Betting on the Leverage Effect*

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Abstract

We show that betting on the leverage effect pays: stocks with a more negative correlation between returns and variance innovations earn higher returns. Decomposing the leverage effect into upside and downside components based on variance increases and decreases, portfolio sorts reveal annual premiums of 3.72% and 5.76% for the overall and upside correlations, while downside correlation is not priced. The results are confirmed in Fama–MacBeth regressions after controlling for firm characteristics, leverage, skewness, jump variation, and standard risk factors. Relative to conventional skewness measures, realized correlation exhibits greater persistence and captures return asymmetry more reliably, enhancing cross-sectional predictability.

Keywords: Leverage effect; Return-variance correlation; Cross-section of stock returns; Asymmetric risk; High-frequency data

JEL Classification: G11, G12, G17

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1 Introduction

The relation between stock returns and volatility has received considerable attention in the financial economics literature. There is a wealth of evidence that this correlation is statistically and economically significant negative at the market level, with estimates around -0.7 for U.S. data.[1] At the firm level, this correlation exhibits substantial cross-sectional variation, ranging from strongly negative to weakly positive (Christie, 1982; Cheung and Ng, 1992; Duffee, 1995; Figlewski and Wang, 2000). Despite this heterogeneity, the implications of the leverage effect for the cross section of expected stock returns remain largely unexplored.

From an asset pricing perspective, stocks with more negative return–volatility correlations are riskier because they experience larger increases in volatility during stock price declines. This exposure to asymmetric downside risk should command higher expected returns. An equivalent motivation is that the return–volatility correlation is directly linked to the asymmetry of the return distribution. Heston (1993), Das and Sundaram (1999), and Neuberger and Payne (2021) show that the correlation between returns and variance innovations affects return skewness. Negative return–variance correlations generate negatively skewed return distributions, which should command a risk premium. The return–volatility correlation can thus also be thought of as a proxy for the economically relevant asymmetry in returns.

Most of the existing empirical literature instead uses measures of return skewness to proxy these asymmetries. However, a central challenge in the empirical skewness literature is that skewness measures are difficult to estimate precisely and often exhibit low persistence. Indeed, while the literature on skewness as a cross-sectional determinant of returns goes back several decades, Bali, Engle, and Murray (2016) show that stock sorts based on skewness estimated over short horizons do not generate reliable cross-sectional predictions. Longer estimation windows, however, may fail to capture time variation in firm risk. Several studies therefore propose alternative approaches to measure skewness-related risks, which either rely on historical return data or alternative information from options or firm characteristics.[2]

[1] Bandi and Renò (2012) document substantial time variation in this market-level leverage effect.

[2] For examples of alternative approaches, see Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), Amaya, Christoffersen, Jacobs, and Vasquez (2015), Xing, Zhang, and Zhao (2010), Cremers and Weinbaum (2010), Conrad, Dittmar, and Ghysels (2013), Stilger, Kostakis, and Poon (2017), Kim and Park (2018), Bali, Hu, and Murray (2019), Langlois (2020), Jiang, Wu, Zhou, and Zhu (2020), Bollerslev, Li, and Zhao (2020), Huang and Li (2019), Jiang and Yao (2013), Kozhan, Neuberger, and Schneider (2013), and Pederzoli (2025).

While this literature has made significant progress, existing empirical measures of skewness remain noisy and often exhibit limited persistence, which weakens their ability to generate reliable cross-sectional predictions.

We contribute to this literature by proposing the correlation between returns and variance innovations as a more precisely estimated proxy for asymmetric risk. We study whether cross-sectional differences in the correlation between stock returns and volatility help explain differences in expected stock returns. Our analysis reveals a strong negative relationship between the leverage effect and subsequent stock returns. Portfolio sorts show that stocks in the first (lowest) quintile of realized correlations outperform those in the highest (fifth) quintile by 31 basis points per month (3.72% per annum). Note that the lowest quintile includes the stocks with the most negative correlation, or the largest leverage effect. A long-short portfolio that is short the fifth quintile and long the first therefore bets on, not against, the leverage effect. Furthermore, while we refer to this correlation as the leverage effect, the economic determinants of return–volatility correlations remain debated, and this terminology does not indicate a preferred explanation of this stylized fact. Black (1976) and Christie (1982) emphasize that the debt-to-equity ratio mechanically increases when the stock price declines, making the firm riskier and increasing return volatility. This mechanism is referred to as the leverage effect. An alternative explanation is volatility feedback, whereby anticipated increases in volatility lead to higher expected returns and contemporaneous stock price declines.[3]

When we decompose the correlation into upside and downside components according to the sign of the variance innovations (positive versus negative variance innovations), we find that the cross-sectional relationship is driven entirely by correlations based on positive variance shocks. The upside correlation component generates a monthly premium of 48 basis points (5.76% per annum), larger than the overall correlation, while correlations based on negative variance shocks do not exhibit a systematic relation with subsequent returns. The alphas for both the long-short return based on the overall correlation and the upside correlation remain highly significant after adjusting for various factor models.

Fama-MacBeth cross-sectional regressions confirm these findings from portfolio sorts. In

[3]On the volatility feedback effect, see for instance Pindyck (1984), French, Schwert, and Stambaugh (1987), Campbell and Hentschel (1992), Bekaert and Wu (2000), Bollerslev, Litvinova, and Tauchen (2006), Turner, Startz, and Nelson (1989), Mayfield (2004), and Wu (2001). See Bollerslev, Sizova, and Tauchen (2012) on the role of volatility risk.

univariate specifications, the leverage effect generates a 44 basis points monthly premium, which increases to 74 basis points for the upside correlation component. These estimates remain economically and statistically significant when controlling for a battery of firm-level characteristics studied in the existing literature. The significance of the correlation measures in Fama-MacBeth regressions is also robust to the inclusion of alternative proxies for distribution asymmetry, including daily and high-frequency realized skewness and relative signed jump variation measures. While all asymmetric distribution measures exhibit the expected negative risk premia in univariate regressions, including the correlation measures results in insignificant estimates for skewness and jump variation measures in multivariate specifications. These results highlight that the correlation measures contain unique information about the cross-section of returns that is not captured by traditional skewness and jump variation measures, or alternatively that they measure the relevant information more precisely.

Our paper contributes to the literature on skewness risk premia and asymmetric risk in asset pricing. The theoretical link between skewness and expected returns is well established: Investors should demand higher expected returns from assets with more negative skewness due to the increased likelihood of large losses during adverse market conditions.[4] However, the empirical evidence is mixed. A possible explanation is that conventional skewness measures are difficult to estimate precisely, and as discussed above the literature has proposed many alternative approaches to measure skewness-related risks. We attempt to contribute to this literature by proposing the correlation between returns and variance innovations as a more reliable measure of economically relevant asymmetry. We provide evidence in favor of this hypothesis with a Monte Carlo analysis of a stochastic volatility setup, in which realized correlation isolates the diffusive component of asymmetric risk.

