial IV overreactions, related reversals in the underlying ETF after high volumes (Da and Shive, 2018) and quick decay of the informational value of the trading volume once the price discovery is achieved. Higher volumes also reduce uncertainty by improving market efficiency, while lower volumes impair information processing, leading to elevated volatility expectations. High trading volumes are typically related to market events elevating the sectoral implied volatilities, which, however, tend to revert in the short-term.

Furthermore, changes in VIX are partially transmitted to sectoral implied volatilities with a lag of one to two days, consistent with findings in Table 8. Positive VIX returns indicate rising market-wide implied volatility, whereas negative VIX returns reflect declining overall volatility expectations. Given that systematic factors such as VIX and systematic returns significantly influence sector implied volatilities (as demonstrated previously in Tables 6 and 8), the slow IV response of sector ETFs to shifts in market-wide volatility expectations represents an important finding. These results are consistent with theoretical frameworks of slow-moving capital, gradual information diffusion, and real-world constraints to arbitrage.

Accounting for the delayed sectoral IV response to changes in VIX improves the precision of short-term implied volatility forecasts and enhances the profitability of associated trading strategies (Table 10). Section 6.2 presents the out-of-sample performance of the short-term IV forecasts developed in Table 9, highlighting the economic relevance of the thesis's core findings.

6.2 Out-of-sample Performance of the Short-term IV-forecasts

Table 10 reports out-of-sample test results for the Table 9 IV forecast model over January 2020–September 2024. An expanding-window estimation (baseline 2015–2019) updates daily, and only forecasts strong enough, exceeding ±0.05 percentage points, trigger a trade. Consequently, approximately 65% of the forecasts lead to taking a position.

Neglecting the weak signals improves the significance and accuracy of the IV-forecasts in Table 10. However, as presented in Figure 2, straddle-returns and related information ratios are higher, when taking a position from the weaker signals, too. This suggests that also the weaker signals are valuable, despite being less accurate predictions than signals beyond ±0.05 percentage points.

Key takeaways from Table 10 are that the IV decreases are easier to predict than increases, and that the forecasts generally succeed in identifying the sign of upcoming IV changes. This is intuitive: volatility increases are often driven by unforeseen shocks whereas volatility declines tend to reflect slower, more predictable adjustments and market inefficiencies.

Across all sectors, the forecasts predict the sign of the IV-change with accuracy of more than 50%, leading to statistically significant *Actual %ΔIV* results, positive in Panel A and negative in Panel B. Despite being harder to forecast, coefficients for *Actual %ΔIV* across sectors are more significant for IV increases than decreases, in line with earlier results on the sharp reactions to negative news and muted reactions to positive news. Forecasted IV decreases generate more consistent straddle returns.

When IV-increases (decreases) are forecasted, a long (short) ATM-straddle is entered. All straddle positions are delta-neutral, and the long (short) strategy premiums pay (earn) risk-free interest over the one day holding period. While sector-specific returns are mostly positive, suggesting that the forecasts work, they lack significance individually. When averaged across sectors, straddle returns are statistically significant based on a cross-sectional t-test using the standard error.

Table 10: Out-of-sample Test

Table 10 reports out-of-sample testing results for the Table 9 IV forecast model over January 2020–September 2024. An expanding-window estimation (baseline 2015–2019) updates daily, and only forecasts exceeding ±0.05 percentage points trigger a trade. Panel A presents the actual results when an increase in IV is forecasted (long straddle entry), while Panel B shows results for days with a forecasted decrease in IV (short straddle entry). Each entry uses the closest-to-money, near-term options (with at least 25 days until expiration) to form a delta-neutral, ATM straddle; short straddle premiums earn, while long straddle premiums are financed at the 1-month T-bill rate for a one-day holding period. The "Avg." column reports the cross-sectional mean, with the standard deviation below indicating variation across sector-level means. The asterisks denote significance at the *10%, **5%, and ***1% levels. The data is obtained from the FirstRate.

