

Return-volatility correlations and option returns^{*}

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Abstract

This paper uncovers a robust negative relation between equity option returns and the return-volatility correlation (RVC). Sorting options by RVC reveals a persistent decline in delta-hedged returns from low- to high-RVC portfolios. Traditional leverage-based explanations cannot account for this relation, while the evidence suggests that conventional risk-based explanations are insufficient. Instead, the evidence points to a combined demand- and supply-side channel: market makers face lower hedging risk for options with more negative RVC, while end users favor high-RVC options for cleaner volatility exposure, together generating the observed negative relation between RVC and option returns.

Keywords: Return-volatility correlation; option returns; volatility risk premium; leverage effect; demand pressure

JEL Classifications: G12, G13.

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1 Introduction

The negative correlation between equity returns and return volatilities is often termed as “leverage effect” by statisticians (e.g., [Ait-Sahalia, Fan, and Li, 2013](#); [Wang and Mykland, 2014](#); [Ait-Sahalia, Fan, Laeven, Wang, and Yang, 2017](#); [Kalnina and Xiu, 2017](#)) and option pricers (e.g., [Heston, 1993](#); [Bates, 2000](#); [Bakshi, Cao, and Chen, 1997](#); [Duffie, Pan, and Singleton, 2000](#)), motivated by the hypothesis in [Black \(1976\)](#), who finds that this negative return-volatility correlation (RVC) can be explained by financial leverage.¹ [Figlewski and Wang \(2000\)](#), [Hasanhodzic and Lo \(2011\)](#), and [Carr and Wu \(2017\)](#) argue that this labelled terminology is indiscriminate, as the negative RVC is not driven by Black’s (1976) financial leverage. More generally, the negative RVC is also called “asymmetric volatility effect” in the literature (e.g., [Bekaert and Wu, 2000](#); [Jackwerth and Vilkov, 2019](#)). Regardless, the negative RVC is a well-established phenomenon in financial markets, and it is important for option pricing.

Despite the theoretical importance of RVC, the empirical link between RVC and option returns remains unexplored. A rich literature establishes that financial leverage drives the cross-section of equity and asset volatilities ([Choi and Richardson, 2016](#)) and stock returns ([Doshi, Jacobs, Kumar, and Rabinovitch, 2019](#)). In the options market, leverage has been shown to increase put prices by fattening the left tail of the return distribution ([Bai, Goldstein, and Yang, 2019](#)) and driving default risk premia ([Vasquez and Xiao, 2024](#)). However, these studies focus exclusively on financial leverage. To the best of our knowledge, this paper is the first to investigate the relation between the RVC and option returns.²

To test this, we use U.S. individual equity option data from OptionMetrics Ivy DB between January 1996 and August 2023, merged with CRSP stock returns and Compustat balance sheet variables, as well as analyst forecast data from I/B/E/S. Each month, we filter the option universe to retain only liquid contracts following the methodology of [Duarte, Jones, Khorram, Mo, and Wang \(2025\)](#) and [Horenstein, Vasquez, and Xiao \(2025\)](#). To mitigate

¹According to [Black \(1976\)](#), as asset prices decline, firms become mechanically more leveraged because the value of their debt rises relative to equity. Consequently, their stocks are expected to carry greater risk and exhibit higher volatility.

²Recently, as an independent study, [Doshi, Jacobs, and Sert \(2026b\)](#) show that the market leverage effect, estimated from high-frequency index returns, negatively predicts SPX call returns and positively predicts SPX put returns. By contrast, our analysis focuses on the cross-section of individual equity option returns.

illiquidity biases, we exclude options whose underlying stock prices fall below five dollars at initiation or where dividend events occur before portfolio formation. For each eligible stock at month-end, we select the at-the-money (ATM) call and put options with the shortest maturity beyond one month, resulting in a clean, representative set of contracts. After applying all filters, our final sample contains 249,141 call option-months and 197,933 put option-months. Consistent with the literature (e.g., [Bakshi and Kapadia, 2003](#); [Duarte, Jones, and Wang, 2024](#); [Horenstein et al., 2025](#)), we compute delta-hedged option returns by holding a long position in an option and shorting the appropriate number of shares, rebalancing the hedge daily until maturity. Returns are expressed relative to the underlying stock price to ensure comparability across firms. We also construct our key explanatory variable, the RVC, as the correlation between daily stock returns and daily changes in implied volatility over the past year, requiring at least 200 valid observations. Implied volatility is measured as the average of ATM call and put implied volatilities with 30-day maturity. This approach ensures a forward-looking, market-based proxy for volatility dynamics, avoiding biases from realized volatility estimates. In addition, we collect a range of control variables that prior work has shown to predict option returns. These controls allow us to test whether the explanatory power of RVC is incremental to known determinants of option returns.

Subsequently, we turn to the empirical analysis of the RVC and its role in predicting option returns. Using a large sample of delta-hedged call and put options between 1996 and 2023, we sort them into quintiles based on RVC and find a striking monotonic pattern for both calls and puts: returns decline sharply as RVC increases. For calls, the spread between high- and low-RVC portfolios ranges from -0.31% to -0.64% per month depending on the weighting scheme, while for puts the spread ranges from -0.25% to -0.63% . These differences are not only statistically significant but also economically meaningful, highlighting a strong and robust negative relation between RVC and option returns. Importantly, this pattern persists after controlling for equity and option-based risk factors, including the Fama-French five factors in [Fama and French \(2015\)](#), momentum in [Jegadeesh and Titman \(1993\)](#), and the four option-return factors proposed by [Horenstein et al. \(2025\)](#). Even after full adjustment, the alpha of the high-minus-low RVC portfolio remains significantly negative, indicating that the RVC effect cannot be subsumed by known risk factors. We further

examine the robustness of this relation through bivariate portfolio sorts and cross-sectional regressions. Double-sorted portfolio analyses show that the negative RVC-return spread remains significant across a wide range of characteristics. Likewise, monthly Fama-MacBeth regressions confirm that RVC continues to load significantly negative even after jointly controlling for multiple option and stock characteristics. These results reinforce the conclusion that RVC captures an independent pricing dimension in the cross-section of option returns.

To ensure that our main findings are not artifacts of return construction, correlation measurement, market frictions, or conditional market states, we conduct an extensive battery of robustness checks. First, we redefine option returns in several alternative ways, including scaling by option value or absolute hedged portfolio value, shortening the holding horizon, and monthly rebalancing. Across all definitions, the monotonic decline in option returns from low- to high-RVC portfolios persists, with spreads remaining large and statistically significant. Second, we test the sensitivity of our results to alternative RVC proxies. Using a short-window (one-month) correlation and a log-changes specification, we again find nearly identical patterns, confirming that the negative RVC-return relation does not depend on the exact construction of the RVC measure. Third, we account for realistic transaction costs by adjusting portfolio returns under varying effective-to-quoted spread assumptions according to [Goyal and Saretto \(2025\)](#). Even under conservative estimates of trading frictions, the High-Low RVC spread remains economically meaningful and statistically significant. Finally, we examine whether the effect is state-dependent by splitting the sample into up and down market conditions. Both calls and puts display robustly negative High-Low spreads in each state, with magnitudes remarkably similar across subsamples.

To explain the negative relation between RVC and option returns, we explore three potential explanations: leverage-based, risk-based, and demand-based mechanisms. First, we test the classic leverage-effect hypothesis by incorporating financial leverage into [Fama and MacBeth \(1973\)](#) regressions alongside RVC. We find that financial leverage is only weakly related to option returns, while the predictive power of RVC remains economically and statistically strong. This evidence contradicts the leverage story: if more negative RVC merely reflected higher leverage, option returns should be lower rather than higher.

Second, we examine whether RVC represents a priced risk factor. In option markets,

investors are willing to pay higher premia to hedge undesirable risks such as high implied volatility (IV) and volatility-of-volatility (VOV), causing these characteristics to predict lower subsequent option returns (Cao and Han, 2013; Ruan, 2020; Cao, Vasquez, Xiao, and Zhan, 2023; Horenstein et al., 2025). Under the conventional interpretation that more negative RVC reflects greater downside risk, our evidence is inconsistent with a standard risk-premium explanation, as options on stocks with more negative RVC earn significantly *higher*, rather than lower, delta-hedged returns. We further show that although higher RVC is positively correlated with several established option risk measures, it is also positively related to characteristics associated with investor demand and informed trading, leaving open the possibility that RVC reflects both risk and demand. So, the evidence suggests that risk alone is unlikely to fully explain the negative RVC–return relation, motivating the demand-based mechanism developed in the following section.

Finally, we propose a demand-based explanation that integrates both market makers’ hedging efficiency and end users’ option demand, following Garleanu, Pedersen, and Poteshman (2009). On the supply side, more negative RVC strengthens the natural hedge between delta and vega exposures, reducing hedging inefficiency, lowering required premia, and improving risk-sharing for market makers. Empirically, hedging inefficiency, measured by the volatility of daily delta-hedged returns, rises monotonically from low- to high-RVC portfolios, with economically and statistically significant High-Low spreads. These findings indicate that lower hedging costs for low-RVC options compress the volatility risk premium, leading to higher delta-hedged returns for option buyers. On the demand side, investors systematically favor high-RVC options, which provide cleaner volatility exposure. Relative measures of open interest and open value show monotonic increases with RVC, with significant High–Low spreads for both calls and puts, consistent with this preference. The joint effect of these supply- and demand-side channels explains the negative RVC–return relation: market makers charge lower premia for low-RVC options due to enhanced hedging efficiency, while end-user demand elevates prices and implied volatilities of high-RVC options, reducing their subsequent delta-hedged returns. This unified framework illustrates how the distinct objectives of market participants jointly shape option pricing and returns.

This paper contributes to the finance literature in a number of ways. First, this paper

contributes to the growing literature on the cross-section of option returns. The existing literature has documented that option returns can be predicted by the volatility related characteristics or its higher moments (Goyal and Saretto, 2009; Cao and Han, 2013; Boyer and Vorkink, 2014; Blau, Bowles, and Whitby, 2016; Byun and Kim, 2016; Vasquez, 2017; Ruan, 2020; Hu and Jacobs, 2020; Vasquez and Xiao, 2024). Moreover, recent literature find the underlying stock characteristics or option characteristics have return predictability for the future option returns (Christoffersen, Goyenko, Jacobs, and Karoui, 2018b; Ramachandran and Tayal, 2021; Zhan, Han, Cao, and Tong, 2022; Heston, Jones, Khorram, Li, and Mo, 2023; Bali, Beckmeyer, Moerke, and Weigert, 2023). However, most existing studies focus on characteristics of either the stock or the option in isolation. How does the return-volatility correlation affect the option returns remains an open question. Our paper, motivated by Heston (1993), studies the joint dynamics of return and volatility and its return predictability for delta-hedged option returns.³

Secondly, the paper extends the study of RVC. While the negative correlation between returns and volatility is a well-established phenomenon, often termed the “leverage effect” (Black, 1976), recent studies have argued this terminology can be misleading as the effect is not driven solely by financial leverage (Figlewski and Wang, 2000; Carr and Wu, 2017). Despite its importance, there is little literature studying the relation between the RVC and equity or equity option returns. Prior cross-sectional research has primarily focused on the impact of *financial leverage* on stock and option returns (Doshi et al., 2019; Vasquez and Xiao, 2024), rather than the predictive power of the correlation measure itself. To the best of the authors’ knowledge, this paper is the first to directly investigate the relationship between RVC and the cross-section of individual equity option returns. This shift in focus from the effects of leverage to the correlation itself is a key contribution.

Finally, this paper is related to studies of demand-based option pricing. Option demand can affect option prices in imperfect markets because market makers cannot perfectly hedge their inventories (Bollen and Whaley, 2004; Garleanu et al., 2009). Prior literature highlights several determinants of option demand, including skewness and lottery preferences (Boyer and

³Jeon, Kan, and Li (2025) show that the return autocorrelation of underlying stock is an important determinant of expected equity option returns. However, they do not study the relationship between return-volatility correlation and option returns.

Vorkink, 2014; Blau et al., 2016; Byun and Kim, 2016), short-sale constraints (Ramachandran and Tayal, 2021), and investor attention or inattention (Eisdorfer, Sadka, and Zhdanov, 2022; Choy and Wei, 2023), all of which influence option returns. Our paper contributes to this literature by documenting that options with higher RVC are associated with larger hedging errors, prompting market makers to charge higher option prices. In addition, we provide evidence that option buyers systematically prefer high-RVC options, creating stronger demand pressure and contributing to systematic overpricing. Together, these supply- and demand-side channels offer a unified explanation for the negative RVC-return relation observed in the options market.

The remainder of the paper is organized as follows. Section 2 shows the data and variables. In Section 3, we examine the cross-section of option returns and in Section 4, we conduct various robustness checks. The potential explanations are investigated in Section 5 and concluding remarks are in Section 6.

2 Data and variables

2.1 Data and sample coverage

We use individual stock option data sourced from the OptionMetrics Ivy DB database, covering the period from January 1996 to August 2023. Implied volatilities and option Greeks are computed by OptionMetrics based on the binomial tree approach developed by Cox, Ross, and Rubinstein (1979). Information on stock returns is retrieved from the Center for Research on Security Prices (CRSP), while balance sheet variables are obtained from Compustat. The analyst coverage and forecast data are from I/B/E/S.

The sample includes only U.S. common stocks traded in New York Stock Exchange (NYSE), American Stock Exchange (Amex), and National Association of Securities Dealers Automated Quotation (NASDAQ) with CRSP share codes of 10 or 11 and exchange codes of 1, 2, or 3. We link OptionMetrics to CRSP based on the WRDS linking table that provides historical matching of the OptionMetrics SECID with the CRSP PERMNO at a daily level.⁴ At the end of each month, as a robustness check for the quality of the matching,

⁴We drop unmatched options with a linking score of 6. Merging options and stocks at a daily level is due

we retain an observation only if the closing price of the underlying stock from CRSP differs by more than 3% from the corresponding closing price in the OptionMetrics database. To make sure that the results are not driven by small and illiquid stocks, we also drop options if its underlying price is less than five dollars when opening the position.

At the end of each month, we select a call option and a put option that are both closest to being at-the-money (ATM) and have the shortest maturity among those with more than one month remaining until expiration.⁵ We adopt the filtering methodology outlined by Duarte et al. (2025) and Horenstein et al. (2025) to eliminate any potential forward-looking bias. Options are included in the sample only if they meet the following criteria:

1. The option expires at the market opening of the last trading day, rather than the close (am_set_flag is zero).
2. Special settlement flag (ss_flag) is zero;
3. Implied volatility is non-missing;
4. The absolute value of delta does not exceed 1;
5. The bid price is positive and the midpoint of the bid-ask quotes for both the call and put options is no less than \$1/8;
6. Midpoint quotes must comply with no-arbitrage;⁶
7. The options must have a positive open interest and trading volume when the position is initiated;
8. We exclude any options where the bid is greater than or equal to the ask price at the time of portfolio formation;
9. Only options with moneyness, defined as the ratio of strike price to underlying stock price, in the range of 0.8 to 1.2 are retained. For each eligible stock, we select the ATM call and put options with the shortest time to maturity, provided that their remaining

to floating starting and ending link dates (i.e., sdate and edate) in the WRDS linking table.

⁵Table C3 shows that the negative RVC-return relation remains robust and highly significant across alternative moneyness levels of $K/S = 1.05$, 1.00, and 0.95.