Our work is also related to several other strands of literature. First, the decomposition of the overall correlation in upside and downside correlation is inspired by the literature on downside risk[5] and the differential pricing of upside and downside variance.[6] Second,

[4]See Arditti (1967), Kraus and Litzenberger (1976), Conine Jr and Tamarkin (1981), Harvey and Siddique (2000), Mitton and Vorkink (2007), and Barberis and Huang (2008).

[5]For contributions to and extensions of this literature, see for instance Ang, Chen, and Xing (2006a), Hong, Tu, and Zhou (2007), Feunou, Jahan-Parvar, and Tédongap (2013), Lettau, Maggiori, and Weber (2014), Farago and Tédongap (2018), Atilgan, Demirtas, and Gunaydin (2020), Levi and Welch (2020), and Bollerslev, Patton, and Quaedvlieg (2022).

[6]See for instance Feunou, Lopez Aliouchkin, Tédongap, and Xu (2017), Feunou and Okou (2019), Kilic

we measure the variance using high-frequency returns. An extensive literature instead uses high frequency returns to measure stocks' market betas, semibetas, and correlations between individual stock and market returns, as well as their dynamics and pricing implications.[7] A third related literature studies the pricing of variance risk and the cross-sectional relation between (idiosyncratic) volatility and returns (Ang, Hodrick, Xing, and Zhang, 2006b). This literature is in turn related to studies of the beta anomaly. Liu, Stambaugh, and Yuan (2018) show that the beta anomaly is due to the positive correlation between beta and idiosyncratic volatility. Asness, Frazzini, Gormsen, and Pedersen (2020) decompose betting against beta (BAB) into two factors: betting against correlation (BAC) and betting against volatility (BAV).

The paper proceeds as follows. Section 2 discusses the computation of realized correlation and its decomposition, as well as data sources and descriptive statistics. Section 3 presents the predictive cross-sectional results. Section 4 examines why realized correlation measures asymmetric risk more effectively than conventional skewness measures. Section 5 presents additional robustness analyses, and Section 6 concludes.

2 Methodology and Data

This section describes the computation of the realized correlation between a firm's stock return and its variance innovations, as well as its decomposition into components conditional on the sign of the variance innovations. We then describe the data sources used in the empirical analysis and present descriptive statistics for the main variables used.

2.1 Measuring Realized Correlation

We denote by $r_{t,d,j}^{(k)}$ the intraday log-return of asset j on day d in month t, where k indexes the 5-minute interval within the trading day. We compute the daily realized variance ($RV_{t,d,j}$)

and Shaliastovich (2019), Feunou et al. (2013), Patton and Sheppard (2015), and Bekaert, Engstrom, and Ermolov (2015).

[7] See for instance Bollerslev and Zhang (2003), Todorov and Bollerslev (2010), Patton and Verardo (2012), Hollstein and Prokopczuk (2016), Hollstein, Prokopczuk, and Wese Simen (2020), and Bollerslev et al. (2022).

as the sum of 5-minute squared log-returns,

$$RV_{t,d,j} = \sum_{k=1}^{78} (r_{t,d,j}^{(k)})^2. \tag{1}$$

The realized correlation is defined as the correlation between the daily returns and the daily variance innovations, computed over all trading days within month t for stock j:[8,9]

$$\begin{aligned} \rho_{t,j} = \mathrm{Corr}\left(r_{t,d,j}, \Delta RV_{t,d,j}\right) &= \frac{\mathrm{E}\left[r_{t,d,j} \cdot \Delta RV_{t,d,j}\right]}{\sqrt{\mathrm{Var}\left[r_{t,d,j}\right]}\sqrt{\mathrm{Var}\left[\Delta RV_{t,d,j}\right]}} &(2)\\ &= \frac{\sum_{d=1}^{D} r_{t,d,j} \Delta RV_{t,d,j}}{\sqrt{\sum_{d=1}^{D} r_{t,d,j}^2}\sqrt{\sum_{d=1}^{D} \Delta RV_{t,d,j}^2}}, &(3) \end{aligned}$$

where $r_{t,d,j}$ is the return of stock j on day d, $\Delta RV_{t,d,j}$ is the change in realized variance from day $d-1$ to day d, and D denotes the total number of trading days in month t.

We next decompose ρ into components conditional on the sign of the variance innovations. This approach is motivated by prior literature that decomposes risk measures to isolate distinct dynamics that may be obscured in aggregate measures (see, for example, Ang et al. (2006a), Bollerslev et al. (2020), and Bollerslev et al. (2022)). In our setting, the decomposition allows positive and negative variance innovations to have heterogeneous effects on the return–variance relation. We define the signed daily variance innovations as $\Delta V_{t,d,j}^{+} = \max(\Delta RV_{t,d,j}, 0)$ and $\Delta V_{t,d,j}^{-} = \min(\Delta RV_{t,d,j}, 0)$. The realized correlation can then be decomposed as:

[8]We construct realized correlation using high-frequency data and do not de-mean returns. Barndorff-Nielsen and Shephard (2004) show that realized betas provide consistent estimates of true latent betas as the return sampling frequency increases. Our implementation follows Bollerslev et al. (2022), who ignore the mean when estimating realized semibetas. Ang et al. (2006a) incorporate the sample mean in their estimation of downside beta and co-skewness measures. Incorporating the sample mean does not qualitatively affect our results.

[9]Bandi and Renò (2016) and Bollerslev and Todorov (2023) document the role of price–volatility co-jumps in the leverage effect.

$$\rho_{t,j} = \frac{\mathrm{E}\left[r_{t,d,j} \cdot \Delta RV_{t,d,j} \cdot \mathbf{1}_{(\Delta RV_{t,d,j}>0)}\right]}{\sqrt{\mathrm{Var}\left[r_{t,d,j}\right]}\sqrt{\mathrm{Var}\left[\Delta RV_{t,d,j}\right]}} + \frac{\mathrm{E}\left[r_{t,d,j} \cdot \Delta RV_{t,d,j} \cdot \mathbf{1}_{(\Delta RV_{t,d,j}<0)}\right]}{\sqrt{\mathrm{Var}\left[r_{t,d,j}\right]}\sqrt{\mathrm{Var}\left[\Delta RV_{t,d,j}\right]}}, \tag{4}$$

$$= \frac{\sum_{d=1}^{D} r_{t,d,j} \Delta V_{t,d,j}^{+}}{\sqrt{\sum_{d=1}^{D} r_{t,d,j}^2}\sqrt{\sum_{d=1}^{D} \Delta RV_{t,d,j}^2}} + \frac{\sum_{d=1}^{D} r_{t,d,j} \Delta V_{t,d,j}^{-}}{\sqrt{\sum_{d=1}^{D} r_{t,d,j}^2}\sqrt{\sum_{d=1}^{D} \Delta RV_{t,d,j}^2}}, \tag{5}$$

$$\equiv \rho_{t,j}^{\Delta V^+} + \rho_{t,j}^{\Delta V^-}. \tag{6}$$

2.2 Data and Descriptive Statistics

We obtain high-frequency consolidated transaction data from the Trades and Quotes (TAQ) database for the period spanning January 1996 to December 2023. The TAQ database provides intraday transaction records timestamped with millisecond precision across 16 exchanges, including the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ. Transactions are filtered according to criteria described in the Appendix, retaining only trades occurring between 9:30 AM and 4:00 PM. We use the resulting sample to construct five-minute intraday returns for each stock, which are then aggregated to compute daily realized variance.