Panel A: IV increase predicted

	Energy	Tech.	Disc.	Mater.	Industrial	Utilities	Health	Staples	**Avg.**
OBS	392	520	480	442	441	357	347	389	**421**
Actual ΔIV positive (%):	52.0	51.9	53.3	55.0**	52.4	54.6*	59.1***	56.6***	**54.4*** **
Actual %ΔIV:									
Mean (%)	0.96***	0.74**	0.77***	1.14***	1.10***	1.27***	1.69***	1.63***	**1.16*** **
St.Dev	5.96	6.62	6.32	6.42	6.51	7.05	6.62	7.37	0.36
Top decile	6.62	9.38	8.16	8.67	9.51	7.84	8.23	9.10	
Bottom decile	-4.59	-5.86	-5.99	-5.76	-6.67	-5.69	-5.32	-6.64	
Long DH Straddle return:									
Mean (%)	0.09	0.08	0.21	0.13	-0.02	0.40	-0.04	0.03	**0.11***
St.Dev	5.96	5.09	5.31	5.89	5.33	7.16	5.65	5.87	0.14
Top decile	6.29	6.23	6.57	5.69	6.92	7.87	5.65	6.94	
Bottom decile	-5.85	-4.74	-4.61	-5.06	-5.37	-5.75	-5.45	-6.17	

Panel B: IV decrease predicted

	Energy	Tech.	Disc.	Mater.	Industrial	Utilities	Health	Staples	**Avg.**
OBS	429	384	301	325	347	367	356	290	**350**
Actual ΔIV negative (%):	63.6***	62.2***	60.5***	61.2***	59.1***	61.0***	63.5***	60.6***	**61.5*** **
Actual %ΔIV:									
Mean (%)	-0.34	-0.53	-0.57	-0.97**	-0.57	-0.80***	-1.15***	-1.22***	**-0.77*** **
St.Dev	6.30	7.29	6.74	7.23	7.75	5.53	6.65	7.37	0.32
Top decile	5.67	7.74	7.02	6.00	8.48	5.06	6.60	6.64	
Bottom decile	-5.63	-7.65	-7.36	-8.65	-8.92	-6.37	-8.21	-8.66	
Short DH Straddle return:									
Mean (%)	-0.26	0.16	0.23	0.50	0.45	0.11	0.60**	0.51	**0.29** **
St.Dev	7.10	5.44	5.14	5.61	5.90	5.65	5.21	6.77	0.29
Top decile	5.15	5.45	5.13	6.11	6.35	5.59	5.58	6.40	
Bottom decile	-6.43	-6.41	-4.86	-5.96	-6.05	-6.11	-5.69	-4.99	

Defensive sectors, including Utilities, Healthcare and Consumer Staples with lowest average implied volatility levels, show high percentages of correctly predicted IV-changes and significant actualized changes in IV. In addition, they exhibit some of the highest r-squared values in the forecasting regressions of Table 9. Some reasons for this could be lower exposure to cyclical risk and macroeconomic shocks, fewer number of speculative traders and slower-moving investor base, adjusting their positions more gradually. When facing market events, investors likely rebalance their more market-sensitive exposures before these more stable investments.

Figure 2 illustrates the economic value of the sectoral IV predictability. Blue and orange lines serve as benchmarks, showing cumulative returns from continuously holding long and short straddles over 2020–2024. The black and grey lines display cumulative returns from the forecast based IV strategies, which enter positions when the predicted change in implied volatility exceeds ±0.00 or ±0.05 percentage points, respectively. On days when no signal is triggered, the grey strategy remains out of the market, and the sector's return is recorded as zero in the daily average.