⁶The risk-free rate is US 1-Month Treasury bill rate downloaded from Kenneth French's Data Library.

maturity exceeds one month. We drop options whose maturity is different from most options;

10. Options are also excluded if the underlying stock paid a dividend during the holding period when the dividend is announced before portfolio formation.

Our final sample contains 249,141 option-month observations for call options and 197,933 option-month observations for put options on individual stocks.

2.2 Option Returns

Because options are derivatives based on underlying stocks, their raw returns are highly responsive to fluctuations in stock prices. To address this, and consistent with prior research (e.g., [Cao and Han, 2013](#); [Doran, Fodor, and Jiang, 2013](#); [Ruan, 2020](#); [Zhan et al., 2022](#); [Cao et al., 2023](#); [Bali et al., 2023](#); [Vasquez and Xiao, 2024](#); [Goyal and Saretto, 2025](#); [Horenstein et al., 2025](#)), we analyze the returns of delta-hedged option portfolios, which are constructed to be neutral to movements in the underlying stock price. Following [Bakshi and Kapadia \(2003\)](#), the delta-hedged option gain over a period $[t, t + \tau]$ can be defined as

$$\Pi_{t,t+\tau} \equiv C_{t+\tau} - C_t - \int_t^{t+\tau} \Delta_u dS_u - \int_t^{t+\tau} r_u (C_u - \Delta_u S_u) du, \quad (1)$$

where C_t denotes the price of a European option at time t , S_t denotes the stock price at time t , $\Delta_t = \frac{\partial C_t}{\partial S_t}$ is the option delta at time t , and r_t is the annualized risk-free rate at time t . Considering a portfolio of an option (e.g., call option) that is hedged discretely N times over a period $[t, t + \tau]$, where the hedge is rebalanced at each of the dates t_i , $i = 0, 1, \dots, N - 1$ (where we define $t_0 = t$ and $t_N = t + \tau$), the daily rebalanced delta-hedged gain is calculated as follows.

$$\Pi_{t,t+\tau} = C_{t+\tau} - C_t - \sum_{i=0}^{N-1} \Delta_{t_n} (S_{t_{n+1}} - S_{t_n}) - \sum_{n=0}^{N-1} r_{t_n} \tau_{t_n} (C_{t_n} - \Delta_{t_n} S_{t_n}), \quad (2)$$

where Δ_{t_n} is the delta of the option at date t_n ; r_{t_n} is the annualized risk-free rate at date t_n ; and τ_{t_n} is the number of calendar days between t_n and t_{n+1} scaled by 365. The daily risk-free rate is obtained from Kenneth French's Data Library. The trading strategy initiates

the position at the end of each month and holds until the maturity, resulting in monthly return observations for the empirical analysis. Delta hedging is conducted on a daily basis. In cases where the delta value is unavailable for a given day, the most recently observed delta is carried forward.

It is important to note that the initial cost of establishing a delta-hedged option portfolio is zero, i.e., $\Pi_{t,t} = 0$. Consequently, $\Pi_{t,t+\tau}$ represents the dollar return of the delta-hedged portfolio over the holding period. In line with [Bakshi and Kapadia \(2003\)](#) and [Horenstein et al. \(2025\)](#), we scale the dollar return $\Pi_{t,t+\tau}$ by the underlying price S_t , in order to ensure comparability across stocks that may have significantly different market prices.⁷

2.3 Stock return-volatility correlation

[Ait-Sahalia et al. \(2013\)](#) report that the empirical correlation between daily returns and changes in daily volatility, estimated from high-frequency data, is close to zero for most assets, even though there are strong economic arguments for anticipating a negative correlation.⁸ [Bollerslev, Sizova, and Tauchen \(2012\)](#) and [Andersen, Bondarenko, and Gonzalez-Perez \(2015\)](#) find that incorporating option-implied volatility makes correlation estimation substantially more stable. To avoid the bias resulting from estimation error induced by the use of frequency realized volatility, we directly use implied volatility to proxy the daily volatility and define the stock return-volatility correlation (RVC) in month t as follows.⁹

$$RVC_{i,t} = \text{Corr}(dIV_{i,d}, RET_{i,d}), \quad (3)$$

where $dIV_{i,d} = IV_{i,d} - IV_{i,d-1}$ is the daily implied volatility (IV) change and $RET_{i,d}$ is the stock return on day d for stock i during the past year (250 trading days) as of the end of month t with the restriction that at least 200 non-missing return observations should exist in the past year. IV is the average of the ATM call and put implied volatilities, using the

⁷We also scale the dollar return $\Pi_{t,t+\tau}$ by the absolute value of the underlying position $|C_t - \Delta_t S_t|$ and the option price C_t in our robustness checks.

⁸We also use the EGARCH model to estimate the daily volatility and then compute the correlation. We indeed find that the EGARCH model generates a very symmetric correlation distribution with a zero mean, closely resembling the correlation estimates reported by [Doshi, Jacobs, and Sert \(2026a\)](#) based on high-frequency stock returns.

⁹For the S&P 500 index, [Kalnina and Xiu \(2017\)](#) and [Heston, Jacobs, and Kim \(2024\)](#) also use the observable VIX to represent the stochastic volatility.

volatility surface standardized options with a delta of 0.50 and maturity of 30 days.

2.4 Other variables

Previous research (e.g., [Goyal and Saretto, 2009](#); [Cao and Han, 2013](#); [Vasquez, 2017](#); [Ruan, 2020](#); [Zhan et al., 2022](#); [Jeon et al., 2025](#)) has highlighted a variety of stock and option characteristics that influence option returns.

1. Implied Volatility (IV): Implied volatility is the average of the ATM call and put implied volatilities, using the volatility surface standardized options with a delta of 0.50 and maturity of 30 days, on the last trading day of each month.
2. Realized-Implied Volatility Spread (RV_IV): Following [Goyal and Saretto \(2009\)](#), realized-implied volatility spread is the difference between RV and IV , where the annualized realized volatility (RV) of stock i in month t is defined as the square root of 252 times the standard deviation of daily returns over month t , $RV_{i,t} = sd(R_{i,d}) \times \sqrt{252}$.
3. Volatility Term Structures (VTS): Following [Vasquez \(2017\)](#), $VTS = IV6M - IV$, where $IV6M$ is the average of the ATM call and put implied volatilities, using the volatility surface standardized options with a delta of 0.50 and maturity of six months. VTS in this paper captures the slope of the implied volatility term structure between one month and six months.
4. Volatility of Volatility (VOV): Following [Ruan \(2020\)](#), VOV is defined as the standard deviation of the ATM 30-day IV .
5. Implied Volatility Slope (SLOPE): The slope of the IV curve in [Heston et al. \(2023\)](#) is defined as the difference between the IV of a 30-day call with a delta of 0.3 and the IV of a 30-day put with a delta of -0.3 .
6. Option-Implied Skewness (ISKEW): 30-day option-implied skewness of stock i in month t is interpolated and calculated using OTM call and put option prices following [Bakshi, Kapadia, and Madan \(2003\)](#).

7. Realized Skewness (RSKEW): Realized skewness of stock i in month t is defined as the skewness of daily returns over the most recent 12 months (Blau et al., 2016).
8. Option Bid-Ask Spread (BID-ASK): Christoffersen et al. (2018b) find that option liquidity can significantly forecast future option returns. We calculate the Option bid-ask spread as the ratio of the difference between ask and bid quotes of option over the midpoint of bid and ask quotes at the end of each month.
9. Option Momentum (OPMOM): Option momentum based on zero-delta straddles, as defined in Heston et al. (2023), is computed as the simple average of monthly straddle returns over the past 12 months, excluding the most recent month. Consistent with Heston et al. (2023), we do not impose any requirement for positive open interest or trading volume when constructing the zero-delta straddles used to calculate return momentum.¹⁰
10. Idiosyncratic Volatility (IVOL): Following Cao and Han (2013), we run the market model at the daily frequency,

$$r_{i,d} - r_{f,d} = \alpha_i + \beta_{i,MKT}MKT_d + \beta_{i,SMB}SMB_d + \beta_{i,HML}HML_d + \varepsilon_{i,d}, \quad (4)$$

where $r_{i,d}$ is the return on stock i on day d , MKT_d is the market return on day d , and $r_{f,d}$ is the risk-free rate on day d . Idiosyncratic volatility of each stock in month t is defined as the standard deviation of daily residuals in month t , $IVOL_{i,t} = sd(\varepsilon_{i,d})$.

11. Stock Return Autocorrelation (AC): Following Jeon et al. (2025), stock return autocorrelation of stock i in month t is defined the first-order autocorrelation of the stock returns over most recent 12 months.
12. SIZE: In line with Zhan et al. (2022), firm size, as a strong option return predictor, is measured as the natural log of the market value of equity at the end of the month for each stock.

¹⁰We construct the straddle at the end of last trading day of month t and hold the straddle for one month. By removing the requirement for positive open interest or trading volume, we obtain 557,780 option-month observations for both call and put options over our sample period.

13. Log of stock price (LnPrice): The log of stock price at the end of last month, proposed by Zhan et al. (2022) is also a strong option return predictor.

3 Empirical results

Table 1 presents descriptive statistics for the delta-hedged returns and key characteristics of the call and put options in our sample. Panel A reports results for calls, while Panel B reports results for puts.

The average monthly delta-hedged return is negative for both calls and puts, at -0.20% and -0.33% , respectively, with standard deviations of approximately 3.15% for calls and 3.22% for puts. The median returns are slightly more negative, indicating a modest left skew in the distribution. These negative averages are consistent with prior literature documenting that option sellers earn positive expected returns as compensation for bearing volatility risk.

The options in our sample are close to ATM by construction. For calls, the average moneyness (strike-to-price ratio) is 102.8% , whereas for puts it is 98.15% , reflecting the opposite positioning relative to the underlying price. The average time to maturity is 50 days for both calls and puts, with an interquartile range of only a few days, confirming our focus on short-dated contracts.

Implied volatilities average 50% for calls and 47% for puts, though with wide dispersion (standard deviations around 25-26 percentage points), highlighting substantial cross-sectional variation in option riskiness. Trading activity is moderate but heterogeneous: the median daily volume is 15 contracts for calls and 13 for puts, while mean volumes are considerably higher due to occasional heavy trading days. The open interest distribution is similarly skewed, with means (medians) of 1,128 (169) contracts for calls and 933 (126) contracts for puts.

As expected, average deltas are close to 0.5 for calls and -0.43 for puts, confirming that the contracts are near at-the-money. Bid-ask spreads are moderate, with median values of 0.13 for calls and 0.11 for puts, and interquartile ranges indicating relatively liquid markets for the majority of our sample.

Overall, the table confirms that our filtering procedures yield a sample of short-dated,

near-the-money, and actively traded options, which mitigates concerns about illiquidity or stale prices affecting the empirical results.

[Insert Table 1 Here]

Table C1 reports additional distributional statistics for RVC and other option characteristics. For both calls and puts, the mean RVC is negative (around -0.32 to -0.34), consistent with the leverage effect, and shows substantial cross-sectional variation, with values ranging from roughly -0.60 at the lower tail to close to zero at the upper tail. The standard deviation of about 0.19 indicates meaningful dispersion across the sample. Table C2 shows that RVC has generally low correlations with other variables (absolute values mostly below 0.25), suggesting it captures an independent dimension of variation in option markets.

3.1 Univariate sorting

To examine the relation between the RVC and option returns, we sort the sample each month into quintiles based on the RVC of the underlying stock. Quintile 1 (Low) contains option portfolios with the most negative RVC values, while Quintile 5 (High) contains those with the most positive RVC values. For each quintile, we form portfolios of at-the-money options using three weighting schemes: equally weighted (EW), open interest-weighted (OI), and value-weighted (VW) based on firms' market capitalization. Portfolios are rebalanced monthly and returns are computed using the delta-hedged strategy described in Section 2. The final column of Table 2 reports the return difference between High and Low RVC portfolios (High-Low), with Newey and West (1987) t -statistics (6 lags) reported in parentheses.

Panel A of Table 2 shows that delta-hedged call returns decline monotonically as RVC increases. Under equal weighting, returns fall from 0.013% in the Low RVC quintile to -0.50% in the High quintile, resulting in a High-Low spread of -0.51% with a t -statistic of -9.07 . The OI- and VW-weighted results show similar patterns, with spreads of -0.64% ($t = -8.53$) and -0.31% ($t = -7.50$), respectively.

Panel B presents analogous results for puts. The EW returns drop from -0.078% in the Low quintile to -0.63% in the High quintile, yielding a spread of -0.55% ($t = -8.58$). The OI-weighted spread is -0.63% ($t = -5.65$), and the VW-weighted spread is -0.25% ($t =$

−6.11). In all cases, the High-Low spreads are negative, economically large, and statistically significant at the 1% level.

[Insert Table 2 Here]

We further examine whether the RVC-sorted portfolio returns can be explained by standard equity and option-based risk factors. Specifically, we estimate eight alternative models that sequentially incorporate the Fama-French five factors from [Fama and French \(2015\)](#), the momentum factor from [Jegadeesh and Titman \(1993\)](#), and the four option-return risk factors documented in [Horenstein et al. \(2025\)](#).¹¹ The results are reported in Table 3.

For delta-hedged calls (Panel A), the High-Low RVC portfolio produces significantly negative alphas across all model specifications. In the baseline CAPM (Model 1), the alpha is −0.52% per month ($t = -9.48$), and this magnitude remains virtually unchanged when adding size, value, profitability, investment, and momentum factors (Models 2-4). Including the option-specific factors (Models 6-8) reduces the absolute magnitude of the alpha somewhat, but it remains economically and statistically significant, ranging from −0.21% to −0.23% per month (t -statistics between −3.23 and −3.93). The FRVIV and FCH factors emerge as the most important among the option-based controls, both loading negatively and significantly, suggesting that part of the RVC effect is related to innovations in realized-implied volatility spreads and call-put hedging costs.

For delta-hedged puts (Panel B), the pattern is similar. The High-Low RVC portfolio’s alpha is −0.56% per month ($t = -8.98$) in the CAPM specification and remains negative and significant across all models. After including option-based factors (Model 6), the alpha declines to −0.47% ($t = -2.73$) but retains significance at the 1% or 5% level. As in the call regressions, FRVIV exhibits a strong negative loading, while other option-specific factors are largely insignificant.

[Insert Table 3 Here]

Overall, the univariate sorting results reveal a remarkably robust and economically significant negative relation between RVC and delta-hedged option returns. The return spread is

¹¹EWOP is the equally weighted option returns across all firms in each month.

monotonic across RVC quintiles, appears consistently for both call and put options, and persists under alternative portfolio weighting schemes. More importantly, the abnormal returns remain statistically significant after controlling for a comprehensive set of equity and option-based risk factors, indicating that the RVC effect cannot be explained by existing pricing models. These findings motivate the investigation of its underlying economic mechanisms in the following section.

3.2 Bivariate sorting

To examine whether the RVC effect is driven by other known option characteristics, we perform double-sorted portfolio analyses. Specifically, we first sort all option-month observations into quintiles based on a given control variable, and then within each control quintile, we independently sort into quintiles based on RVC. The High-Low RVC spread is then computed within each control quintile and averaged across them to obtain the double-sort spread. We repeat this procedure for a range of control variables: implied volatility (IV), realized-implied volatility spread (RV_IV), variance term structure (VTS), variance-of-variance (VOV), volatility slope (SLOPE), option-implied skewness (ISKEW), realized skewness (RSKEW), bid-ask spread (BID-ASK), option momentum (OPMOM), idiosyncratic volatility (IVOL), Amihud illiquidity (AC), underlying firm size (SIZE), and log option price (LnPrice).