We obtain daily and monthly stock return data from the Center for Research in Security Prices (CRSP) database, which provides information on stock returns, trading volume, shares outstanding, security types, and value-weighted market returns. Daily returns are used to compute monthly realized correlation measures and firm-level control variables, while monthly returns are used in the portfolio sorts and Fama–MacBeth cross-sectional regressions. Consistent with the prior literature, our sample includes only common stocks with prices above \$5 listed on the NYSE, NASDAQ, and AMEX exchanges. To be eligible for inclusion in the portfolio formation sample, stocks must exhibit non-zero trading volume on at least 10 trading days during the preceding month. We obtain accounting information from Compustat to construct the book-to-market ratio following Fama and French (1993). On average, the sample contains 3,575 stocks per month.

Table 1 presents summary statistics and pairwise correlations for ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. For each month, we compute the cross-sectional distribution of each variable and the corresponding pairwise correlations, and then report the time-series averages of these monthly statistics. Panel A shows that, on average, ρ is negative but close to zero, consistent with the existing literature. The mean and median of $\rho^{\Delta V^+}$ are smaller (in absolute value) than those of ρ and $\rho^{\Delta V^-}$. Panel B reports the pairwise correlations among ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. The average correlation between ρ and $\rho^{\Delta V^+}$ is high at 88%, indicating that $\rho^{\Delta V^+}$ captures a substantial share of the variation in ρ. In contrast, the average correlation between ρ and $\rho^{\Delta V^-}$ is considerably lower at 59%. The correlation between $\rho^{\Delta V^+}$ and $\rho^{\Delta V^-}$ is lower, averaging only 14%, suggesting that the two components capture largely distinct dimensions of variation in ρ. Figure 1 plots the unconditional densities of the overall, upside, and downside correlation measures across all firms and months in the sample. The distributions of all three measures are approximately symmetric around zero, but the distribution of $\rho^{\Delta V^-}$ has a lower standard deviation.

Figure 2 presents the monthly 25th, 50th, and 75th percentiles of ρ, annualized volatility, and skewness, together with the percentage of stocks with negative ρ each month. Panel A shows substantial cross-sectional variation in ρ: the 75th percentile is positive in nearly all months, whereas the 25th percentile is consistently negative. Panel B further highlights this heterogeneity, with approximately 60% of stocks exhibiting negative correlations in a typical month. The upward time trend additionally indicates that an increasing fraction of stocks display negative correlations over time. Panels C and D show that volatility spikes sharply during financial crises, whereas skewness does not exhibit similarly distinct patterns around recessionary periods. In contrast, ρ exhibits pronounced downward spikes during crisis episodes, particularly during the COVID-19 period. This is more consistent with the intuition that risk proxies increase during crisis periods.

Lastly, Figure 3 plots the monthly median values of ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. The figure shows that the median of $\rho^{\Delta V^+}$ fluctuates around zero, while both ρ and $\rho^{\Delta V^+}$ exhibit pronounced downward spikes during the COVID-19 period. In contrast, although $\rho^{\Delta V^-}$ remains predominantly negative, it does not show distinct patterns around recessionary episodes. Consistent with the high cross-sectional correlation between ρ and $\rho^{\Delta V^+}$ reported in Table 1, their time-series correlation based on monthly cross-sectional medians is 87%. In contrast, the corresponding correlation between ρ and $\rho^{\Delta V^-}$ is substantially lower at 23%, while the correlation between $\rho^{\Delta V^+}$ and $\rho^{\Delta V^-}$ is negative at -28%. Although our analysis focuses primarily on cross-sectional variation, the time-series behavior of the median correlations closely mirrors the cross-sectional patterns documented in Table 1, confirming that $\rho^{\Delta V^+}$ captures most of the variation in ρ.

3 Empirical Results

This section presents the empirical analysis of the predictive power of ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$ for the cross-section of stock returns. We begin with univariate portfolio sorts to examine the return patterns associated with each measure. The results indicate that both ρ and $\rho^{\Delta V^+}$ exhibit a robust, statistically significant negative relation with subsequent returns, with $\rho^{\Delta V^+}$ displaying stronger predictive power. These findings are further corroborated by Fama–MacBeth regressions incorporating firm-level control variables.

3.1 Univariate Portfolio Sorts

At the end of each month, we construct quintile portfolios by sorting stocks on their realized correlation measures estimated over the preceding month. For each portfolio, we compute both value-weighted and equal-weighted returns in the subsequent month. In addition to the quintile portfolios, we construct a high-minus-low portfolio that takes a long position in the highest quintile and a short position in the lowest quintile, thereby capturing the return spread between the two extremes.

Table 2 reports the time-series average returns of the quintile portfolios, together with Newey–West adjusted t-statistics that account for potential autocorrelation and heteroskedasticity in the return series. Panel A presents the results of univariate sorts based on ρ, revealing a nearly monotonic decline in value-weighted average returns from 98 basis points (bps) in the lowest quintile to 67 bps in the highest quintile. This yields a statistically significant high-minus-low return spread of -31 bps with a robust t-statistic of -2.25, indicating a negative relation between ρ and subsequent stock returns. The equal-weighted sorts exhibit a similar pattern, with a high-minus-low return spread of -33 bps and a robust t-statistic of -3.64.

Panels B and C of Table 2 report the results of univariate portfolio sorts based on the decomposition of ρ into $\rho^{\Delta V^+}$ and $\rho^{\Delta V^-}$. Panel B presents the results for portfolios sorted on $\rho^{\Delta V^+}$. Both the value-weighted and equal-weighted portfolios exhibit a monotonic decline in average returns from the lowest to the highest quintile. The corresponding high-minus-low return spreads are -48 bps and -49 bps, with robust t-statistics of -3.46 and -4.49, respectively. Both the economic magnitude and statistical significance of these spreads exceed those observed for portfolios sorted on ρ, highlighting the importance of the upside component in explaining cross-sectional return variation. Panel C presents the results for portfolios sorted on $\rho^{\Delta V^-}$. Unlike the results based on $\rho^{\Delta V^+}$, the quintile portfolios do not exhibit a monotonic pattern, and the high-minus-low portfolio generates a statistically insignificant positive return.