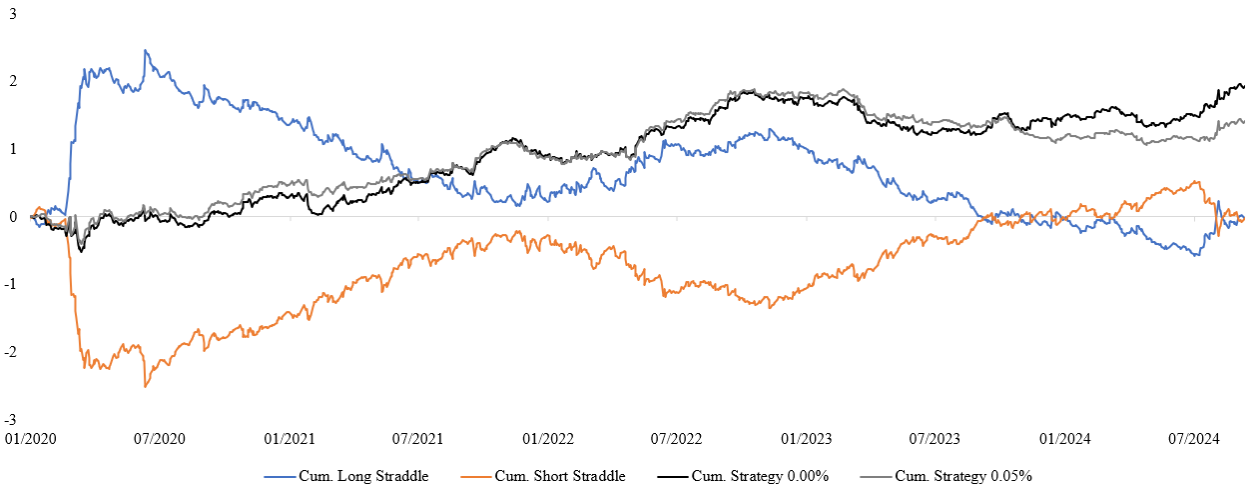
An equal amount is allocated daily to each sector-specific strategy, resulting in daily returns computed as the average of individual sector returns for each strategy. In line with option pricing theory, delta-neutral long and short straddles yield near-zero returns over the long term. The long-straddle performs well during periods of market turbulence (e.g. COVID), whereas the short-straddle earns positive returns in more stable markets by collecting option premia when prices remain near the strikes.

The black strategy (0.00%) takes a daily position in each sector regardless the magnitude of the signal and outperforms the grey strategy with zero sector-returns for the days with weak signals. Although stronger signals are better predictors, staying out of the market on the weak signal days decreases the performance. Despite exhibiting higher return volatility, the black strategy delivers superior Sharpe ratio, suggesting that maintaining exposure — even on days with less certain forecasts — enhances the risk-adjusted performance of the option strategy.

Below the cumulative returns in Figure 2 are the average daily returns, daily standard deviations, and annualized Sharpe ratios of the black and grey strategies. As expected, the average daily returns align closely with the average sector-specific straddle returns presented in Table 10. Standard deviations for the black and grey strategies are lower, reflecting diversification benefits from averaging sector-specific positions that alternate between long and short straddles, reducing exposure to market turbulence. Sharpe ratios are high for the strategies, ranging between 0.69 and 0.83.

Figure 2: Out-of-sample strategy performance 2020-2024

Figure 2 shows cumulative returns for straddle strategies over January 2020–September 2024. Blue and orange lines represent naïve benchmarks that go long or short an ATM straddle for each sector daily. Daily returns are the average of sector-level returns, as equal capital is allocated to each sector each day. Black and grey lines implement forecast-based strategies: a sector straddle is bought (sold) if the sector IV is predicted to rise (fall). Grey, however, triggers a trade only for signals stronger than ±0.05 percentage points. Each entry uses the closest-to-money, near-term options (with at least 25 days until expiration) to form a delta-neutral, ATM straddle; short straddle premiums earn, while long straddle premiums are financed at the 1-month T-bill rate for a one-day holding period. Below the figure are presented the average daily returns and their standard deviations, with the related annualized information ratios. The data is obtained from the FirstRate.



	Long straddle	Short straddle	Strategy (0.00%)	Strategy (0.05%)
Mean	-0.00 %	0.00 %	0.16 %	0.12 %
St. Dev.	4.55 %	4.54 %	3.14 %	2.77 %
Sharpe ratio	-0.00	0.00	0.83	0.69

7 Conclusions

This research provides new evidence on the short-term dynamics and predictability of sectoral implied volatilities, offering insights into how new information, capital reallocation and real-world market frictions shape volatility expectations and option prices. The results reveal underreactions to systematic shocks and overreactions to idiosyncratic sector-specific shocks. The findings align with established theories of demand-based option pricing, slow-moving capital and constraints of arbitrage.