[Insert Table 4 Here]

Table 4 reports the average monthly returns (in percentage) for RVC-sorted portfolios after controlling for each characteristic. For delta-hedged calls (Panel A), the High-Low RVC spread is negative and highly significant across all control variables, with magnitudes ranging from -0.30% to -0.52% per month and t -statistics from -5.96 to -9.87 . The consistency of these spreads suggests that the monotonic decline in option returns from Low to High RVC portfolios is not attributable to common option-level characteristics such as moneyness, liquidity, volatility risk, or pricing slope.

Panel B shows analogous results for delta-hedged puts. Again, the High-Low RVC spread remains negative and statistically significant for every control variable, ranging from -0.34%

to -0.55% per month, with t -statistics frequently exceeding -8 . This robustness holds even when controlling for microstructure proxies (BID-ASK, AC), volatility-related factors (IV, RV_IV, VTS, VOV), skewness- or jump-related factors (SLOPE, ISKEW, RSKEW), and contract-specific attributes (SIZE, LnPrice).

Table 4 ultimately demonstrates that the RVC effect is not subsumed by any single known cross-sectional determinant of option returns. The negative High-Low spreads remain economically large and statistically significant, reinforcing the conclusion from the univariate analysis that RVC captures a distinct dimension of option pricing.

3.3 Fama and MacBeth (1973) regression

The univariate and bivariate sorting results reveal a robust and economically large negative relation between RVC and delta-hedged option returns. To further assess whether this pattern survives a full multivariate framework and is distinct from the influence of other known option characteristics, we estimate monthly Fama and MacBeth (1973) cross-sectional regressions of option returns on RVC and a set of control variables. This approach allows us to jointly control for multiple characteristics while obtaining standard errors that account for time-series variation in coefficients.

For each month, we run the following cross-sectional regression:

$$r_{i,t,t+\tau} = \alpha_t + \beta_t^{\text{RVC}} \text{RVC}_{i,t} + \sum_k \gamma_{k,t} X_{i,t}^{(k)} + \varepsilon_{i,t}, \quad (5)$$

where $r_{i,t,t+\tau}$ denotes the delta-hedged option return for contract i from t to $t + \tau$, and $X_{i,t}^{(k)}$ are control variables. We report time-series averages of the monthly slope estimates along with Newey and West (1987) t -statistics (6 lags) in Table 5.

[Insert Table 5 Here]

Table 5 shows that for delta-hedged calls (Panel A), the RVC coefficient is negative and highly significant in all specifications. In the univariate regression (column 1), the RVC slope is -0.98 with a t -statistic of -9.08 , implying that a one-standard-deviation increase in RVC is associated with a substantial drop in monthly returns. Even after including all

controls simultaneously (column 13), the coefficient remains negative (-0.47) and significant at the 1% level. This persistence suggests that the RVC effect is not explained away by other characteristics such as volatility level, slope, or liquidity measures.

Panel B reports analogous results for delta-hedged puts. The RVC coefficient again remains negative and statistically significant across all specifications, ranging from -1.05 in the univariate case to -0.69 in the fully specified model. Control variables behave as expected: IV, VOV, and IVOL load negatively, while OPMOM loads positively, consistent with prior literature.

Taken together, the [Fama and MacBeth \(1973\)](#) results reinforce the negative relation documented in the sorting exercises: the negative RVC-return relationship is economically large, statistically robust, and not subsumed by standard cross-sectional predictors of option returns. This persistence across univariate sorts, bivariate sorts, and fully controlled regressions suggests that RVC captures a distinct dimension of risk or mispricing in option markets that is not well explained by existing theories.

4 Robustness checks

In this section, we examine the robustness of the negative RVC-return relation documented above. We explore four dimensions: (i) alternative definitions of option returns, (ii) alternative measures of the correlation proxy, (iii) the role of transaction costs, and (iv) up and down months. These tests aim to ensure that our findings are not an artifact of a particular return construction, measurement choice, frictionless setting, or market condition.

4.1 Different option returns

In our main table, the option returns are the delta-hedged gains scaled by the underlying price and options are held until the maturity. As robustness checks, we consider option returns defined as the delta-hedged gains scaled by the absolute values of $\Delta S - C$ as well as option price C , held one month. Finally, we also consider monthly rebalanced option returns.

In our main analysis, option returns are defined as delta-hedged gains scaled by the underlying price, with the option held to maturity. As a robustness check, we consider

several alternative definitions:

1. Delta-hedged gains scaled by the absolute value of delta-hedged portfolio $|\Delta S - C|$;
2. Delta-hedged gains scaled by the option price C ;
3. Delta-hedged gains from holding the delta-hedged position for one month rather than to maturity;
4. Monthly rebalanced delta-hedged returns.

[Insert Table 6 Here]

Table 6 reports the univariate RVC sorts under each return definition. Panel A presents results for delta-hedged calls, and Panel B for delta-hedged puts. Across all specifications, the key empirical pattern persists: returns decline monotonically from Low to High RVC portfolios, and the High-Low spread remains economically large and statistically significant.

For example, when scaling by $|\Delta S - C|$, the High-Low spread for calls is -1.30 with a t -statistic of -8.66 , while for puts it is -1.10 with a t -statistic of -9.26 . Even when returns are based on one-month holding or monthly rebalancing, the spreads remain negative and significant. This persistence confirms that the RVC effect is not driven by the specific choice of return scaling or holding horizon.

4.2 Alternative correlation measure

As a further robustness check, we examine whether our results depend on the specific construction of the RVC measure. In the main analysis, $RVC_{i,t}$ is computed as the correlation between daily changes in implied volatility (IV) and underlying returns over the past one year. We consider two alternative specifications:

1. Short-window correlation: RVC computed over the past **one month** instead of one year, denoted RVC^{1m} ;
2. Log IV change: RVC computed using changes in the log of IV instead of raw changes, over the past one year, which parallels the standard log-return definition:

$$RVC_{i,t}^{Log} = \text{corr}(d \log IV_{i,d}, \text{RET}_{i,d}), \quad (6)$$

during the past year (250 trading days) as of the end of month t with the restriction that at least 200 non-missing return observations should exist in the past year.

[Insert Table 7 Here]

Table 7 presents the univariate sorts using these alternative measures. Panel A reports results for delta-hedged calls, and Panel B for delta-hedged puts. Across both alternative definitions, the central pattern remains intact: option returns decline monotonically from Low to High RVC portfolios, and the High-Low spreads are economically meaningful and statistically significant.

For instance, when using the one-month correlation (RVC^{1m}), the High-Low spread for calls is -0.35 with a t -statistic of -9.72 , while for puts it is -0.38 with a t -statistic of -8.21 . The results are similar for the log IV change measure (RVC^{Log}), with spreads of -0.52 and -0.57 for calls and puts, respectively.

These findings indicate that the negative RVC-return relation is not driven by the specific time horizon used to estimate the correlation, nor by whether IV changes are measured in levels or logs. The negative relation therefore persists even under substantially different constructions of the RVC proxy.

4.3 Transaction cost

To assess the economic feasibility of the RVC effect after accounting for market frictions, we follow the approach in Goyal and Saretto (2025) and compute portfolio returns net of transaction costs. Transaction costs are modeled as a proportion of the quoted bid-ask spread, with effective-to-quoted spread ratios (ESPR/QSPR) set to 0%, 10%, 20%, and 30%. For each ratio, we adjust monthly returns by subtracting the corresponding transaction cost from both the Low- and High-RVC portfolios before computing the Low-High spread.

[Insert Table 8 Here]

Table 8 reports the results. Panel A presents delta-hedged call portfolios, and Panel B presents delta-hedged put portfolios. Without transaction costs (0% case), the Low-High spread is 0.51% per month for calls ($t = 9.07$) and 0.55% for puts ($t = 8.58$). Even with a

30% effective-to-quoted spread ratio, the spreads remain economically meaningful at 0.18% (calls, $t = 3.91$) and 0.26% (puts, $t = 4.65$) per month.

These results indicate that the RVC effect is not merely a statistical anomaly that disappears once realistic trading frictions are considered. While the magnitude of the spread declines as assumed costs increase, the persistence of statistically significant returns across all cost scenarios underscores that the negative relation survives even after conservative adjustments for transaction costs.

4.4 Up and down months

One possible concern is that the effect of RVC on option returns may vary systematically with contemporaneous market conditions. In particular, when the underlying stock experiences negative returns (down months), the leverage effect is stronger and volatility tends to rise. Conversely, during nonnegative return periods (up months), volatility innovations are more muted. If RVC primarily captures investors' asymmetric sensitivity to volatility in down markets, then its impact on option returns could differ across up and down states.

To investigate this possibility, we split the sample based on the sign of the underlying stock return in the current month. Following this definition, observations with nonnegative returns are labeled as up months, while those with negative returns are classified as down months. We then re-compute the High-Low RVC-sorted delta-hedged returns separately within up and down states. For comparability, we report equal-weighted returns, consistent with the main results in Table 2. Table 9 summarizes the findings.

[Insert Table 9 Here]

Panel A of Table 9 shows that for delta-hedged calls, the High-Low spread is significantly negative in both up and down markets (-0.26 , $t = -7.76$ and -0.26 , $t = -7.87$, respectively). Similarly, Panel B shows that delta-hedged puts also exhibit significantly negative High-Low spreads in both states (-0.26 , $t = -8.73$ in up markets, and -0.29 , $t = -6.40$ in down markets). Importantly, the magnitude of the High-Low spread is stable across up and down subsamples, suggesting that the monotonic decline in option returns across RVC portfolios is not driven by conditional market states.

Overall, this robustness test indicates that the RVC effect on option returns is not state-dependent. Whether markets are rising or falling, options on stocks with more negative RVC systematically deliver less negative (i.e., higher) delta-hedged returns. This finding strengthens our interpretation that RVC captures a persistent component of option pricing related to the volatility risk premium, rather than being an artifact of contemporaneous stock return realizations.

5 Potential explanations

5.1 Leverage-based explanation

A natural starting point for explaining the negative relation is the well-known *leverage effect*. In equity and option markets, firms with higher financial leverage are typically viewed as riskier, which in turn affects both volatility dynamics and expected returns. For example, [Vasquez and Xiao \(2024\)](#) show that higher financial leverage is associated with *lower* option returns, as option buyers require higher premia to compensate for the elevated default and volatility risks. Under the standard leverage-effect framework, a more negative RVC mechanically reflects higher leverage—because stock price declines increase the firm’s leverage ratio, inducing stronger negative co-movement between returns and volatility. If this mechanism were the primary driver of cross-sectional variation in option returns, then portfolios with more negative RVC should exhibit *lower* delta-hedged returns. Instead, our empirical results reveal the opposite pattern: more negative RVC predicts *higher* option returns.

To evaluate whether traditional leverage measures can account for this relationship, we compute financial leverage (LEV) following [Vasquez and Xiao \(2024\)](#), defined as the sum of total debt and the par value of preferred stock, minus deferred taxes and investment tax credit, scaled by market equity. We then estimate [Fama and MacBeth \(1973\)](#) regressions of monthly delta-hedged option returns on RVC, both with and without controlling for LEV. Table 10 presents the results. Across all specifications, RVC retains a strong and highly significant negative coefficient. For calls, the RVC coefficient ranges from -0.96 to -0.47 ; for puts, from -1.05 to -0.68 , all significant at the 1% level. These magnitudes remain economically large even after including an extensive set of control variables.

[Insert Table 10 Here]

Financial leverage itself exhibits limited explanatory power. In the call regressions, LEV is statistically insignificant across all specifications, and in the put regressions it is only weakly significant in a few columns, with coefficients far too small to account for the magnitude of the RVC effect. Moreover, once LEV is included, the coefficient on RVC barely attenuates, indicating that the RVC-return relation is not mediated by financial leverage. This result is further supported by the low empirical correlation between RVC and LEV (0.055), suggesting that RVC captures cross-sectional variation unrelated to firms' balance-sheet leverage.

These findings echo earlier studies such as Figlewski and Wang (2000) and Hasanhodzic and Lo (2011), who argue that negative RVC is not primarily driven by financial leverage and cannot be fully explained by the classical leverage-effect hypothesis. Our evidence reinforces this conclusion. Not only does financial leverage fail to subsume the RVC effect, but the direction of prediction implied by leverage-based theories directly contradicts the observed pattern in option returns.

5.2 Risk-based explanation

A second potential explanation is that RVC proxies for a priced risk factor. In option markets, investors are willing to pay higher premia to hedge undesirable risks, such as high IV and high VOV (Cao and Han, 2013; Ruan, 2020; Cao et al., 2023; Horenstein et al., 2025). Consequently, options exposed to these risks command higher prices and deliver lower subsequent delta-hedged returns. More generally, if investors dislike a particular source of risk, that risk should be associated with lower expected returns for option buyers.

The implication for RVC, however, depends on which direction of the return-volatility correlation is viewed as risky. Existing theories, including the leverage effect hypothesis, generally associate *more negative* RVC with adverse market conditions, as falling stock prices are accompanied by rising volatility. Under this conventional interpretation, more negative RVC represents greater downside risk. Option buyers should therefore be willing to pay higher premia for options exposed to such risk, implying lower subsequent option returns. Our empirical evidence is exactly the opposite: options written on stocks with more negative RVC earn significantly higher delta-hedged returns. This inconsistency suggests that the negative

RVC-return relation cannot be explained by the conventional risk-based interpretation of RVC.

An alternative possibility is that investors regard *higher* (less negative) RVC as the undesirable state. Under this interpretation, higher-RVC options would command larger risk premia and consequently lower future returns, which is qualitatively consistent with our empirical findings. Table C2 provides mixed evidence on this interpretation.

On the one hand, RVC is positively correlated with several well-established option risk measures, including IV, IVOL, and VOV. Since higher IV, IVOL, and VOV are generally associated with greater option risk and lower subsequent option returns (Cao and Han, 2013; Ruan, 2020; Cao et al., 2023; Horenstein et al., 2025), these positive correlations suggest that higher-RVC options may indeed be riskier from the perspective of individual equity options.

On the other hand, RVC is also positively correlated with SLOPE and ISKEW. This evidence is less supportive of a pure risk-based interpretation. Existing studies show that SLOPE and ISKEW positively predict future option returns (Xing, Zhang, and Zhao, 2010; Chordia, Lin, and Xiang, 2021). Their predictive power has frequently been interpreted as reflecting informed trading or demand imbalances, rather than compensation for systematic risk, consistent with the demand-based option pricing framework of Garleanu et al. (2009). If SLOPE and ISKEW primarily capture such demand effects, their positive correlations with RVC suggest that RVC may also be related to investor demand rather than solely to risk.