Figure 4 plots the cumulative log returns of the value-weighted low-minus-high portfolios based on ρ and $\rho^{\Delta V^+}$ over the 1996–2023 period, together with the cumulative log return of the market portfolio. The figure highlights the superior long-run performance of the upside-correlation strategy relative to the overall-correlation strategy. Although the market portfolio exhibits a higher average return than the long-short portfolios based on ρ and $\rho^{\Delta V^+}$, it experiences substantially deeper drawdowns, particularly during recessionary periods. This difference is reflected in the annualized Sharpe ratios: the upside-correlation factor delivers the strongest risk-adjusted performance with a Sharpe ratio of 0.59, followed by the market portfolio at 0.52 and the overall-correlation factor at 0.39.

Overall, the portfolio-sort evidence indicates a strong negative relation between realized correlation measures and subsequent stock returns, with the predictive relation driven primarily by the upside component $\rho^{\Delta V^+}$.

3.2 Evidence from Fama-MacBeth Regressions

This section presents additional evidence on cross-sectional prediction using the leverage effect based on Fama–MacBeth regressions, supporting the results from the portfolio sorts in Table 2. Next, we include controls in the Fama–MacBeth regressions, discuss the relation with financial leverage, and control for well-known factors. Finally, we discuss the industry composition of the portfolios.

3.2.1 The Leverage Effect

Table 3 presents the results of the univariate Fama–MacBeth regressions based on ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. For each month, we estimate predictive cross-sectional regressions and report the time-series averages of the estimated coefficients together with Newey–West robust t-statistics computed using three lags. The findings are consistent with the portfolio sorts reported in Table 2, indicating that both ρ and $\rho^{\Delta V^+}$ are associated with statistically significant negative risk premiums. Specifically, the estimated risk premiums are -44 bps and -74 bps, with the corresponding robust t-statistics of -3.89 and -4.47, respectively. In contrast, $\rho^{\Delta V^-}$ does not exhibit statistically significant predictive power for future returns. These results suggest that $\rho^{\Delta V^+}$ captures the economically significant component of ρ that is most strongly related to cross-sectional variation in expected returns.

3.2.2 Alternative Cross-Sectional Predictors

While the portfolio sorts and the Fama–MacBeth regressions indicate a strong predictive relation between the realized correlation measures and future stock returns, these specifications do not account for other firm characteristics known to explain cross-sectional return variation. We therefore begin by reporting average firm characteristics across quintile portfolios sorted on ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. We then conduct predictive monthly Fama–MacBeth regressions of stock returns on ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$, controlling for a comprehensive set of firm-level variables from the literature: size (ME) and book-to-market ratio (BM) (Fama and French (1993)), momentum (MOM) (Jegadeesh and Titman (1993)), realized volatility (RVOL) (Andersen, Bollerslev, Diebold, and Ebens (2001)), reversal (REV) (Jegadeesh (1990); Lehmann (1990)), idiosyncratic volatility (IVOL) (Ang et al. (2006b)), illiquidity (ILLIQ) (Amihud (2002)), co-skewness (CSK) and co-kurtosis (CKT) (Harvey and Siddique (2000); Ang et al. (2006a)), and the maximum (MAX) and minimum (MIN) daily return (Bali et al. (2011)).

Table 4 reports value-weighted averages of firm characteristics in the ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$ quintile portfolios from Table 2. Across all correlation-sorted portfolios, we observe clear monotonic patterns in $Size$, $RVOL$, $ILLIQ$, and MOM, while REV, MAX, and MIN follow the same patterns for ρ and $\rho^{\Delta V^+}$ but not for $\rho^{\Delta V^-}$. Firm size declines monotonically from the lowest to the highest quintile, indicating that larger firms tend to exhibit more negative ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. Note that whereas size is negatively related to returns, the relation is also negative for ρ and $\rho^{\Delta V^+}$ but positive for $\rho^{\Delta V^-}$. Other (nearly) monotonic relations appear for $RVOL$ and $ILLIQ$, both of which increase from the lowest to the highest quintile. Short-term return reversal (REV) is one of the characteristics that does not share a common monotonic pattern across the three correlation measures: it rises from the lowest to the highest quintile for ρ and $\rho^{\Delta V^+}$, but declines for $\rho^{\Delta V^-}$. This differential exposure of upside and downside correlations to REV may in turn influence the estimated pricing effect of ρ. Turning to higher-moment characteristics, CSK becomes steadily less negative from the lowest to the highest quintile for ρ and $\rho^{\Delta V^+}$, while CKT declines, indicating that low-correlation portfolios exhibit stronger downside co-skewness and fatter-tail comovement. Consistent with this, MAX increases (and MIN becomes less negative) across quintiles for ρ and $\rho^{\Delta V^+}$, whereas these patterns are much weaker for $\rho^{\Delta V^-}$. Overall, these patterns indicate that the correlation-sorted portfolios load on firm characteristics in a way that is not fully captured by standard anomalies, suggesting that the correlation premia contain information about expected returns beyond existing risk or mispricing effects.

3.2.3 Fama–MacBeth Regressions with Control Variables

Panel A of Table 5 reports the results from univariate Fama–MacBeth regressions for each firm-specific characteristic. The estimated coefficients exhibit signs consistent with economic intuition and the prior literature. Among the variables considered, ME, BM, MOM, ILLIQ, CKT, and MIN yield statistically insignificant coefficients. The insignificance of ME and BM is consistent with Hou and Van Dijk (2019) and Gonçalves and Leonard (2023), which document that the traditional BM and ME signals are substantially weaker in the post-1996 period.

Panel B reports the results of multivariate Fama–MacBeth regressions including ρ, $\rho^{\Delta V^+}$, $\rho^{\Delta V^-}$, and the full set of firm-level control variables. Specifications I and III–V demonstrate that ρ remains statistically significant and negatively associated with future stock returns across various combinations of firm-specific controls. In particular, Specification I, which includes all firm-level characteristics, indicates that a two-standard-deviation decrease in ρ is associated with a 1.55% increase in annualized returns ($2 \times 0.307 \times 0.21/100 \times 12$). Specifications III–V incorporate different subsets of control variables, and the risk premiums associated with ρ remain statistically significant in all models, ranging from -35 to -19 basis points, with corresponding t-statistics between -4.17 and -2.48. Notably, in Specification V, where skewness-related proxies—co-skewness (CSK) and maximum daily return (MAX)—are included as additional controls, the effect of ρ remains robust and significant. In contrast, CSK loses its statistical significance and MAX is associated with a positive coefficient, which is inconsistent with theoretical predictions related to the skewness effect. This sign reversal for MAX is consistent with the evidence in Bollerslev et al. (2020), where MAX changes sign once other skewness-related controls are included.