First, this study replicates Marks and Simon (2017) on the dynamics of sectoral implied volatility, using a new and comprehensive dataset of Sector SPDR ETF options from 2015 to 2024. Consistent with prior results, I document significant daily reversals in at-the-money implied volatilities and persistent long-term relationships between sector and market volatility premiums, resulting in daily sector IV adjustments. I also confirm asymmetric IV responses to sector returns, as IVs increase more in response to negative returns than decrease in response to positive returns.

However, unlike earlier results that attribute this IV asymmetry solely to systematic returns, I find that it persists for both systematic and idiosyncratic returns. Notably, the asymmetry in systematic returns disappears when accounting for one-day lagged responses, as sector IVs adjust slowly and cautiously to positive market-wide shocks. For idiosyncratic returns, the asymmetry persists even after allowing for the delay.

Building on this foundation, the study shows that sector implied volatilities respond positively to option demand, underlying ETF trading volumes, and market-wide volatility (VIX). However, the effects of ETF volumes tend to reverse the following day. The same applies to sector ETF returns, both indicating initial IV overreactions. In contrast, the influence of VIX is transmitted to sector IVs with a one- to two-day delay, indicating underreactions to systematic IV, consistent with slow-moving capital. These over- and underreactions in sectoral IVs exhibit predictability that results in accurate out-of-sample forecasts and significant related trading strategy returns.

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A: Appendix

Appendix A: Control variables in Table 8 regressions

Appendix A presents the control variables used in regression Table 8. Weekday dummies to control for the intraweek dynamics in IV changes. TTM -4-0 means the option expiration week, -4 days to expiry until the day 0, the third Friday of the month. TTM 1-5 means the week after the option expiration day. TTM:s are dummy variables. Parentheses contain Newey–West standard errors with five lags, and asterisks denote significance at the *10%, **5%, and ***1% levels. The sample period extends from January 2015 to September 2024, and the data is obtained from FirstRate.

	Energy	Tech.	Disc.	Materials	Industrials	Utilities	Health	Staples
Tuesday	-0.003***	0.002	0.001	-0.003**	0.000	-0.004***	-0.002*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Wednesday	-0.004***	-0.003**	-0.002**	-0.004***	-0.002**	-0.007***	-0.005***	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Thursday	-0.002***	-0.002*	-0.001	-0.004***	-0.001	-0.007***	-0.004***	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Friday	-0.004***	-0.003**	-0.002**	-0.003***	-0.002**	-0.006***	-0.005***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TTM -4-0	-0.004***	-0.004***	-0.003***	-0.004***	-0.004***	-0.003***	-0.002***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TTM 1-5	0.002**	0.002*	0.002*	0.001	0.002**	0.000	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Appendix B: Control variables in Table 9 regressions

Appendix B presents the control variables used in regression Table 9. Weekday dummies to control for the intraweek dynamics in IV changes. TTM -4-0 means the option expiration week, -4 days to expiry until the day 0, the third Friday of the month. TTM 1-5 means the week after the option expiration day. TTM:s are dummy variables. Parentheses contain Newey–West standard errors with five lags, and asterisks denote significance at the *10%, **5%, and ***1% levels. The sample period extends from January 2015 to September 2024, and the data is obtained from FirstRate.

	Energy	Tech.	Disc.	Materials	Industrials	Utilities	Health	Staples
Tuesday	-0.006***	-0.002	-0.002	-0.006***	-0.003	-0.005***	-0.006***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wednesday	-0.007***	-0.008***	-0.007***	-0.009***	-0.007***	-0.010***	-0.011***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Thursday	-0.005***	-0.005***	-0.004**	-0.007***	-0.004**	-0.009***	-0.007***	-0.004**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Friday	-0.009***	-0.009***	-0.008***	-0.009***	-0.008***	-0.009***	-0.011***	-0.008***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
TTM -4-0	-0.002*	-0.002*	-0.002	-0.004***	-0.003**	-0.003***	-0.002	-0.003**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TTM 1-5	0.001	0.001	0.001	0.000	0.001	0.000	0.003	0.004**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)

Appendix C: VIF values in Table 8 regressions

Appendix C presents the Variance Inflation Factor (VIF) values in Table 8 regressions to ensure that the results are not driven by the multicollinearity among the explanatory variables.