Overall, the evidence does not allow us to completely rule out a risk-based explanation. The positive correlations between RVC and IV, IVOL, and, to a lesser extent, VOV suggest that higher-RVC options may carry greater risk at the individual-stock level. However, the positive correlations of RVC with SLOPE and ISKEW, together with the persistence of the RVC effect after controlling for these characteristics and the conflicting evidence from the index-option literature, indicate that risk alone is unlikely to provide a complete explanation. These findings naturally motivate the demand-based explanation developed in the following subsection.¹²

¹²To further investigate the risk-based interpretation, Appendix A develops a stochastic risk-based model in which volatility and RVC are both priced state variables. The model shows that the volatility-risk channel has an unambiguous prediction: when the volatility risk premium is negative, as implied by investors' aversion to volatility risk, the positive volatility sensitivity of option prices generates a negative relation between the volatility state and expected delta-hedged option returns. In contrast, the prediction for RVC is inherently

5.3 Demand-based explanation

To understand the negative relation between RVC and option returns, it is essential to distinguish the fundamentally different roles, objectives, and risk exposures of the two key option market participants: market makers (MMs) and end users (EUs). Market makers supply liquidity and manage inventory risk through continuous hedging, whereas end users take directional or volatility positions based on their beliefs.

5.3.1 Market makers' hedging errors

Market makers quote option prices while managing their inventory through dynamic delta hedging. Their objective can be formalized as minimizing the variance of the gains from the delta-hedged portfolio:

$$\min_{\Delta_{hedge}} \text{Var} [d\Pi_t^{\text{MM}}], \quad (7)$$

where Π_t denotes the value of the delta-hedged inventory at time t .

For illustration, consider that market makers sell an option $O_t := O(S_t, IV_t)$ and hedge with Δ_{hedge} shares of the underlying S_t . The inventory value is therefore

$$\Pi_t^{\text{MM}} = -[O_t - \Delta_{hedge} S_t]. \quad (8)$$

Over an infinitesimal interval dt , the change in option value can be approximated by $dO_t \approx \Delta_{true} dS_t + \mathcal{V}_t dIV_t$, following Equations (A.4) and (A.5), where $\mathcal{V}_t$ captures the sensitivity of the option price to implied volatility movements. The change in the hedged inventory then becomes

$$d\Pi_t^{\text{MM}} \approx (\Delta_{hedge} - \Delta_{true}) dS_t - \mathcal{V}_t dIV_t. \quad (9)$$

Thus, the variance of the delta-hedged portfolio is

$$\text{Var}(d\Pi_t^{\text{MM}}) = (\Delta_{true} - \Delta_{hedge})^2 \text{Var}(dS_t) + \mathcal{V}_t^2 \text{Var}(dIV_t) + 2(\Delta_{true} - \Delta_{hedge}) \mathcal{V}_t \text{Cov}(dS_t, dIV_t), \quad (10)$$

where $\text{Cov}(dS_t, dIV_t)$ can be written as $\rho \sigma(dS_t) \sigma(dIV_t)$, with ρ denoting the instantaneous ambiguous because the RVC component of expected option returns depends on both the correlation risk premium and the option's sensitivity to RVC, neither of which has an unambiguous sign.

return-volatility correlation, $\sigma(dS_t)$ the volatility of underlying returns, and $\sigma(dIV_t)$ the volatility of implied volatility innovations.

Minimizing (10) with respect to Δ_{hedge} yields the first-order condition

$$\frac{\partial \text{Var}(d\Pi_t^{\text{MM}})}{\partial \Delta_{hedge}} = -2(\Delta_{true} - \Delta_{hedge}) \text{Var}(dS_t) - 2\mathcal{V}_t \rho \sigma(dS_t) \sigma(dIV_t) = 0, \quad (11)$$

which leads to the optimal hedging delta

$$\Delta_{hedge}^* = \Delta_{true} + \underbrace{\frac{\mathcal{V}_t \rho \sigma(dIV_t)}{\sigma(dS_t)}}_{\text{Hedge Adjustment}}. \quad (12)$$

Substituting Δ_{hedge}^* into (10) yields the minimal variance of hedging errors:

$$\text{Var}^*(d\Pi_t^{\text{MM}}) = \mathcal{V}_t^2 \text{Var}(dIV_t) (1 - \rho^2). \quad (13)$$

Expression (13) shows that a more negative RVC reduces hedging risk by lowering the covariance-driven component of inventory variance. Therefore, market makers have a strong preference for options with low or highly negative RVC, as these positions imply smaller hedging errors. Conversely, options with high RVC (close to zero) generate substantially larger hedging variance, so market makers charge higher prices when selling such positions to compensate for the increased risk.

Although Equation (13) implies a quadratic relation between the minimum variance of hedging errors ($\text{Var}^*(d\Pi_t^{\text{MM}})$) and ρ , this distinction is of little empirical importance in our sample. The correlation between ρ and $|\rho|$ exceeds -0.94 (unreported), indicating that the magnitude of RVC is almost a monotonic transformation of RVC itself. Consequently, the relation between $\text{Var}^*(d\Pi_t^{\text{MM}})$ and ρ is nearly monotonic over the observed range of RVC values.

We quantify this mechanism by decomposing option returns into daily hedged components:

$$r_{t,t+\tau} = \sum_{i=0}^{N-1} r_{t_n}, \quad (14)$$

where the daily return component is defined as

$$r_{t_n} = \frac{(C_{t_{n+1}} - C_{t_n}) - \Delta_{t_n} (S_{t_{n+1}} - S_{t_n}) - r_{t_n} \tau_{t_n} (C_{t_n} - \Delta_{t_n} S_{t_n})}{S_t}. \quad (15)$$

We define the *hedging inefficiency* (or error) measure $VOR_{t,t+\tau}$ as the standard deviation of the daily returns within the holding period (Tian and Wu, 2023):

$$VOR_{t,t+\tau} = \text{sd}_{t_n \in [t, t+\tau]}(r_{t_n}). \quad (16)$$

Intuitively, VOR captures how well delta-hedging performs in practice: higher values indicate greater residual risk left unhedged, implying higher costs and larger premia required by option writers.

Following the same portfolio-sorting approach used in earlier sections, we sort $VOR_{t,t+\tau}$ into quintiles based on RVC and compute the High-Low differences. If our hedging-efficiency mechanism holds, we should observe that more negative RVC portfolios exhibit lower hedging inefficiency.

[Insert Table 11 Here]

Putting these pieces together, Table 11 provides direct empirical support for the hedging-efficiency channel implied by Equations (9)–(13). Hedging inefficiency, measured by $VOR_{t,t+\tau}$, rises monotonically from the Low- to the High-RVC portfolios under all weighting schemes. The High-Low differences are economically meaningful and statistically significant for both calls and puts, ranging from 0.17 to 0.35. This pattern is exactly what Equation (13) predicts: options written on stocks with more negative return–volatility correlation generate smaller residual hedging variance for market makers, reducing the required compensation for bearing inventory risk. Accordingly, market makers charge lower premia for low-RVC options, leaving buyers with higher (less negative) delta-hedged returns. Conversely, options on high-RVC stocks impose larger hedging variance, leading market makers to demand higher compensation and resulting in lower subsequent returns to option buyers. This supply-side mechanism—rooted in how RVC shapes the covariance structure of delta and vega exposures—provides a coherent explanation for the negative RVC-return relation observed in the data.

5.3.2 Option end-user demand

By contrast, end users value options for their volatility exposure. Their objective is closer to maximizing the expected gain of the delta-hedged position:

$$\max_q \mathbb{E}[\Pi_{t,t+\tau}^{\text{EU}}(q)], \quad (17)$$

where q represents the position size, contract selection, moneyness (K/S), or maturity (τ). Here, $\Pi_{t,t+\tau}$ denotes the cumulative gain from holding a delta-hedged option over $[t, t + \tau]$.

Over an infinitesimal interval dt , the evolution of the end user's hedged position, which is the opposite of the market maker's position in (9), is approximately

$$d\Pi_t^{\text{EU}} = -d\Pi_t^{\text{MM}} \approx \mathcal{V}_t dIV_t - (\Delta_{\text{hedge}} - \Delta_{\text{true}}) dS_t. \quad (18)$$

We argue that end-user demand is conditional on the RVC environment. When the correlation between price and volatility is high ($|\text{Corr}(dS_t, dIV_t)| \approx 1$), volatility dynamics are largely redundant. In this regime, options function primarily as leveraged directional bets. For an investor seeking pure volatility exposure, this is structurally inefficient: one must construct a complex, costly trade to access a risk factor that is effectively just a non-linear transformation of the underlying stock price. In contrast, when RVC is high ($|\text{Corr}(dS_t, dIV_t)| \approx 0$), volatility behaves as an orthogonal risk factor unspanned by the underlying asset. This offers a unique value proposition: because hedging errors are uncorrelated with the volatility payoff, investors can capture the volatility premium ‘cleanly’, without the signal being drowned out by systematic directional noise. This highlights a key complementary channel through which end users develop a strong preference for high-RVC options.

Building on the theoretical insight above, we examine whether end users' preference for high-RVC options manifests in observable market activity. Specifically, if high-RVC options indeed offer cleaner volatility exposure, we should observe higher relative trading and positioning in these contracts. Following [Ni, Pearson, Poteshman, and White \(2021\)](#) and [Goez and Goyenko \(2022\)](#), we use open and close trade profile data from the International Securi-

ties Exchange (ISE) and the Chicago Board Options Exchange (CBOE). The ISE data cover the period from January 1, 2006 to 31 August 2023, while the CBOE data span January 1, 2011 to May 16, 2022. These datasets provide detailed information on daily trading activity for individual equity option contracts. For our final sample, we aggregate the information from the ISE and CBOE datasets.

For each option, the data classify trading volume along four dimensions for both call and put options: opening buys, closing buys, opening sells, and closing sells. Option trading volumes are further reported by trader category. Specifically, the data separate activity by customers and firms. The customer category includes both retail investors and institutional investors, such as hedge funds, who typically use options to express directional views or hedge risk. The firm category represents proprietary trading desks that trade on their own accounts and frequently serve a liquidity provision role in the options market. Because options are in zero net supply, the net position of market makers can be inferred from the market-clearing condition as the residual of customer and firm trading activity. In our analysis, in line with [Golez and Goyenko \(2022\)](#), we focus on customer trades when constructing measures of option investor demand, and we treat firm trades as part of market-making activity.

For each option series j , we separately track buy-initiated and sell-initiated open interest by cumulating daily trading volumes that open and close positions. Specifically, buy open interest evolves according to

$$OpenInterest_{j,t}^{Buy} = OpenInterest_{j,t-1}^{Buy} + Volume_{j,t}^{OpenBuy} - Volume_{j,t}^{CloseSell}, \quad (19)$$

where $Volume_{j,t}^{OpenBuy}$ denotes the volume of buy orders that open new positions, and $Volume_{j,t}^{CloseSell}$ denotes the volume of sell orders that close existing long positions.

Similarly, sell open interest is constructed as

$$OpenInterest_{j,t}^{Sell} = OpenInterest_{j,t-1}^{Sell} + Volume_{j,t}^{OpenSell} - Volume_{j,t}^{CloseBuy}, \quad (20)$$

where $Volume_{j,t}^{OpenSell}$ captures sell orders that open new short positions, and $Volume_{j,t}^{CloseBuy}$ captures buy orders that close existing short positions.

Using these components, the net open interest for option series j at time t is defined as

$$NetOpenInterest_{j,t} = OpenInterest_{j,t}^{Buy} - OpenInterest_{j,t}^{Sell}, \quad (21)$$

which measures the imbalance between long and short positions in that option series.

Then, we separately aggregate net open interest across all call and put option series to obtain the stock-level net open interest,

$$NOI_t = \sum_j NetOpenInterest_{j,t}. \quad (22)$$

In line with [Cao and Han \(2013\)](#); [Zhan et al. \(2022\)](#) and [Ramachandran and Tayal \(2021\)](#), we construct two additional measures of option demand. The first one is the relative open interest (ROI), defined as

$$ROI_t = \frac{NOI_t}{\mathcal{O}_t} \times 10^3, \quad (23)$$

and the second one is the relative open value (ROV), defined as¹³

$$ROV_t = \frac{NOI_t \times C_t}{\mathcal{O}_t \times S_t} \times 10^3, \quad (24)$$

where C_t is the option price in the option portfolio, S_t is the stock price, and $\mathcal{O}_t$ is number of shares outstanding of the stock over the month t .

At the end of each month t , we sort the options into quintiles based on RVC and calculate average ROI and ROV for each quintile group and High-Low group. The results are reported in Table 12.

[Insert Table 12 Here]

Table 12 strongly supports the prediction that end-user demand is increasing in RVC.

¹³Our baseline measure first aggregates net open interest across all call or put option series to construct the stock-level NOI, and then computes the ROV according to Equation (24). As a robustness check, we alternatively compute the value-weighted measure at the option-series level,

$$ROV_t = \frac{\sum_j NetOpenInterest_{j,t} \times C_{j,t}}{\mathcal{O}_t S_t} \times 10^3.$$

This alternative measure yields qualitatively similar results and does not affect our conclusions.

Across both calls (Panel A) and puts (Panel B), all three demand measures (NOI, ROI, and ROV) increase substantially from the Low- to the High-RVC portfolios. The High–Low spreads are economically large and statistically significant across nearly all specifications. For call options, the High–Low spreads equal 846 contracts for NOI ($t = 5.07$), 744 for ROI ($t = 6.17$), and 78.7 for ROV ($t = 5.29$). Similar patterns are observed for put options. Net open interest increases from -339 in the Low-RVC portfolio to 71.9 in the High-RVC portfolio, with a significant High–Low spread of 411 ($t = 2.18$). Likewise, ROI and ROV increase monotonically across the RVC portfolios, with significant High–Low spreads of 113 and 22.0 , respectively. These results consistently indicate that end users systematically allocate larger positions to options written on stocks with higher RVC.

These findings complement the demand-based option pricing literature of [Cao and Han \(2013\)](#), [Zhan et al. \(2022\)](#), and [Ramachandran and Tayal \(2021\)](#), which argues that option prices are jointly determined by investors’ demand and market makers’ inventory considerations rather than by risk alone. In our setting, the monotonic increase in customer positioning across RVC portfolios indicates that investor demand is systematically related to the return-volatility correlation. Stronger demand for high-RVC options raises their prices and implied volatilities, leaving subsequent delta-hedged returns lower.

Collectively, the supply-side and demand-side channels offer a unified explanation for the negative RVC-return relation. On the supply side, market makers face lower hedging risk for options on stocks with more negative RVC, reducing the required risk premia and leaving buyers with higher delta-hedged returns. On the demand side, end users prefer options with higher RVC, which provide cleaner volatility exposure. This preference drives greater positioning in high-RVC options, raising their prices and implied volatilities, and consequently lowering subsequent delta-hedged returns. The interplay of these opposing forces—lower premia for low-RVC options due to efficient hedging and higher premia for high-RVC options due to end-user demand—creates the empirically robust negative relation between RVC and option returns. Our new mechanisms in this paper illustrate how the distinct roles and objectives of market participants jointly shape option pricing and returns in accordance with the negative relation.¹⁴

¹⁴Appendix B provides a complementary theoretical benchmark based on the [Heston \(1993\)](#) stochastic

6 Conclusion

This paper uncovers a robust negative relationship between the return-volatility correlation (RVC) and the cross-section of individual equity option returns. Sorting options on RVC reveals a stark, monotonic decline in delta-hedged returns from the most negative to the least negative correlation portfolios for both call and put options. This finding directly contradicts established theoretical models and index-level evidence, which predict that investors demand a positive premium for bearing negative RVC risk, implying a positive relation between RVC and option returns.