Furthermore, consistent with earlier findings suggesting that $\rho^{\Delta V^+}$ isolates the economically and statistically significant component of ρ, Specifications II and VI–VIII demonstrate that $\rho^{\Delta V^+}$ remains statistically significant and negatively associated with future stock returns. Moreover, the magnitude of its estimated coefficient implies a higher price of risk relative to ρ, highlighting its stronger predictive power in the cross-section. Specifically, Specification II shows that a two-standard-deviation decrease in $\rho^{\Delta V^+}$ is associated with a 2.29% increase in annualized returns ($2 \times 0.251 \times 0.38/100 \times 12$). Specifications VI–VIII incorporate different sets of control variables analogous to those used in Specifications III–V. Across all models, the effect of $\rho^{\Delta V^+}$ remains statistically significant and negatively related to future returns, with the associated risk premiums ranging from -72 to -36 basis points and corresponding t-statistics ranging from -5.05 to -3.37.

The Fama–MacBeth regressions confirm that ρ contains information about future stock returns that is not captured by standard firm-level characteristics. The negative and statistically significant risk premiums associated with ρ persist across various model specifications, even after controlling for a comprehensive set of return predictors. While ρ maintains a robust negative association with returns, $\rho^{\Delta V^+}$ consistently demonstrates stronger explanatory power and implies a higher price of risk. These results highlight the economic relevance of ρ and $\rho^{\Delta V^+}$ in explaining cross-sectional variation in stock returns.

3.3 Financial Leverage, Realized Correlation, and Returns

The results so far show that the predictive power of the realized correlation measures is not subsumed by standard cross-sectional return predictors. An important remaining question, however, is whether the realized correlation measures primarily proxy for financial leverage. This possibility is particularly relevant given the longstanding interpretation of the return–volatility relation through the leverage effect channel. We therefore examine the relation between financial leverage, realized correlation, and expected stock returns.

Financial leverage is another natural candidate predictor of expected cross-sectional returns because, in structural models, equity is an option claim on firm value, so higher leverage mechanically amplifies equity's exposure to shocks to underlying assets (see Merton (1974)).

Yet the empirical evidence is mixed. Early tests find that average returns increase with market leverage (e.g., Bhandari (1988) and Fama and French (1992)), while other results show weak, zero, or even negative relations for book leverage (e.g., Fama and French (1992) and George and Hwang (2010)), and zero or negative explanatory power for market leverage once size and book-to-market are controlled for (e.g., Penman, Richardson, and Tuna (2007)). Related work frames this as a puzzle and offers resolutions (see George and Hwang (2010), Gomes and Schmid (2010), and Ippolito, Steri, Tebaldi, and Villa (2025)).[10]

Another strand of this literature links financial leverage to asymmetric variance. Under the leverage effect hypothesis, a negative stock return lowers the market value of equity and mechanically raises leverage, making equity riskier and increasing volatility (Black, 1976; Christie, 1982). Consistent with the leverage channel, Daouk and Ng (2011) show that scaling equity volatility by the equity-to-firm-value ratio to obtain unlevered (asset) volatility yields volatility that is largely symmetric at the firm level but not at the index level. However, Figlewski and Wang (2000) show that financial leverage appears insufficient to explain the magnitude and negativity of the return-volatility correlation. Consistent with this, Hasanhodzic and Lo (2019) show that the leverage effect persists even among zero-leverage firms.

In this section, we revisit the relation between financial leverage and the cross-section of stock returns, and examine how financial leverage relates to our correlation measures. Following Halling, Yu, and Zechner (2016), we employ three financial leverage variables: book leverage ($BLEV$), market leverage ($MLEV$), and net book leverage ($NBLEV$).[11] Panels A and B of Table 6 report the relation between financial leverage and our correlation variables. Panel A presents the value-weighted average financial leverage characteristics across monthly quintile portfolios sorted on ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$, along with the high-minus-low spread, with Newey-West robust t-statistics reported in parentheses. While the theory suggests that more highly levered firms should have more negative ρ, we instead find a statistically significant positive high-minus-low spread. This means that more negative ρ values are associated with

[10]Doshi, Jacobs, Kumar, and Rabinovitch (2019) argue the return–leverage relation is nonlinear; unlevering returns sharply weakens the value premium and the volatility puzzle.

[11]We use quarterly Compustat data to construct the financial leverage variables. $BLEV$ is the total debt to total assets (book value) ratio, $MLEV$ is the total debt to total assets (market value) ratio, and $NBLEV$ is the total debt less cash and short-term investments to total assets (book value) ratio. Each quarterly leverage observation is carried forward and matched to all months in the subsequent quarter until the next Compustat quarter is available.

firms with lower financial leverage. Panel B reports equal-weighted and value-weighted means of ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$ across financial leverage bottom and top quintiles and for subsamples defined by financial leverage restrictions. We form quintile portfolios based on each financial leverage measure and report the difference between the average correlation measures in the bottom quintile and the average correlation measures in the top quintile (bottom minus top). Theory predicts a significantly positive bottom-minus-top difference. The equal-weighted results support this prediction, whereas the value-weighted results are of the opposite sign, consistent with the evidence in Panel A. Overall, the portfolio approach shows that the financial leverage–correlation relation is highly sensitive to weighting. Further, we examine firms with zero financial leverage (Leverage = 0 or Net Leverage= 0), and firms with negative net leverage (Net Leverage < 0).[12] If ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$ proxy only for financial leverage, then the correlation measures should be statistically indistinguishable from zero within the subsamples defined by these leverage restrictions. However, Panel B reports statistically significant average correlations, under both equal and value weighting and for all three measures, across all restricted subsamples. These results imply that firm size plays an important role in the relation between the correlation measures and financial leverage, and that our correlation measures capture return–variance comovement beyond financial leverage, consistent with Figlewski and Wang (2000) and Hasanhodzic and Lo (2019).

Panel C of Table 6 reports predictive Fama-MacBeth regressions of stock returns on our correlation measures and financial leverage controls. The column labeled "Univariate" reports the univariate regression coefficients. In univariate specifications, all financial leverage variables are insignificant with negative coefficients. In multivariate specifications from I to VI, we first estimate regressions that include ρ together with each financial leverage measure, and then analogous regressions that include $\rho^{\Delta V^+}$ and $\rho^{\Delta V^-}$ alongside financial leverage controls. The results show that the coefficients on ρ and $\rho^{\Delta V^+}$ are significantly negative across all specifications, whereas the financial leverage variables exhibit no predictive power. Lastly, following the literature (e.g., Penman et al. (2007)), Specifications VII and VIII additionally control for size and book-to-market from Fama and French (1993). The results show that ρ and $\rho^{\Delta V^+}$ are significantly negative while the coefficient on $BLEV$ is marginally negative. The negative coefficient on book leverage after controlling for size and book-to-market is

[12] A firm must have zero debt to have zero leverage, but it can have zero (or negative) net leverage if its cash holdings are equal to (or exceed) its debt.

consistent with Fama and French (1992), Penman et al. (2007), and George and Hwang (2010). Overall, the return predictability of ρ and $\rho^{\Delta V^+}$ is distinct from, and not subsumed by, financial leverage.