	Energy	Tech.	Disc.	Materials	Industrials	Utilities	Health	Staples
% ΔIV_{t-1}	2.02	2.56	2.85	2.28	2.70	1.62	2.45	1.88
% VP_{t-1}^{ID}	1.05	1.09	1.05	1.06	1.07	1.11	1.04	1.10
$RET+_{t}$	1.68	1.76	1.73	1.69	1.63	1.54	1.69	1.59
$RET-_{t}$	1.80	2.24	2.12	2.10	2.12	1.61	2.08	1.79
Option Volume $_{t}$	2.57	2.74	2.01	1.70	1.87	2.73	2.39	1.16
Δ ETF Volume $_{t}$	1.18	1.18	1.14	1.11	1.18	1.18	1.17	2.01
VIX return $_{t}$	1.36	2.10	1.96	1.80	1.95	1.17	1.74	1.48
VIX return $_{t-1}$	1.97	2.53	2.90	2.29	2.72	1.54	2.45	1.85
VIX return $_{t-2}$	1.04	1.05	1.04	1.04	1.05	1.03	1.05	1.05
Tuesday	2.17	2.18	2.16	2.16	2.19	2.20	2.17	2.18
Wednesday	2.18	2.20	2.18	2.17	2.22	2.20	2.18	2.19
Thursday	2.13	2.14	2.13	2.12	2.15	2.14	2.12	2.14
Friday	2.14	2.19	2.17	2.15	2.19	2.15	2.14	2.15
TTM -4-0	1.48	1.47	1.45	1.45	1.45	1.46	1.45	1.45
TTM 1-5	1.42	1.42	1.42	1.42	1.43	1.43	1.43	1.44
Mean VIF:	**2.16**	**2.34**	**2.29**	**2.16**	**2.25**	**2.11**	**2.26**	**2.10**

Appendix D: VIF values in Table 9 regressions

Appendix D presents the Variance Inflation Factor (VIF) values in Table 9 regressions to ensure that the results are not driven by the multicollinearity among the explanatory variables.

	Energy	Tech.	Disc.	Materials	Industrials	Utilities	Health	Staples
% ΔIV_{t-1}	2.54	2.85	3.31	2.70	3.04	1.98	3.12	2.11
% VP_{t-1}^{ID}	1.06	1.08	1.05	1.05	1.07	1.09	1.05	1.08
$RET+_{t-1}$	1.96	1.93	1.91	1.99	1.89	1.74	2.09	1.75
$RET-_{t-1}$	2.34	2.49	2.30	2.51	2.46	1.97	2.63	2.11
ETF Volume $_{t-1}$	4.75	3.39	3.50	4.14	4.30	4.62	4.58	4.24
VIX return $_{t-1}$	1.96	2.86	3.05	2.42	2.95	1.52	2.55	1.93
VIX return $_{t-2}$	1.03	1.05	1.05	1.04	1.06	1.04	1.05	1.06
Tuesday	1.54	1.43	1.49	1.50	1.50	1.53	1.50	1.50
Wednesday	1.53	1.42	1.48	1.54	1.50	1.58	1.52	1.52
Thursday	1.57	1.44	1.49	1.55	1.54	1.64	1.56	1.54
Friday	1.54	1.45	1.48	1.53	1.55	1.63	1.53	1.55
TTM -4-0	1.37	1.35	1.37	1.34	1.36	1.37	1.35	1.36
TTM 1-5	1.33	1.33	1.34	1.32	1.34	1.33	1.33	1.34
Mean VIF:	**1.88**	**1.85**	**1.91**	**1.89**	**1.97**	**1.77**	**1.99**	**1.78**

Appendix E: Daily return autocorrelation in sector ETFs

Appendix E presents the correlation coefficients between contemporaneous, and one-day lagged sector ETF returns. Sectoral ETF-returns are calculated as simple returns, as a percentage.

RET	Energy	Tech.	Disc.	Materials	Industrials	Utilities	Health	Staples
RET_{t-1}	-0.037	-0.138	-0.057	-0.057	-0.058	-0.083	-0.093	-0.102