In search of an explanation, we systematically investigate several conventional alternatives. We first show that the classic leverage effect cannot account for our findings. Although RVC is mechanically related to financial leverage, the standard measure of financial leverage (Vasquez and Xiao, 2024) does not subsume the strong negative predictive power of RVC. We then examine whether RVC represents a priced risk factor. While the conventional interpretation that more negative RVC reflects greater downside risk is inconsistent with our evidence, the positive association between RVC and several established option risk measures suggests that risk alone cannot be completely ruled out. Instead, our findings indicate that risk-based arguments are insufficient to fully explain the negative RVC–return relation. This paper, therefore, advances a demand-based explanation for the negative RVC–return relation, emphasizing the hedging activities of option market makers. Specifically, more negative RVC naturally decreases market makers’ hedging errors, leading market makers to demand higher compensation and resulting in lower subsequent returns to option buyers. Empirically, hedging inefficiency increases from low to high RVC portfolios. Concurrently, end-user demand rises with RVC, as investors systematically favor high-RVC options for cleaner volatility exposure, reinforcing overpricing and the observed negative RVC–return relation.

Our study makes several contributions to the finance literature. First, we identify RVC as a new and economically significant predictor of the cross section of option returns, extending the growing literature on option return predictability beyond traditional stock and option

volatility model. The model shows that, even within a standard stochastic volatility framework, expected call, put, and straddle returns can decline almost monotonically with RVC, providing a useful benchmark for our proposed supply- and demand-side mechanisms rather than serving as a direct test of either channel.

characteristics. Second, we show that conventional leverage-based explanations cannot account for the predictive power of RVC, while risk-based explanations alone appear insufficient to fully explain the observed relation. Finally, by proposing and validating market-maker-based hedging efficiency and end-user demand channels, we offer a compelling resolution to the negative relation and underscore the importance of demand-based frictions in shaping option prices. These findings open new avenues for research into the cross-sectional determinants of risk premia and the micro-structural foundations of option markets.

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Table 1: Summary statistics

This table reports the descriptive statistics of samples used throughout the paper. “Returns (%)” refers to the return of buying delta-hedged options from the end of month t and holding to maturity. The option moneyness is defined as the option strike price (K) divided by closing stock price (S). Panel A shows the summary statistics for the delta-hedged call. Panel B shows the summary statistics for the delta-hedged put. The sample period is from January 1996 to August 2023 and the data are from Optionmetrics database..

	N	Mean	Median	Std. Dev.	10 th	25 th	75 th	90 th
Panel A: Delta-hedged Calls								
Returns (%)	244,922	-0.20	-0.35	3.15	-2.90	-1.45	0.74	2.45
Days to maturity	244,922	50	50	2	46	49	51	52
Moneyness (K/S) (%)	244,922	102.80	102.13	6.05	96.15	99.21	106.38	110.91
Implied volatility	244,922	0.50	0.44	0.26	0.24	0.32	0.61	0.83
volume	244,922	116	15	604	2	5	54	200
open_interest	244,922	1,128	169	4,574	10	39	702	2,377
delta	244,922	0.47	0.48	0.14	0.27	0.38	0.56	0.62
Bid-ask spread	244,922	0.20	0.13	0.22	0.05	0.08	0.24	0.42
Panel B: Delta-hedged Puts								
Returns (%)	193,966	-0.33	-0.47	3.22	-2.79	-1.48	0.51	2.14
Days to maturity	193,966	50	50	2	46	49	51	52
Moneyness (K/S) (%)	193,966	98.15	98.76	5.96	90.32	95.06	101.32	104.58
Implied volatility	193,966	0.47	0.41	0.25	0.23	0.30	0.57	0.78
volume	193,966	99	13	478	1	5	47	160
open_interest	193,966	933	126	3,802	9	29	542	1,902
delta	193,966	-0.43	-0.43	0.13	-0.59	-0.50	-0.34	-0.25
Bid-ask spread	193,966	0.18	0.11	0.21	0.04	0.07	0.20	0.36

Table 2: Univariate portfolio sorting result

This table reports average returns and t -statistics from univariate quintile sorts. At the end of each month, options are sorted into quintiles based on RVC (defined in (3) and hold until maturity. EW refers to the equal-weighted result and OI refers to the open interest weighted result, while VW refers to the value weighted result by the firm's market value. Panel A shows the univariate sorting result for the delta-hedged call. Panel B shows the univariate sorting result for the delta-hedged put. The sample period is from January 1996 to August 2023. Average returns are in percent and [Newey and West \(1987\)](#) t -statistics (6 lags) are in parentheses.

	Low	2	3	4	High	High-Low
Panel A: Delta-hedged Calls						
EW	0.013 (0.18)	-0.0073 (-0.11)	-0.11 (-1.58)	-0.20 (-2.94)	-0.50 (-6.50)	-0.51*** (-9.07)
OI	-0.042 (-0.55)	-0.11 (-1.65)	-0.22 (-2.76)	-0.36 (-5.15)	-0.68 (-9.12)	-0.64*** (-8.53)
VW	0.037 (0.55)	0.025 (0.38)	-0.042 (-0.68)	-0.091 (-1.47)	-0.28 (-4.15)	-0.31*** (-7.50)
Panel B: Delta-hedged Puts						
EW	-0.078 (-0.89)	-0.13 (-1.75)	-0.22 (-3.48)	-0.32 (-4.84)	-0.63 (-8.79)	-0.55*** (-8.58)
OI	-0.19 (-2.63)	-0.20 (-2.35)	-0.34 (-4.31)	-0.48 (-5.39)	-0.83 (-7.19)	-0.63*** (-5.65)
VW	-0.14 (-2.17)	-0.12 (-1.86)	-0.19 (-3.17)	-0.23 (-3.62)	-0.39 (-5.89)	-0.25*** (-6.11)

Table 3: Spanning test for RVC strategy

This table reports the spanning test results relative to different risk factors. Specifically, we regress the equal-weighted quintile sorted long-short portfolio returns on different stock and option risk factors. Models 1-4 correspond to stock risk factor models CAPM (Sharpe, 1964), Fama-French 3 factors (Fama and French, 1993), Fama-French 5 factors (Fama and French, 2015), and augmented with momentum factor (Jegadeesh and Titman, 1993). Models 5-7 correspond to option risk factor models proposed by Horenstein et al. (2025). Model 8 incorporates both the stock and option risk factor models. Panel A shows the spanning test results for the delta-hedged call. Panel B shows the spanning test results for the delta-hedged put. The sample period is from January 1996 to August 2023. Coefficients estimates are in percent and Newey and West (1987) t -statistics (6 lags) are in parentheses below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1%.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A: Delta-hedged Calls								
α	-0.52*** (-9.48)	-0.52*** (-9.67)	-0.50*** (-9.33)	-0.50*** (-9.26)	-0.52*** (-8.97)	-0.23*** (-3.93)	-0.21*** (-3.23)	-0.21*** (-3.27)
Mktrf	0.017* (1.78)	0.020** (2.02)	0.013 (1.30)	0.011 (1.03)				0.0047 (0.49)
SMB		-0.023 (-1.59)	-0.027* (-1.67)	-0.026 (-1.60)				-0.014 (-1.04)
HML		-0.015 (-1.38)	0.0041 (0.26)	-0.000041 (-0.0026)				0.011 (0.75)
RMW			-1.31 (-0.73)	-1.20 (-0.66)				-1.42 (-0.83)
CMA			-0.037* (-1.94)	-0.034* (-1.85)				-0.035* (-1.87)
UMD				-0.0077 (-1.13)				-0.0048 (-0.61)
EWOP					-0.024 (-0.29)	-0.070 (-1.29)	-0.045 (-0.82)	-0.031 (-0.51)
FVOV						0.042 (0.59)	0.023 (0.33)	0.017 (0.23)
FRVIV						-0.30*** (-4.71)	-0.27*** (-4.21)	-0.24*** (-3.70)
FCH						-0.22*** (-3.22)	-0.21*** (-3.08)	-0.21*** (-3.15)
FOPMOM							-0.13* (-1.74)	-0.13* (-1.78)
Adj. R^2 (%)	1.20	2.54	2.97	2.97	-0.21	18.6	19.6	20.2

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	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel B: Delta-hedged Puts								
α	-0.56*** (-8.98)	-0.56*** (-8.98)	-0.55*** (-8.33)	-0.54*** (-8.43)	-0.56*** (-8.79)	-0.47*** (-2.73)	-0.51** (-2.32)	-0.51** (-2.29)
Mktrf	0.0072 (0.71)	0.0095 (0.80)	0.0057 (0.50)	0.0018 (0.14)				-0.0011 (-0.11)
SMB		-0.015 (-0.87)	-0.017 (-1.02)	-0.016 (-0.92)				-0.0085 (-0.60)
HML		-0.0019 (-0.14)	0.0091 (0.43)	0.0025 (0.11)				-0.0046 (-0.14)
RMV			-0.77 (-0.41)	-0.59 (-0.32)				0.31 (0.14)
CMA			-0.021 (-0.90)	-0.016 (-0.69)				0.0044 (0.14)
UMD				-0.012 (-1.08)				-0.020 (-1.25)
EWOP					-0.037 (-0.48)	0.052 (0.47)	0.015 (0.18)	0.044 (0.49)
FVOV						-0.16 (-0.88)	-0.13 (-0.91)	-0.15 (-0.97)
FRVIV						-0.30*** (-4.45)	-0.34*** (-3.67)	-0.35*** (-3.47)
FCH						0.14 (0.55)	0.12 (0.56)	0.13 (0.58)
FOPMOM							0.19 (0.72)	0.20 (0.74)
Adj. R^2 (%)	-0.17	-0.53	-0.99	-0.92	-0.19	6.91	7.98	7.42

Table 4: Bivariate sorting results

This table reports the bivariate portfolio sorting results. At the end of each month, we first sort all options into quintiles based on a control variable (defined in Section 2.4) and then within each control quintile, we further sort the options into quintiles based on RVC (defined in equation (3)). We average delta-hedged return for each RVC quintile across the control quintiles, which leaves us five quintile returns. The table reports the excess return of the quintile 1 to 5 and the High-Low (5-1) portfolios. Panel A shows the bivariate sorting result for the delta-hedged call. Panel B shows the bivariate sorting result for the delta-hedged put. The sample period is from January 1996 to August 2023. Average returns are in percent and Newey and West (1987) t -statistics (6 lags) are in parentheses.

	Low	2	3	4	High	High-Low
Panel A: Delta-hedged Calls						
IV	-0.049 (-0.63)	-0.064 (-0.89)	-0.14 (-2.04)	-0.20 (-3.10)	-0.35 (-5.38)	-0.30*** (-5.96)
RV_IV	-0.032 (-0.44)	-0.053 (-0.79)	-0.12 (-1.75)	-0.21 (-3.12)	-0.39 (-5.52)	-0.36*** (-7.73)
VT5	-0.027 (-0.27)	-0.030 (-0.35)	-0.072 (-0.86)	-0.18 (-2.18)	-0.43 (-5.33)	-0.40*** (-5.96)
VOV	-0.00076 (-0.010)	-0.045 (-0.64)	-0.12 (-1.82)	-0.19 (-2.84)	-0.45 (-6.15)	-0.45*** (-7.90)
SLOPE	-0.020 (-0.28)	-0.038 (-0.54)	-0.15 (-2.16)	-0.22 (-3.28)	-0.39 (-5.42)	-0.37*** (-7.13)
ISKEW	0.0027 (0.036)	-0.0059 (-0.082)	-0.057 (-0.83)	-0.14 (-2.08)	-0.36 (-5.04)	-0.36*** (-6.78)
RSKEW	0.012 (0.16)	-0.017 (-0.25)	-0.12 (-1.72)	-0.22 (-3.01)	-0.47 (-6.63)	-0.49*** (-9.01)
BID-ASK	0.0096 (0.13)	-0.048 (-0.72)	-0.11 (-1.73)	-0.21 (-2.97)	-0.45 (-5.92)	-0.46*** (-8.18)
OPMOM	-0.00054 (-0.0074)	-0.025 (-0.37)	-0.13 (-1.96)	-0.23 (-3.51)	-0.50 (-6.80)	-0.50*** (-9.87)
IVOL	-0.023 (-0.31)	-0.048 (-0.70)	-0.092 (-1.30)	-0.22 (-3.28)	-0.43 (-6.41)	-0.41*** (-7.58)
AC	0.025 (0.32)	-0.022 (-0.32)	-0.12 (-1.82)	-0.20 (-2.95)	-0.50 (-6.55)	-0.52*** (-9.22)

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	Low	2	3	4	High	High-Low
SIZE	-0.024 (-0.32)	-0.074 (-1.08)	-0.11 (-1.57)	-0.21 (-3.16)	-0.39 (-6.07)	-0.36*** (-7.42)
LnPrice	-0.040 (-0.53)	-0.081 (-1.11)	-0.11 (-1.71)	-0.21 (-3.18)	-0.36 (-5.34)	-0.32*** (-6.29)
Panel B: Delta-hedged Puts						
IV	-0.14 (-1.59)	-0.19 (-2.63)	-0.25 (-3.90)	-0.31 (-4.68)	-0.49 (-8.23)	-0.34*** (-5.69)
RV_IV	-0.16 (-2.18)	-0.12 (-1.44)	-0.24 (-3.57)	-0.34 (-5.35)	-0.51 (-7.74)	-0.35*** (-8.19)
VTs	-0.14 (-1.20)	-0.18 (-1.97)	-0.24 (-2.84)	-0.30 (-3.90)	-0.55 (-7.54)	-0.40*** (-4.80)
VOV	-0.099 (-1.14)	-0.16 (-2.29)	-0.23 (-3.49)	-0.33 (-5.20)	-0.56 (-8.18)	-0.46*** (-7.98)
SLOPE	-0.11 (-1.49)	-0.11 (-1.31)	-0.26 (-4.05)	-0.33 (-5.11)	-0.57 (-8.71)	-0.45*** (-9.28)
ISKEW	-0.062 (-0.61)	-0.10 (-1.43)	-0.20 (-2.89)	-0.31 (-4.68)	-0.56 (-8.20)	-0.49*** (-6.46)
RSKEW	-0.11 (-1.37)	-0.11 (-1.35)	-0.23 (-3.58)	-0.34 (-4.97)	-0.60 (-8.99)	-0.49*** (-9.81)
BID-ASK	-0.12 (-1.62)	-0.13 (-1.52)	-0.22 (-3.41)	-0.31 (-4.91)	-0.60 (-8.29)	-0.48*** (-8.60)
OPMOM	-0.084 (-0.93)	-0.15 (-1.98)	-0.23 (-3.72)	-0.33 (-5.01)	-0.63 (-9.09)	-0.55*** (-8.49)
IVOL	-0.12 (-1.31)	-0.15 (-2.10)	-0.24 (-3.71)	-0.34 (-5.20)	-0.54 (-8.86)	-0.42*** (-7.05)
AC	-0.082 (-0.94)	-0.14 (-1.93)	-0.21 (-3.25)	-0.33 (-5.29)	-0.62 (-8.77)	-0.54*** (-8.64)
SIZE	-0.12 (-1.36)	-0.19 (-2.74)	-0.23 (-3.49)	-0.33 (-5.05)	-0.51 (-8.08)	-0.39*** (-6.67)
LnPrice	-0.14 (-1.54)	-0.19 (-2.52)	-0.26 (-4.09)	-0.31 (-4.98)	-0.49 (-7.27)	-0.35*** (-6.12)