3.4 Factor-Adjusted Long-Short Portfolio Returns

We next examine whether the return predictability associated with the realized correlation measures is captured by existing asset pricing factors and firm-characteristic-based factors. Figure 4 provides preliminary evidence that market returns are not highly correlated with the long-short portfolio returns based on ρ and $\rho^{\Delta V^+}$. Table 7 further investigates this relation using time-series regressions of the monthly value-weighted long-short portfolio returns constructed from ρ and $\rho^{\Delta V^+}$. We report the intercepts from these regressions, which correspond to abnormal returns unexplained by the factor models.

Panel A of Table 7 reports the results based on standard asset pricing factor models from the literature. Specifically, we consider the CAPM, the three-factor model of Fama and French (1993) (FF3), the FF3 model augmented with the momentum factor of Carhart (1997) (FFC4), the five-factor model of Fama and French (2015) (FF5), and the augmented q^5 model of Hou, Mo, Xue, and Zhang (2021). The abnormal returns associated with $\rho^{\Delta V^+}$ are negative and statistically significant, ranging from -43 to -46 bps per month. These estimates closely match the -48 bps high-minus-low return spread from the univariate portfolio sorts. In the case of the total correlation (ρ), the abnormal returns range from -24 to -36 bps per month, which is also close to the univariate estimate of -31 bps. Although the statistical significance weakens somewhat under the FFC4 specification, it remains largely unchanged across the other factor models.

Panel B reports time-series regressions using factors based on firm characteristics including RVOL, IVOL, REV, and ILLIQ. As in Panel A, we report the intercepts of these regressions, which correspond to abnormal returns unexplained by the factors. The abnormal returns associated with $\rho^{\Delta V^+}$ and ρ remain negative and statistically significant, with magnitudes close to those obtained from the univariate portfolio sorts. While REV explains some portion of the variation in ρ, resulting in t-statistics on the abnormal returns of -1.91, the results for $\rho^{\Delta V^+}$ remain strong with t-statistics of -3.09. Overall, the abnormal returns for $\rho^{\Delta V^+}$ continue to be negative and statistically significant across all specifications, indicating that existing factor models and factors based on firm characteristics do not account for the cross-sectional predictability associated with ρ and $\rho^{\Delta V^+}$.

Overall, the factor-adjusted results confirm that the realized correlation measures contain predictive information for the cross-section of stock returns that is not captured by standard asset pricing factors. In particular, the evidence suggests that the predictive relation is driven primarily by the upside component $\rho^{\Delta V^+}$.

3.5 Portfolio Composition

Having established that the predictive power of ρ and $\rho^{\Delta V^+}$ is robust to standard risk factors, we next examine the composition of the correlation-sorted portfolios and how it evolves over time. Figure 5 presents time-series heatmaps based on the 12 Fama–French industries. For each industry-year, we identify the dominant quintile portfolio as the portfolio in which that industry has the highest representation, measured as the ratio of the number of stocks from that industry in the portfolio to the total number of stocks in the portfolio during that year.

Panel A reports the time-series industry composition of the ρ-sorted quintile portfolios, while Panel B reports the corresponding composition for the $\rho^{\Delta V^+}$-sorted portfolios, with blue indicating low-correlation portfolios and red indicating high-correlation portfolios. The ρ- and $\rho^{\Delta V^+}$-sorted portfolios exhibit both common and distinct industry patterns. While several industries switch across low- and high-quintile portfolios in both panels, the heatmap for ρ is more dispersed across quintiles, whereas the $\rho^{\Delta V^+}$ portfolios display a more concentrated and persistent industry composition, particularly for the low-quintile portfolio.

Specifically, industries indexed by 6, 9, 10, and 12 are persistently assigned to the high-ρ portfolio. These correspond to business equipment (computers, software, and electronic equipment), wholesale, healthcare (healthcare, medical equipment, and drugs), and "other" (mines, construction, building materials, transportation, hotels, business services, and entertainment). By contrast, the high-$\rho^{\Delta V^+}$ portfolio is dominated by industries 6, 10, and 12, while industry 9 (wholesale) is strikingly concentrated in the low-$\rho^{\Delta V^+}$ portfolio. For the first half of the sample, industry 3 (manufacturing) is predominantly assigned to the low-$\rho^{\Delta V^+}$ portfolio, whereas its allocation across the ρ portfolios is more mixed.

4 Does the Leverage Effect Outperform Skewness?

The previous sections establish that ρ and particularly $\rho^{\Delta V^+}$ exhibit strong and robust predictive power for the cross section of stock returns. An important remaining question is how these measures relate to existing proxies for asymmetric risk, including realized skewness and signed jump variation. Does the predictive power of realized correlation reflect information already captured by traditional asymmetry measures, or does it provide a distinct and more reliable measure of asymmetric risk? In this section, we compare the persistence and predictive performance of ρ and $\rho^{\Delta V^+}$ with alternative asymmetric risk measures. We find that realized correlation outperforms these other measures, and we provide intuition for this strong performance.

4.1 Skewness and Asymmetric Variance Proxies

The literature has investigated the cross-sectional predictive power of various other proxies for skewness and asymmetric variance. We compare ρ and $\rho^{\Delta V^+}$ with realized skewness (RSK) (Amaya et al. (2015)) and relative signed jump variation (RSJ) (Bollerslev et al. (2020)). We construct RSK and RSJ using high-frequency returns, and RSK_D and RSJ_D using daily returns, as described in the Appendix. While prior studies construct these measures at the weekly frequency, we aggregate them to the monthly level to match our focus on monthly returns.

Panel A of Table 8 reports the average monthly cross-sectional correlations between ρ, $\rho^{\Delta V^+}$, and the alternative asymmetric variance proxies. Each month, we compute pairwise cross-sectional correlations across all variables and then report their time-series averages. The correlation between ρ and $\rho^{\Delta V^+}$ is 0.88, and both variables exhibit strong correlations with RSK_D and RSJ_D, ranging from 0.44 to 0.67, consistent with their role as proxies for skewness. In contrast, their correlations with the high-frequency counterparts, RSK and RSJ, are substantially lower, ranging from 0.08 to 0.19.[13]

[13]Consistent with Bollerslev et al. (2020), RSK and RSJ exhibit a correlation of 0.89, while their daily counterparts exhibit a correlation of 0.94.

4.2 Univariate Portfolio Sorts and Persistence

We next examine the predictive power of ρ, $\rho^{\Delta V^+}$, and the alternative asymmetric variance proxies. A key challenge with conventional skewness measures is their low persistence and weak empirical performance when estimated over short windows, as emphasized by Bali et al. (2016). We therefore investigate the persistence of these signals over time. Each month, stocks are sorted into quintile portfolios based on the lagged values of each variable, and we compute value-weighted high-minus-low portfolio returns. Panel B of Table 8 reports these returns together with the average ex-post realizations of the sorting variables in the high-minus-low portfolios, allowing us to assess both return predictability and signal persistence.[14]

Panel B of Table 8 shows that both ρ and $\rho^{\Delta V^+}$ yield negative and statistically significant high-minus-low portfolio returns. Importantly, both measures satisfy the persistence criterion for a firm characteristic, with ρ exhibiting stronger persistence. In contrast, Bali et al. (2016) show that skewness measures estimated using shorter windows lack persistence and fail to generate robust risk premiums in value-weighted portfolio sorts and Fama–MacBeth regressions. Consistent with these findings, although the high-minus-low portfolios based on RSK_D and RSJ_D generate significantly negative returns, the variables themselves exhibit weak persistence and even reversal patterns. This lack of persistence makes it difficult to interpret RSK_D and RSJ_D as stable firm characteristics. By contrast, the high-frequency counterparts, RSK and RSJ, display strong persistence, yet their associated high-minus-low portfolio returns are not significantly different from zero.[15]

Overall, these results highlight ρ, and particularly $\rho^{\Delta V^+}$, as the variables that most consistently combine return predictability with persistence, supporting their interpretation as stable firm-level characteristics linked to skewness.

4.3 Bivariate Sorts with Alternative Asymmetry Measures

Table 9 presents double-sort results controlling for realized skewness (RSK) and relative signed jump variation (RSJ) in the predictive relation between ρ, $\rho^{\Delta V^+}$, and future stock returns. Each month, we first sort stocks into quintiles based on RSK or RSJ and then,

[14] The corresponding results under alternative portfolio sorts are reported in Table A.1.

[15] Bollerslev et al. (2020) note that while RSJ predicts returns at the weekly horizon, its predictive power becomes statistically insignificant at the monthly horizon.

within each quintile, sort stocks into quintiles based on ρ or $\rho^{\Delta V^+}$.

The results show that both ρ and $\rho^{\Delta V^+}$ remain economically and statistically significant after controlling for RSK and RSJ under both value- and equal-weighting. In particular, the return spreads associated with $\rho^{\Delta V^+}$ remain large and highly significant across specifications, indicating that the predictive power of realized correlation is not subsumed by high-frequency skewness and jump-based asymmetry measures.

Table A.2 in the Appendix reports analogous double-sort results controlling for the daily-return counterparts, RSK_D and RSJ_D. The results are qualitatively similar. While the daily skewness measures absorb part of the predictive content of ρ in value-weighted portfolios, $\rho^{\Delta V^+}$ continues to generate economically and statistically significant return spreads under both value- and equal-weighting.

Overall, the results indicate that the predictive power of ρ and particularly $\rho^{\Delta V^+}$ is robust to controlling for existing asymmetric risk measures.

4.4 Fama-MacBeth Regressions with Asymmetric Risks

Beyond portfolio sorts, we compare the predictive power of ρ, $\rho^{\Delta V^+}$, and the alternative asymmetric variance proxies using Fama–MacBeth regressions controlling for the firm characteristics used in Table 5. Panel A of Table 10 reports univariate predictive regressions for RSK_D, RSJ_D, RSK, and RSJ. Consistent with Amaya et al. (2015) and Bollerslev et al. (2020), all variables exhibit statistically significant negative relations with subsequent stock returns, indicating that negative asymmetry in return distributions is associated with higher expected returns.

Panel B reports multivariate regressions that first include either ρ or $\rho^{\Delta V^+}$ together with the alternative asymmetric variance proxies, and then additionally incorporate the firm-level controls used in Table 5. This approach allows us to assess the explanatory power of ρ and $\rho^{\Delta V^+}$ beyond RSK and RSJ (and their daily counterparts). Specifications I–IV show that ρ remains statistically significant and negatively associated with future stock returns. In contrast, RSK_D changes sign once we control for ρ and RSJ_D.[16] Likewise, RSJ becomes insignificant once we control for ρ and RSK, while RSK loses its marginal statistical significance once the firm-specific controls are included, suggesting that their predictive power

[16]Bollerslev et al. (2020) argue that the sign change in RSK_D after controlling for RSJ_D is driven by the high correlation between the two measures.

is subsumed by the firm-level controls and the information captured by ρ. Interestingly, RSJ_D remains significantly negative alongside ρ. Specifications V–VIII yield similar results when $\rho^{\Delta V^+}$ is employed as the main explanatory variable. Consistent with our earlier findings, $\rho^{\Delta V^+}$ exhibits larger estimated risk premiums and stronger t-statistics than ρ, indicating a stronger and more robust association with future stock returns.

4.5 Monte Carlo Evidence

The empirical results show that ρ and particularly $\rho^{\Delta V^+}$ exhibit stronger persistence and more robust return predictability than conventional skewness measures. In this section, we provide intuition for these findings using a simple stochastic volatility framework and Monte Carlo evidence.

Consider a stochastic volatility model with jumps:

$$dp_t = (\mu - \frac{1}{2}V_t - \bar{\mu}_J\lambda)dt + \sqrt{V_t}dW_t^{(1)} + JdN_t, \tag{7}$$

$$dV_t = \kappa(\theta - V_t)dt + \sigma\sqrt{V_t}dW_t^{(2)}, \tag{8}$$

where the Brownian motions satisfy $\mathrm{corr}(dW_t^{(1)}, dW_t^{(2)}) = \rho$. The definition of the volatility parameters is standard, $R = p_T - p_0$ denotes the log return, and N_t is a Poisson jump process with jump size J, jump frequency λ, and average jump size μ_J and jump variance σ_J^2. The drift correction term $\bar{\mu}_J$ is equal to $\exp(\mu_J + \sigma_J^2/2) - 1$. In this setting, total cubic variation can be decomposed into jump and diffusive components:[17]

$$\mathrm{E}_0\Big[(R - \mathrm{E}_0[R])^3\Big] = \lambda\big(\mu_J^3 + 3\mu_J\sigma_J^2\big)\,T + \frac{3\rho\sigma}{\kappa}\Big[V_0\,\frac{1 - e^{-\kappa T}(\kappa T + 1)}{\kappa} + \theta\Big(\frac{e^{-\kappa T}(\kappa T + 2) - 2}{\kappa} + T\Big)\Big]. \tag{9}$$

The first term corresponds to the jump component of cubic variation, which in the empirical literature has been proxied by realized skewness (Amaya et al. (2015)) and realized signed jump variation (Bollerslev et al. (2020)). The second term corresponds to the diffusive component, which is directly linked to the return–variance correlation ρ. Thus, realized skewness converges to the jump part of the total cubic variation and does not account for

[17]The formula omits the $O(T^{5/2})$ remainder, which is negligible at our simulation and empirical horizons.

the diffusive components (Neuberger and Payne, 2021). This contrasts with realized variance, which converges to the total quadratic variation of the process.