Table 5: Fama-MacBeth regression

This table reports the Fama-MacBeth regression results. The dependent variable delta-hedged option return is multiplied by 100 and the explanatory variables are defined in Section 2.4. Panel A shows the Fama-MacBeth regressions result for the delta-hedged call. Panel B shows the Fama-MacBeth regressions result for the delta-hedged put. The sample period is from January 1996 to August 2023. Coefficient estimates are in percent and Newey and West (1987) t -statistics (6 lags) are in parentheses below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: Delta-hedged Calls															
RVC	-0.98*** (-9.08)	-0.52*** (-4.53)	-0.89*** (-9.22)	-0.86*** (-6.37)	-0.88*** (-8.29)	-0.91*** (-8.98)	-0.77*** (-7.21)	-1.01*** (-9.13)	-0.96*** (-8.63)	-1.01*** (-9.65)	-0.78*** (-7.42)	-0.97*** (-9.02)	-0.70*** (-6.82)	-0.63*** (-5.87)	-0.50*** (-3.23)
IV		-1.60*** (-10.8)													-1.28*** (-3.78)
RV_IV			0.73*** (5.99)												1.69*** (5.56)
VTs				3.26*** (6.16)											1.14*** (2.23)
VOV					-2.13*** (-6.37)										-2.01*** (-4.99)
SLOPE						-1.21*** (-5.19)									-2.54*** (-4.87)
ISKEW							-0.14*** (-5.61)								0.023 (0.81)
RSKEW								-0.029* (-1.85)							0.0023 (0.11)
BID-ASK									-0.070 (-0.64)						-0.091 (-0.76)
OPMOM										0.72*** (10.4)					0.93*** (9.24)
IVOL											-10.7*** (-7.19)				-18.9*** (-5.33)
AC												0.38** (2.28)			0.16 (0.80)
SIZE													0.087*** (5.39)		-0.11*** (-5.74)
LnPrice														0.24*** (5.90)	0.038 (0.66)
Constant	-0.47*** (-6.31)	0.42*** (5.24)	-0.45*** (-6.21)	-0.38*** (-4.84)	-0.26*** (-3.59)	-0.46*** (-6.39)	-0.43*** (-5.82)	-0.48*** (-6.61)	-0.44*** (-5.23)	-0.49*** (-6.83)	-0.17*** (-2.74)	-0.47*** (-6.28)	-1.08*** (-7.10)	-1.18*** (-7.96)	1.58*** (5.40)
R^2	0.011	0.043	0.025	0.030	0.019	0.020	0.016	0.017	0.015	0.018	0.023	0.014	0.020	0.023	0.137

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel B: Delta-hedged Puts															
RVC	-1.05*** (-9.62)	-0.53*** (-4.55)	-0.97*** (-9.68)	-0.85*** (-6.43)	-0.95*** (-8.68)	-1.09*** (-10.2)	-1.03*** (-8.55)	-1.04*** (-9.71)	-1.06*** (-9.35)	-1.10*** (-9.70)	-0.79*** (-7.70)	-1.05*** (-9.49)	-0.81*** (-6.66)	-0.74*** (-6.15)	-0.79*** (-3.32)
IV		-1.61*** (-9.70)													-1.30*** (-3.70)
RV_IV			0.64*** (5.98)												1.66*** (6.33)
VTs				2.93*** (5.49)											0.97 (1.43)
VOV					-2.71*** (-8.61)										-2.69*** (-4.75)
SLOPE						1.09*** (3.68)									1.15 (1.42)
ISKEW							0.045 (1.30)								0.12*** (3.25)
RSKEW								-0.045*** (-2.97)							-0.0033 (-0.14)
BID-ASK									0.082 (0.78)						0.24 (0.80)
OPMOM										0.72*** (7.57)					0.91*** (8.51)
IVOL											-12.1*** (-6.60)				-18.5*** (-5.42)
AC												-0.029 (-0.15)			-0.52 (-0.76)
SIZE													0.077*** (5.24)		-0.13*** (-4.98)
LnPrice														0.20*** (5.59)	0.048 (0.57)
Constant	-0.62*** (-8.62)	0.25*** (2.76)	-0.60*** (-8.63)	-0.55*** (-7.02)	-0.37*** (-5.06)	-0.60*** (-8.56)	-0.61*** (-7.67)	-0.62*** (-8.90)	-0.63*** (-7.41)	-0.65*** (-8.99)	-0.29*** (-4.27)	-0.63*** (-8.68)	-1.19*** (-8.38)	-1.23*** (-9.19)	1.55*** (2.93)
R ²	0.012	0.054	0.027	0.033	0.022	0.023	0.019	0.020	0.018	0.021	0.031	0.016	0.023	0.025	0.167

Table 6: Robustness check: different ways to calculate returns

This table reports the robustness check result for sorting on RVC (defined in equation (3)) but using different ways to calculate returns. $\Pi/|\Delta S - C|$ ($\Pi/|\Delta S - P|$) corresponds to the delta-hedged call (put) option gains scaled by the absolute value of initial total investment. Π/C (Π/P) corresponds to the delta-hedged call (put) option gains scaled by option price, where the option price is defined as the mid-point of bid-ask quote. Hold one month corresponds to forming the portfolio at the end of month t and do the daily rebalancing until the end of month $t+1$. Monthly rebalancing correspond to static delta hedging until the end of the holding period. Panel A shows the robustness result for the delta-hedged call. Panel B shows the robustness result for the delta-hedged put. The sample period is from January 1996 to August 2023. Average returns are in percent and Newey and West (1987) t -statistics (6 lags) are in parentheses.

	Low	2	3	4	High	High-Low
Panel A: Delta-hedged Calls						
$\Pi/ \Delta S - C $	0.053 (0.29)	-0.0011 (-0.0064)	-0.27 (-1.54)	-0.51 (-2.85)	-1.24 (-6.12)	-1.30*** (-8.66)
Π/C	0.80 (0.50)	0.41 (0.29)	-0.99 (-0.71)	-1.79 (-1.29)	-4.78 (-3.81)	-5.59*** (-5.46)
Hold one month	0.038 (0.68)	0.034 (0.67)	0.0052 (0.10)	-0.029 (-0.55)	-0.21 (-3.97)	-0.24*** (-6.52)
Monthly rebalancing	0.00061 (0.0051)	0.014 (0.14)	-0.11 (-1.00)	-0.14 (-1.21)	-0.40 (-3.17)	-0.40*** (-4.51)
Panel B: Delta-hedged Puts						
$\Pi/ \Delta S - P $	-0.21 (-1.16)	-0.29 (-1.77)	-0.49 (-3.49)	-0.66 (-4.50)	-1.30 (-8.42)	-1.10*** (-9.26)
Π/P	-2.97 (-1.84)	-3.34 (-2.28)	-4.05 (-2.83)	-4.17 (-3.10)	-8.26 (-6.95)	-5.29*** (-6.24)
Hold one month	-0.00079 (-0.011)	-0.026 (-0.48)	-0.070 (-1.40)	-0.10 (-2.06)	-0.26 (-4.92)	-0.26*** (-4.96)
Monthly rebalancing	-0.16 (-1.33)	-0.11 (-1.13)	-0.26 (-2.44)	-0.29 (-2.53)	-0.54 (-4.29)	-0.38*** (-4.08)

Table 7: Robustness check: alternative correlation measures

This table reports the robustness check result for using alternative correlation measures. The delta hedged option returns are defined as the dollar gains scaled by underlying price and the portfolio returns are all equal-weighted. RVC^{1m} is computed over the past one month. RVC^{log} corresponds to using changes in the log of IV in calculating the RVC (defined in equation (6)). Panel A shows the alternative sorting results for the delta-hedged call. Panel B shows the alternative sorting results for the delta-hedged put. The sample period is from January 1996 to August 2023. Average returns are in percent and [Newey and West \(1987\)](#) t -statistics (6 lags) are in parentheses.

	Low	2	3	4	High	High-Low
Panel A: Delta-hedged Calls						
RVC^{1m}	-0.056 (-0.78)	-0.034 (-0.47)	-0.16 (-2.36)	-0.26 (-4.16)	-0.40 (-6.04)	-0.35*** (-9.72)
RVC^{Log}	0.019 (0.25)	-0.0050 (-0.073)	-0.11 (-1.71)	-0.20 (-3.02)	-0.50 (-6.58)	-0.52*** (-8.96)
Panel B: Delta-hedged Puts						
RVC^{1m}	-0.20 (-2.73)	-0.18 (-2.55)	-0.26 (-3.27)	-0.38 (-6.17)	-0.58 (-8.59)	-0.38*** (-8.21)
RVC^{Log}	-0.061 (-0.69)	-0.14 (-1.91)	-0.21 (-3.43)	-0.33 (-5.03)	-0.63 (-8.92)	-0.57*** (-8.78)

Table 8: Effect of transaction costs

This table reports the portfolio sorting excess return result for considering transaction costs. The delta hedged option returns are defined as the dollar gains scaled by underlying price and the portfolio returns are all equal-weighted. For the row $\frac{ESPR}{QSPR} = 0\%$, we assume the options are transacted at the midpoint of the bid and ask quotes and this result is the same as the result in Table 2 except we calculate Low-High spread. This flipping procedure guarantees that we construct a profitable strategy. The other rows correspond to the variations of this assumption. For example, suppose an option is quoted bid at \$9 and ask at \$10, $\frac{ESPR}{QSPR} = x\%$ means that we buy the options in the bottom quintile (low RVC) at $(9 + 10)/2 + x\%/2 \times (10 - 9)$ and sell the options in the top quintile (high RVC) at $(9 + 10)/2 - x\%/2 \times (10 - 9)$. Panel A shows the effect of transaction cost result for the delta-hedged call. Panel B shows the effect of transaction cost for the delta-hedged put. The sample period is from January 1996 to August 2023. Average returns are in percent and Newey and West (1987) t -statistics (6 lags) are in parentheses.

	Low	High	Low-High
Panel A: Delta-hedged Calls			
$\frac{ESPR}{QSPR} = 0\%$	0.013 (0.18)	-0.50 (-6.50)	0.51*** (9.07)
$\frac{ESPR}{QSPR} = 10\%$	-0.015 (-0.21)	-0.42 (-5.57)	0.40*** (7.64)
$\frac{ESPR}{QSPR} = 20\%$	-0.044 (-0.60)	-0.34 (-4.56)	0.29*** (5.93)
$\frac{ESPR}{QSPR} = 30\%$	-0.073 (-1.00)	-0.26 (-3.50)	0.18*** (3.91)
Panel B: Delta-hedged Puts			
$\frac{ESPR}{QSPR} = 0\%$	-0.078 (-0.89)	-0.63 (-8.79)	0.55*** (8.58)
$\frac{ESPR}{QSPR} = 10\%$	-0.10 (-1.20)	-0.56 (-7.94)	0.46*** (7.44)
$\frac{ESPR}{QSPR} = 20\%$	-0.13 (-1.52)	-0.49 (-7.03)	0.36*** (6.13)
$\frac{ESPR}{QSPR} = 30\%$	-0.16 (-1.83)	-0.42 (-6.07)	0.26*** (4.65)

Table 9: Univariate sorting result on up and down months

This table reports the portfolio sorting excess return results on up and down months. The “Up” corresponds to holding periods when the underlying stock returns are nonnegative. The “Down” corresponds to the holding periods when the underlying stock returns are negative. The “All” is the same as the equal weighted result in Table (2). Panel A shows the effect of transaction cost result for the delta-hedged call. Panel B shows the effect of transaction cost for the delta-hedged put. The sample period is from January 1996 to August 2023. Average returns are in percent and [Newey and West \(1987\)](#) t -statistics (6 lags) are in parentheses.

	Low	2	3	4	High	High-Low
Panel A: Delta-hedged Calls						
Up	-0.034 (-0.90)	-0.060 (-1.82)	-0.077 (-2.24)	-0.13 (-3.55)	-0.29 (-6.24)	-0.26*** (-7.76)
Down	0.048 (1.08)	0.053 (1.28)	-0.029 (-0.74)	-0.073 (-1.89)	-0.21 (-5.43)	-0.26*** (-7.87)
All	0.013 (0.18)	-0.0073 (-0.11)	-0.11 (-1.58)	-0.20 (-2.94)	-0.50 (-6.50)	-0.51*** (-9.07)
Panel B: Delta-hedged Puts						
Up	-0.11 (-2.83)	-0.12 (-3.64)	-0.15 (-4.86)	-0.18 (-5.60)	-0.37 (-9.61)	-0.26*** (-8.73)
Down	0.029 (0.49)	-0.0055 (-0.12)	-0.067 (-1.75)	-0.13 (-3.40)	-0.26 (-6.30)	-0.29*** (-6.40)
All	-0.078 (-0.89)	-0.13 (-1.75)	-0.22 (-3.48)	-0.32 (-4.84)	-0.63 (-8.79)	-0.55*** (-8.58)

Table 10: Controlling for the leverage effect

This table reports the result for controlling the leverage effect in [Fama and MacBeth \(1973\)](#) regressions. The dependent variable is delta-hedged option return, which is multiplied by 100. The “LEV” is the financial leverage, defined as the sum of total debt and par value of preferred stock, minus deferred taxes and investment tax credit, divided by market equity, as in [Vasquez and Xiao \(2024\)](#). Control variables are the all the variables defined in Section 2.4. Panel A shows the effect of financial leverage for the delta-hedged call. Panel B shows the effect of financial leverage for the delta-hedged put. The sample period is from January 1996 to August 2023. Coefficients estimates are in percent and [Newey and West \(1987\)](#) t -statistics (6 lags) are in parentheses below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Delta-hedged Calls						
RVC	-0.98*** (-9.08)		-0.96*** (-9.38)	-0.50*** (-3.23)		-0.48*** (-3.20)
LEV		-0.0013 (-0.22)	-0.0045 (-0.80)		-0.015* (-1.80)	-0.013 (-1.56)
Constant	-0.47*** (-6.31)	-0.19*** (-2.92)	-0.47*** (-6.17)	1.58*** (5.40)	1.49*** (4.84)	1.66*** (5.70)
Controls	NO	NO	NO	YES	YES	YES
R^2	0.011	0.005	0.016	0.137	0.133	0.141
Panel B: Delta-hedged Puts						
RVC	-1.05*** (-9.62)		-1.05*** (-10.1)	-0.79*** (-3.32)		-0.79*** (-3.34)
LEV		-0.0066 (-1.20)	-0.015*** (-2.75)		-0.026** (-2.29)	-0.023** (-2.36)
Constant	-0.62*** (-8.62)	-0.32*** (-4.79)	-0.61*** (-8.34)	1.55*** (2.93)	1.50*** (3.01)	1.66*** (3.10)
Controls	NO	NO	NO	YES	YES	YES
R^2	0.012	0.006	0.018	0.167	0.165	0.172

Table 11: Market maker's hedging error

This table reports the result for the average hedging errors across quintile sorted portfolios. Specifically, we proxy the hedging error (inefficiency) by VOR over the holding period, which is defined in equation (16). At the end of each month, options are sorted into quintiles based on RVC (defined in (3)) and hold until maturity. Then, we calculate the average VOR for the five quintiles and calculate the High-Low differences. EW refers to the equal-weighted result and OI refers to the open interest weighted result, while VW refers to the value weighted result by initial investment. Panel A shows the market maker's hedging error for the delta-hedged call. Panel B shows the market maker's hedging error for the delta-hedged put. The sample period is from January 1996 to August 2023. Coefficients estimates are in percent and Newey and West (1987) t -statistics (6 lags) are in parentheses below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1%.

	Low	2	3	4	High	High-Low
Panel A: Delta-hedged Calls						
EW	0.38 (19.7)	0.43 (21.9)	0.50 (21.9)	0.61 (17.8)	0.73 (18.8)	0.35*** (9.63)
OI	0.32 (20.1)	0.36 (21.7)	0.44 (22.1)	0.54 (19.5)	0.61 (20.6)	0.29*** (11.4)
VW	0.25 (21.4)	0.28 (21.9)	0.33 (18.4)	0.38 (18.9)	0.45 (16.3)	0.20*** (8.79)
Panel B: Delta-hedged Puts						
EW	0.37 (13.8)	0.39 (21.0)	0.45 (20.9)	0.54 (17.9)	0.67 (16.0)	0.30*** (6.61)
OI	0.34 (17.8)	0.36 (20.0)	0.41 (20.2)	0.49 (18.1)	0.60 (16.0)	0.26*** (7.10)
VW	0.25 (20.3)	0.27 (19.5)	0.30 (19.8)	0.35 (18.8)	0.42 (15.0)	0.17*** (7.23)

Table 12: Demand pressures

This table reports the result for the average ISE and CBOE demand pressures across quintile sorted portfolios. Specifically, the net open interest (NOI) is the sum of net open interest across all option series (calls or puts) for each underlying stock. We also report two normalized demand measures: the relative open interest (ROI), defined as $ROI_t = NOI_t / \mathcal{O}_t \times 10^3$, and the relative open value (ROV), defined as $ROV_t = NOI_t C_t / (\mathcal{O}_t S_t) \times 10^3$, where C_t is the option price, S_t is the stock price, and $\mathcal{O}_t$ is the number of shares outstanding of the underlying stock during month t . At the end of each month, options are sorted into quintiles based on RVC (defined in (3)) and then calculate the equal-weighted average NOI, ROI, and ROV for the five quintiles and calculate the High-Low differences. Panel A shows the result for the delta-hedged call. Panel B shows the result for the delta-hedged put. The sample period is from January 2006 to August 2023. Coefficients estimates are in percent and Newey and West (1987) t -statistics (6 lags) are in parentheses below the coefficients estimates. Coefficients marked with *, **, *** are significant at 10%, 5%, and 1%.

	Low	2	3	4	High	High-Low
Panel A: Delta-hedged Calls						
NOI	36.6 (0.31)	877 (3.60)	979 (3.91)	1,202 (3.84)	882 (5.18)	846*** (5.07)
ROI	70.9 (2.25)	271 (5.91)	443 (6.58)	486 (6.75)	815 (6.50)	744*** (6.17)
ROV	7.96 (3.60)	18.6 (6.61)	32.8 (6.84)	39.0 (7.29)	86.7 (5.54)	78.7*** (5.29)
Panel B: Delta-hedged Puts						
NOI	-339 (-2.05)	-238 (-1.64)	-45.6 (-0.61)	21.6 (0.28)	71.9 (1.26)	411** (2.18)
ROI	7.00 (0.35)	68.1 (1.62)	76.3 (2.88)	110 (3.35)	120 (2.19)	113* (1.75)
ROV	1.85 (1.35)	5.51 (1.71)	6.30 (3.42)	9.73 (3.69)	23.9 (2.60)	22.0** (2.34)

Appendix A: A Risk-Based Model

Following the conceptual models in [Bakshi and Kapadia \(2003\)](#); [Pyun \(2019\)](#); [Duarte et al. \(2024\)](#), we denote the stock price, the volatility of stock returns and the return-volatility correlation for firm i as S_t^i, v_t^i and ρ_t^i . In the physical measure $\mathbb{P}$, their dynamics are as follows,

$$\begin{aligned}\frac{dS_t^i}{S_t^i} &= (\phi_t^i + r) dt + \sqrt{v_t^i} dB_{S,t}^i, \\ dv_t^i &= \eta_t^i dt + \sigma_v^i \sqrt{v_t^i} dB_{v,t}^i, \\ d\rho_t^i &= \gamma_t^i dt + \sigma_{\rho,t}^i dB_{\rho,t}^i,\end{aligned}\tag{A.1}$$

where ϕ_t^i is the equity risk premium and r is the risk-free rate; σ_v^i is the volatility of volatility; η_t^i (i.e., the drift term in v_t^i) can be a function of v_t^i ; $B_{S,t}^i$ and $B_{v,t}^i$ are two Brownian motions with a return-volatility correlation (RVC) ρ_t^i and $B_{\rho,t}^i$ is independent of $B_{S,t}^i$ and $B_{v,t}^i$; γ_t^i and $\sigma_{\rho,t}^i$ (i.e., the drift and diffusion terms in ρ_t^i) also can be a function of ρ_t^i .¹⁵

In the risk-neutral measure $\mathbb{Q}$, the dynamics could be expressed as follows,

$$\begin{aligned}\frac{dS_t^i}{S_t^i} &= r dt + \sqrt{v_t^i} d\tilde{B}_{S,t}^i, \\ dv_t^i &= (\eta_t^i - \lambda_{v,t}^i) dt + \sigma_v^i \sqrt{v_t^i} d\tilde{B}_{v,t}^i, \\ d\rho_t^i &= (\gamma_t^i - \lambda_{\rho,t}^i) dt + \sigma_{\rho,t}^i d\tilde{B}_{\rho,t}^i,\end{aligned}\tag{A.2}$$

where all Brownian motions are in the risk-neutral measure; $\lambda_{v,t}^i$ and $\lambda_{\rho,t}^i$ are the volatility and correlation risk premiums, respectively. If we assume that investors dislike volatility, they will pay a premium to enter variance swaps, leading to a negative volatility risk premium (i.e., $\lambda_{v,t}^i < 0$). However, at this stage, we do not know whether investors like or dislike negative correlation or not based on our empirical results. Table C2 shows that RVC is positively correlated with several well-established option risk measures, including IV, IVOL, and VOV. So, we should expected to have a negative correlation risk premium (i.e., $\lambda_{\rho,t}^i < 0$). However, Table C2 also shows that RVC is also positively correlated with SLOPE and ISKEW. This means that investors indeed like positive correlation, which leads to a positive correlation risk premium (i.e., $\lambda_{\rho,t}^i > 0$).

¹⁵Following [Kahnina and Xiu \(2017\)](#), we could set a Jacobi-type process when conducting a Monte Carlo simulation: $d\rho_t = \kappa_\rho(\theta_\rho - \rho_t)dt + \sigma_\rho\sqrt{1 - \rho_t^2}dB_{\rho,t}$.

The dynamics of the stochastic discount factor (SDF) can be given by

$$\frac{dm_t}{m_t} = -r dt - \sum_{i=1}^N \left(\frac{\phi_t^i}{\sqrt{v_t^i}} dB_{S,t}^i + \frac{\lambda_{v,t}^i}{\sigma_v^i \sqrt{v_t^i}} dB_{v,t}^i + \frac{\lambda_{\rho,t}^i}{\sigma_{\rho,t}^i} dB_{\rho,t}^i \right). \quad (\text{A.3})$$

The SDF captures all risks existing in the financial market. As Brownian motions can be correlated, $3 \times N$ Brownian motions can be reduced to a less number of uncorrelated Brownian motions.

At time t , an option price of the stock i with strike K and maturity date T can be denoted as $C_t^i := C(S^i, v^i, \rho^i, t; K, T)$. Following [Bakshi and Kapadia \(2003\)](#), the delta-hedged option gain can be defined as

$$\Pi_{t,t+\tau}^i \equiv C_{t+\tau}^i - C_t^i - \int_t^{t+\tau} \frac{\partial C^i}{\partial S^i} dS_u^i - \int_t^{t+\tau} r \left(C_u^i - \frac{\partial C^i}{\partial S^i} S_u^i \right) du. \quad (\text{A.4})$$

The expected delta-hedged gain therefore can be solved as

$$E_t[\Pi_{t,t+\tau}^i] = E_t \left(\int_t^{t+\tau} \frac{\partial C^i}{\partial v^i} \lambda_{v,u}^i du \right) + E_t \left(\int_t^{t+\tau} \frac{\partial C^i}{\partial \rho^i} \lambda_{\rho,u}^i du \right). \quad (\text{A.5})$$

Assuming $\lambda_{v,t}^i = \lambda_v^i v_t^i < 0$, where $\lambda_v^i < 0$ is a constant, and noting that $\frac{\partial C^i}{\partial v^i} > 0$, our model implies a negative relation between the volatility state v_t^i and expected delta-hedged option returns. This prediction is consistent with the empirical evidence documented in [Cao and Han \(2013\)](#); [Duarte et al. \(2024\)](#); [Horenstein et al. \(2025\)](#), which shows that options associated with higher volatility or volatility-related risks tend to earn lower subsequent delta-hedged returns. The intuition is straightforward: investors require compensation for bearing volatility risk, so a higher volatility state is associated with a larger volatility risk premium and, consequently, lower expected option returns.

In contrast, the relation between $E_t[\Pi_{t,t+\tau}^i]$ and ρ_t^i is substantially less clear. From Equation (A.5), the correlation-risk component of expected option returns is determined by the product

$$\frac{\partial C^i}{\partial \rho^i} \lambda_{\rho,t}^i.$$

There are two fundamental difficulties in determining its sign. First, the sign of the correlation risk premium $\lambda_{\rho,t}^i$ is theoretically ambiguous: the existing evidence does not establish whether investors perceive more negative or more positive RVC as the undesirable state. Second, the sign of the correlation sensitivity $\frac{\partial C^i}{\partial \rho^i}$ is also not generally known. Thus, even if the sign of $\lambda_{\rho,t}^i$ were established, the effect of RVC on expected option returns would remain ambiguous unless the sign of $\frac{\partial C^i}{\partial \rho^i}$ were also known.

Moreover, introducing stochastic correlation makes the option-pricing problem substan-

tially more complicated. The correlation ρ_t^i enters as a stochastic state variable, rendering the model non-affine and precluding a tractable analytical solution for the European option price (Duffie et al., 2000). Monte Carlo simulation therefore provides a natural alternative for studying the correlation-risk channel. However, the numerical error in simulated option prices can be relatively large compared with the magnitude of the correlation risk premium embedded in European option prices. This makes it difficult to obtain a sufficiently precise estimate of $\frac{\partial C^i}{\partial \rho^i}$ and, consequently, to identify the contribution of correlation risk to expected delta-hedged option returns.

Appendix B: RVC and Expected Option Returns in the Heston (1993) Model

To analytically investigate the relation between RVC and expected option returns, we consider the well-known Heston (1993) stochastic volatility model. The model provides a convenient benchmark because the European option price has a closed-form representation, allowing us to isolate the effect of the return-volatility correlation while keeping the other model parameters fixed.

Under the physical measure $\mathbb{P}$, the dynamics of the stock price and its instantaneous variance are given by

$$\begin{aligned}\frac{dS_t}{S_t} &= \mu dt + \sqrt{v_t} dB_{S,t}, \\ dv_t &= \kappa^{\mathbb{P}}(\theta^{\mathbb{P}} - v_t)dt + \sigma_v \sqrt{v_t} dB_{v,t},\end{aligned}\tag{B.1}$$

where μ is the expected stock return, $\kappa^{\mathbb{P}}$ is the variance mean-reversion speed, $\theta^{\mathbb{P}}$ is the long-run variance, and σ_v is the volatility-of-volatility. The Brownian motions $B_{S,t}$ and $B_{v,t}$ satisfy $dB_{S,t}dB_{v,t} = \rho dt$, so that ρ represents the return-volatility correlation.

Under the risk-neutral measure $\mathbb{Q}$, the dynamics become

$$\begin{aligned}\frac{dS_t}{S_t} &= r dt + \sqrt{v_t} d\tilde{B}_{S,t}, \\ dv_t &= \kappa(\theta - v_t)dt + \sigma_v \sqrt{v_t} d\tilde{B}_{v,t},\end{aligned}\tag{B.2}$$

where $\kappa = \kappa^{\mathbb{P}} + \lambda_v$, $\theta = \kappa^{\mathbb{P}}\theta^{\mathbb{P}}/\kappa$, and $\lambda_v < 0$ captures the volatility risk premium.

We define European call options as

$$C_t(r, S_t, K, T - t, \kappa, \theta, \sigma_v, \rho) = e^{-r(T-t)} E_t^{\mathbb{Q}} [(S_T - K)^+] = e^{-r(T-t)} E_t^{\mathbb{Q}} \left[\left(e^{\ln S_T} - e^k \right)^+ \right],\tag{B.3}$$

where $k = \log K$ and K is the strike price, $(\cdot)^+$ denotes $\max\{\cdot, 0\}$ and $(S_T - K)^+$ is the payoff function of the call option at the maturity date T .

The moment-generating function $f(\omega, \tau; \ln S, v) = E_t^{\mathbb{Q}}[e^{\omega \ln S_T}]$ where $\tau = T - t$, can be solved as (Heston, 1993; Cao, Ruan, and Zhang, 2020),

$$f(\omega, \tau) = e^{A(\omega, \tau) + B(\omega, \tau)v_t + \omega \ln S_t}, \quad (\text{B.4})$$

where

$$A(\omega, \tau) = -\frac{\kappa\theta}{\sigma_v^2} \left(\xi_+ \tau + 2 \ln \frac{\xi_+ e^{-\zeta\tau} + \xi_-}{2\zeta} \right) + r\omega\tau, \\ B(\omega, \tau) = \frac{-(\omega - \omega^2)(1 - e^{-\zeta\tau})}{\xi_+ e^{-\zeta\tau} + \xi_-}, \quad \zeta = \sqrt{(\kappa^{\mathbb{Q}} - \rho\sigma_v\omega)^2 + \sigma_v^2(\omega - \omega^2)}, \quad \xi_{\pm} = \zeta \mp (\kappa^{\mathbb{Q}} - \rho\sigma_v\omega).$$

Following Carr and Madan (1999), we rewrite the option price as $\hat{C}_t(k) = e^{ak}C_t$ for $a > 0$, so that $C_t = e^{-ak}\hat{C}_t(k)$, which can be derived as¹⁶

$$C_t = e^{-ak} \left[\frac{1}{2\pi} \int_{-\infty}^{+\infty} e^{-iuk} \left(\int_{-\infty}^{+\infty} e^{iuk} \hat{C}_t(k) dk \right) du \right] = e^{-r(T-t)} \frac{e^{-ak}}{\pi} \int_0^{+\infty} e^{-iuk} \phi(u) du, \quad (\text{B.5})$$

where $\phi(u) = \frac{f(iu + (1+a), \tau)}{a^2 + a - u^2 + i(2a+1)u}$.

We next use the model to examine how the expected option return varies with ρ . In particular, to further isolate the role of volatility-related risk from the directional movement of the underlying stock, we define consider the expected return on a straddle. The straddle combines a call and a put with the same strike and maturity and therefore provides a more symmetric exposure to the underlying price. Its expected gain is defined as

$$\Pi_t^{\text{straddle}} = e^{\mu(T-t)} E_t^{\mathbb{P}} \left[e^{-\mu(T-t)} (S_T - K)^+ \right] + e^{\mu(T-t)} E_t^{\mathbb{P}} \left[e^{-\mu(T-t)} (K - S_T)^+ \right] \\ - \left(E_t^{\mathbb{Q}} \left[e^{-r(T-t)} (S_T - K)^+ \right] + E_t^{\mathbb{Q}} \left[e^{-r(T-t)} (K - S_T)^+ \right] \right). \quad (\text{B.6})$$

The Heston option price under the risk-neutral measure (e.g., $E_t^{\mathbb{Q}} [e^{-r(T-t)} (S_T - K)^+]$) can therefore be evaluated using the closed-form representation in Equation (B.5). Similarly, the Heston option price under the physical measure (e.g., $E_t^{\mathbb{P}} [e^{-\mu(T-t)} (S_T - K)^+]$) can be obtained by evaluating the corresponding Heston formula under the physical-measure parameters $(\mu, \kappa^{\mathbb{P}}, \theta^{\mathbb{P}}, \sigma_v, \rho)$.

There are many studies that estimate Heston-type model parameters for S&P 500 index options (Bakshi et al., 1997; Bates, 2000; Eraker, Johannes, and Polson, 2003; Eraker, 2004; Bardgett, Gourier, and Leippold, 2019), whereas relatively few studies calibrate stochastic volatility models to individual equity options (Christoffersen, Fournier, and Jacobs, 2018a;

¹⁶Put option prices can be calculated from the put-call parity.

Bakshi, Cao, and Zhong, 2021). We therefore use the parameter estimates reported by Bakshi et al. (2021) as a benchmark for our simulation exercise. Specifically, we set $\kappa^{\mathbb{Q}} = 1.59$, $\theta^{\mathbb{Q}} = 0.05$, $\sigma_v = 0.42$, $\lambda_v = -1.72$,¹⁷ which implies the corresponding physical-measure parameters $\kappa^{\mathbb{P}} = 3.31$, $\theta^{\mathbb{P}} = 0.02$. We further set $S_t = 100$, $K = 100$, $\tau = 1/12$, $\mu = 0.05$, $r = 0.01$.

For each value of $\rho \in [-1, 1]$, we conduct 10,000 simulations using different initial variance draws. Specifically, v_t is drawn from the stationary Gamma distribution of the Cox–Ingersoll–Ross variance process, with shape parameter $2\kappa^{\mathbb{P}}\theta^{\mathbb{P}}/\sigma_v^2$ and scale parameter $\sigma_v^2/2\kappa^{\mathbb{P}}$. This procedure allows us to examine the cross-sectional relation between RVC and expected option returns while averaging over variation in the initial volatility state.

[Insert Figure B1 Here]

Figure B1 presents the simulation results. The two panels plot expected straddle returns against ρ , using the straddle price ($C_t + P_t$) and the underlying stock price S_t as scaling variables, respectively. In both cases, expected straddle returns decline almost monotonically as ρ increases from -1 to 1 . When scaled by the straddle price, expected returns decrease from approximately 0.10% at $\rho = -1$ to -4.00% at $\rho = 1$. When scaled by the underlying stock price, the corresponding returns decline from approximately -0.03% to -0.13% . Thus, the model generates a robust negative relation between RVC and expected straddle returns, consistent with the empirical evidence and indicating that the relation is not driven by the choice of return scaling.¹⁸

Appendix C: Other Tables

[Insert Table C1 Here]

[Insert Table C2 Here]

[Insert Table C3 Here]

[Insert Table C4 Here]

¹⁷The variance risk premium $\lambda_v = \gamma\rho\sigma_v$, where the risk aversion parameter $\gamma = 10$ and $\rho = -0.41$.

¹⁸Table C4 provides empirical support for this result, as alternative straddle return definitions and scaling methods consistently produce a negative relation between RVC and option returns.

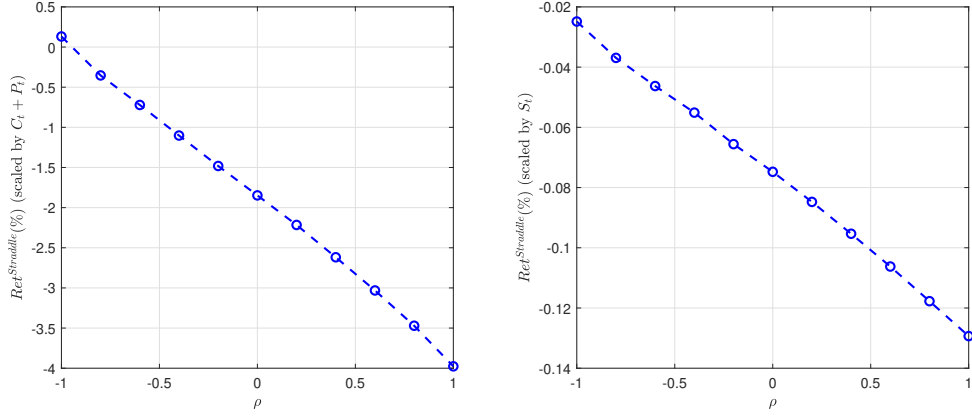


Figure B1: Expected straddle returns

Notes: This figure plots simulated expected straddle returns against the return-volatility correlation ρ in the [Heston \(1993\)](#) model. The parameters are based on [Bakshi et al. \(2021\)](#), with $\kappa^{\mathbb{Q}} = 1.59$, $\theta^{\mathbb{Q}} = 0.05$, $\sigma_v = 0.42$, $\lambda_v = -1.72$, $S_t = K = 100$, $\tau = 1/12$, $\mu = 0.05$, and $r = 0.01$. For each value of $\rho \in [-1, 1]$, 10,000 simulations are conducted using initial variance draws from the stationary Gamma distribution.

Table C1: Summary statistics for RVC and other characteristics

This table reports the descriptive statistics for the monthly time-series RVC and other characteristics for the delta-call and put samples. The statistics are calculated by first taking the cross-sectional average of all characteristics and then computing the average over time. Panel A (B) shows the summary statistics for the delta-hedged call (put). The sample period is from January 1996 to August 2023 and the data are from Optionmetrics and CRSP databases.

	Mean	Median	Std. Dev.	10 th	25 th	75 th	90 th
Panel A: Variables for Delta-hedged Calls							
RVC	-0.32	-0.33	0.19	-0.56	-0.46	-0.19	-0.07
IV	0.49	0.46	0.21	0.27	0.34	0.59	0.75
RV_IV	-0.01	-0.02	0.21	-0.18	-0.10	0.05	0.16
VTs	-0.01	0.00	0.06	-0.07	-0.03	0.02	0.04
VOV	0.09	0.07	0.06	0.04	0.05	0.10	0.14
SLOPE	-0.02	-0.02	0.10	-0.07	-0.04	0.00	0.05
ISKEW	-0.35	-0.29	0.56	-1.03	-0.65	-0.03	0.21
RSKEW	0.23	0.17	1.38	-0.93	-0.25	0.65	1.39
BID-ASK	0.20	0.14	0.20	0.05	0.08	0.25	0.42
OPMOM	-0.01	-0.04	0.19	-0.21	-0.13	0.08	0.21
IVOL	0.03	0.02	0.02	0.01	0.01	0.03	0.04
AC	-0.01	-0.01	0.08	-0.11	-0.06	0.04	0.09
SIZE	7.93	7.82	1.48	6.08	6.84	8.92	9.94
LnPrice	3.42	3.46	0.80	2.32	2.84	3.99	4.42
Panel B: Variables for Delta-hedged Puts							
RVC	-0.34	-0.35	0.19	-0.57	-0.48	-0.21	-0.08
IV	0.47	0.44	0.21	0.26	0.32	0.58	0.73
RV_IV	-0.01	-0.02	0.21	-0.17	-0.09	0.06	0.16
VTs	-0.01	0.00	0.06	-0.07	-0.03	0.02	0.04
VOV	0.09	0.07	0.05	0.04	0.05	0.10	0.14
SLOPE	-0.01	-0.03	0.09	-0.07	-0.04	0.00	0.05
ISKEW	-0.37	-0.32	0.57	-1.05	-0.68	-0.05	0.21
RSKEW	0.21	0.14	1.37	-0.94	-0.27	0.61	1.35
BID-ASK	0.17	0.12	0.18	0.05	0.07	0.20	0.36
OPMOM	-0.01	-0.03	0.19	-0.21	-0.13	0.08	0.21
IVOL	0.02	0.02	0.02	0.01	0.01	0.03	0.04
AC	-0.01	-0.01	0.08	-0.11	-0.06	0.04	0.09
SIZE	8.22	8.15	1.49	6.33	7.13	9.25	10.23
LnPrice	3.53	3.57	0.79	2.45	2.97	4.09	4.50

Table C2: Correlation coefficients between RVC and other variables

This table reports the correlation coefficients between RVC and other characteristics for the delta-call and put samples. Specifically, at the end of each month t , we calculate the cross-sectional correlations between RVC and the other variables. Then, we calculate the time-series average of correlations to obtain the numbers in the table. Panel A shows the correlation coefficients for the delta-hedged call. Panel B shows the correlation coefficients for the delta-hedged put. The sample period is from January 1996 to August 2023 and the data are from Optionmetrics and CRSP databases.

	RVC	IV	RV_IV	VTs	VOV	SLOPE	ISKEW	RSKEW	BID-ASK	OPMOM	IVOL	AC	SIZE	LnPrice
Panel A: Variables for Delta-hedged Calls														
IV	0.26	1.00												
RV_IV	-0.09	-0.16	1.00											
VTs	-0.02	-0.40	0.16	1.00										
VOV	0.08	0.15	0.15	-0.09	1.00									
SLOPE	0.16	-0.02	0.02	0.09	0.01	1.00								
ISKEW	0.21	0.24	-0.04	-0.10	0.01	0.25	1.00							
RSKEW	0.09	0.13	0.01	-0.01	0.02	-0.02	-0.01	1.00						
BID-ASK	0.20	0.00	-0.03	0.04	0.06	0.08	0.10	0.01	1.00					
OPMOM	0.04	0.17	0.14	-0.11	0.05	-0.03	0.01	0.00	-0.02	1.00				
IVOL	0.18	0.61	0.58	-0.16	0.24	0.03	0.16	0.10	0.00	0.22	1.00			
AC	0.06	0.16	-0.01	-0.03	0.01	-0.03	0.03	0.00	-0.02	0.20	0.12	1.00		
SIZE	-0.41	-0.61	0.05	0.07	-0.06	-0.07	-0.25	-0.07	-0.27	-0.09	-0.44	-0.13	1.00	
LnPrice	-0.33	-0.54	0.06	0.07	-0.10	-0.11	-0.33	-0.01	-0.21	-0.04	-0.37	-0.09	0.61	1.00
Panel B: Variables for Delta-hedged Puts														
IV	0.25	1.00												
RV_IV	-0.09	-0.14	1.00											
VTs	-0.02	-0.43	0.16	1.00										
VOV	0.08	0.16	0.16	-0.10	1.00									
SLOPE	0.18	-0.03	0.02	0.12	0.01	1.00								
ISKEW	0.21	0.24	-0.04	-0.10	0.02	0.26	1.00							
RSKEW	0.09	0.13	0.02	0.00	0.03	-0.02	-0.01	1.00						
BID-ASK	0.19	0.05	-0.02	0.01	0.07	0.11	0.10	0.01	1.00					
OPMOM	0.05	0.19	0.14	-0.11	0.05	-0.03	0.02	-0.01	0.00	1.00				
IVOL	0.19	0.62	0.58	-0.18	0.25	0.02	0.17	0.11	0.04	0.23	1.00			
AC	0.08	0.17	-0.01	-0.04	0.02	-0.03	0.04	0.00	0.00	0.20	0.12	1.00		
SIZE	-0.41	-0.61	0.04	0.10	-0.06	-0.06	-0.26	-0.06	-0.28	-0.10	-0.45	-0.15	1.00	
LnPrice	-0.31	-0.53	0.05	0.09	-0.11	-0.12	-0.34	0.01	-0.21	-0.04	-0.37	-0.10	0.58	1.00

Table C3: Univariate portfolio sorting result across moneyness

This table reports average delta-hedged option returns and t -statistics from univariate quintile sorts across different moneyness levels. At the end of each month, for each underlying stock, we select one call option and one put option whose moneyness, defined as K/S , is closest to 1.05, 1.00, and 0.95, respectively. We then sort the selected options into quintiles based on RVC, defined in Equation (3), and hold the options until maturity. Quintile 1 (Low) contains options with the lowest RVC values, while Quintile 5 (High) contains options with the highest RVC values. Panel A reports results for delta-hedged calls, and Panel B reports results for delta-hedged puts. The final column reports the return difference between the Low and High RVC portfolios (Low–High). Average returns are in percent, and [Newey and West \(1987\)](#) t -statistics computed using six lags are reported in parentheses. The sample period is from January 1996 to August 2023. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Low	2	3	4	High	High-Low
Panel A: Delta-hedged Calls						
$K/S = 1.05$	0.017 (0.25)	-0.0039 (-0.059)	-0.10 (-1.59)	-0.18 (-2.70)	-0.47 (-6.33)	-0.49*** (-9.22)
$K/S = 1.00$	0.013 (0.18)	-0.0073 (-0.11)	-0.11 (-1.58)	-0.20 (-2.94)	-0.50 (-6.50)	-0.51*** (-9.07)
$K/S = 0.95$	0.033 (0.43)	0.013 (0.18)	-0.100 (-1.45)	-0.17 (-2.49)	-0.48 (-6.27)	-0.51*** (-8.99)
Panel B: Delta-hedged Puts						
$K/S = 1.05$	-0.092 (-1.06)	-0.15 (-2.13)	-0.22 (-3.53)	-0.29 (-4.63)	-0.63 (-8.70)	-0.53*** (-8.45)
$K/S = 1.00$	-0.078 (-0.89)	-0.13 (-1.75)	-0.22 (-3.48)	-0.32 (-4.84)	-0.63 (-8.79)	-0.55*** (-8.58)
$K/S = 0.95$	-0.053 (-0.57)	-0.11 (-1.52)	-0.20 (-3.12)	-0.31 (-4.63)	-0.61 (-8.40)	-0.55*** (-8.66)

Table C4: RVC-Sorted Straddle Returns

his table reports average straddle returns and t -statistics from univariate quintile sorts based on RVC. At the end of each month, options are sorted into quintiles based on RVC, defined in Equation (3), and held until maturity. Straddle returns are constructed by combining a call and a put and applying the daily-rebalancing strategy described in Equation (2), with C replaced by $C + P$ throughout. Straddle returns are scaled either by the underlying stock price (S) or by the combined option prices ($C + P$). The final column reports the High-Low return spread. The sample period is from January 1996 to August 2023. Average returns are in percent and Newey and West (1987) t -statistics based on 6 lags are reported in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Low	2	3	4	High	High-Low
Π/S	-0.11 (-0.63)	-0.042 (-0.21)	-0.27 (-1.77)	-0.43 (-2.64)	-1.22 (-6.71)	-1.12*** (-7.18)
$\Pi/(C + P)$	-1.23 (-1.01)	-0.79 (-0.63)	-1.54 (-1.53)	-2.14 (-2.15)	-5.35 (-6.10)	-4.12*** (-5.11)