This decomposition helps explain why conventional skewness measures often exhibit weak persistence and unstable predictive power at short horizons. Measures based on cubic returns primarily isolate jump asymmetry and are therefore sensitive to rare events and sampling variation. By contrast, ρ captures the diffusive component of asymmetry embedded in the continuous return–variance relation. To illustrate the importance of this distinction, we conduct a Monte Carlo exercise based on the stochastic volatility model above without price jumps ($\lambda = 0$). The details regarding the simulation design and parameter calibration are provided in the Appendix. Figure 6 compares the cross-sectional ranking implied by the true cubic variation in Equation (9) to the rankings obtained using ρ and sample skewness over one-month, one-year, and five-year horizons. Panels A, C, and E show that ρ closely tracks the true cross-sectional ranking, with the average Spearman rank correlation increasing from 0.574 at the one-month horizon to 0.917 at one year and 0.979 at five years. By contrast, Panels B, D, and F show that sample skewness is substantially noisier, particularly at short horizons. Its average Spearman rank correlation is only 0.011 at the one-month horizon and remains materially below that of ρ even at longer horizons. The gradual increase in this correlation as the horizon increases aligns with the evidence in Bali et al. (2016) that sample skewness is more persistent and its cross-sectional predictive power improves when measured over longer horizons, but longer horizons may of course cause problems if the unknown true skewness is time-varying.

Overall, the decomposition and simulation evidence provide useful intuition for the empirical results in the paper. The leverage effect, measured by ρ, provides a proxy for the diffusive component of cubic variation that is persistent and generates robust cross-sectional predictability, even when measured over relatively short horizons. Conventional realized skewness measures, on the other hand, contain different information that is less robustly measured at shorter horizons. While these results of course depend on the parameterization of equations (7) and (8), we verified that they are robust for reasonable parameterizations.

4.6 Predicted Ranks and Asymmetric Risk Measurement

Langlois (2020) argues that conventional skewness measures suffer from substantial measurement error and proposes forecasting the cross-sectional ranks of skewness using firm characteristics rather than relying on directly estimated measures. The objective of this approach is to improve the persistence and pricing performance of skewness measures by filtering out estimation noise. Motivated by this idea, we examine whether applying a similar predicted-rank methodology to our correlation-based measures leads to additional improvements in predictive performance. If realized correlation already captures asymmetric risk more precisely than conventional skewness measures, then the gains from characteristic-based smoothing should be substantially smaller.

Following Langlois (2020), for each month t we estimate the following panel regression:

$$F(\rho_{i,t-2\to t-1}) = \alpha + F(Y_{i,t-14\to t-3})\theta + F(X_{i,t-3})\gamma + \epsilon_{i,t-2\to t-1}, \tag{10}$$

where $F(x_{i,t}) = \frac{Rank(x_{i,t})}{N_t+1}$ denotes the normalized cross-sectional rank of variable $x_{i,t}$. The vector $Y_{i,t-14\to t-3}$ contains lagged risk measures, while $X_{i,t-3}$ contains firm characteristics including size, momentum, and book-to-market. Using the estimated coefficients from Equation (10), we obtain predicted ranks for ρ and $\rho^{\Delta V^+}$ and construct portfolios based on these predicted ranks.

Table 11 reports the results. Panel A shows that the high-minus-low returns for the predicted-rank portfolios are economically similar to those obtained from the directly estimated correlation measures. In particular, both $\widehat{\rho}$ and $\widehat{\rho}^{\Delta V^+}$ generate negative and statistically significant return spreads that closely match the corresponding spreads for ρ and $\rho^{\Delta V^+}$. Panel B further shows that the return series from the realized and predicted-rank portfolios are highly correlated, with correlations of approximately 93% for ρ and 95% for $\rho^{\Delta V^+}$.

Overall, the results indicate that the directly estimated correlation measures already capture most of the priced information contained in the characteristic-based predicted-rank approach. This finding suggests that measurement error is less severe for the correlation measures than for conventional skewness estimators.

5 Robustness

This section presents additional analyses that further assess the robustness and interpretation of the realized correlation measures. We examine alternative decompositions of realized correlation, reformulate the measures as firm-level and systematic variance exposures, and investigate lead–lag specifications motivated by the leverage effect and volatility-feedback hypotheses.

5.1 Alternative Decompositions of Realized Correlation

We further examine alternative decompositions of the realized correlation, ρ, and compare their performance to the decomposition based on the sign of variance innovations. As a first alternative, we consider a decomposition conditional on return states, separating positive-return ($r^+_{t,d,j} = \max(r_{t,d,j}, 0)$) and negative-return periods ($r^-_{t,d,j} = \min(r_{t,d,j}, 0)$):

$$\begin{aligned}\rho_{t,j} &= \frac{\sum_{d=1}^{D} r^+_{t,d,j}\Delta RV_{t,d,j}}{\sqrt{\sum_{d=1}^{D} r^2_{t,d,j}}\sqrt{\sum_{d=1}^{D} \Delta RV^2_{t,d,j}}} + \frac{\sum_{d=1}^{D} r^-_{t,d,j}\Delta RV_{t,d,j}}{\sqrt{\sum_{d=1}^{D} r^2_{t,d,j}}\sqrt{\sum_{d=1}^{D} \Delta RV^2_{t,d,j}}} \qquad (11)\\ &\equiv \rho^{r^+}_{t,j} + \rho^{r^-}_{t,j}. \qquad (12)\end{aligned}$$

As a second alternative, we consider a joint decomposition based on both return states and variance-innovation states, yielding four distinct components:

$$\begin{aligned}\rho_{t,j} &= \frac{\sum_{d=1}^{D} r^+_{t,d,j}\Delta V^+_{t,d,j}}{\sqrt{\sum_{d=1}^{D} r^2_{t,d,j}}\sqrt{\sum_{d=1}^{D} \Delta RV^2_{t,d,j}}} + \frac{\sum_{d=1}^{D} r^+_{t,d,j}\Delta V^-_{t,d,j}}{\sqrt{\sum_{d=1}^{D} r^2_{t,d,j}}\sqrt{\sum_{d=1}^{D} \Delta RV^2_{t,d,j}}}\\ &\quad + \frac{\sum_{d=1}^{D} r^-_{t,d,j}\Delta V^+_{t,d,j}}{\sqrt{\sum_{d=1}^{D} r^2_{t,d,j}}\sqrt{\sum_{d=1}^{D} \Delta RV^2_{t,d,j}}} + \frac{\sum_{d=1}^{D} r^-_{t,d,j}\Delta V^-_{t,d,j}}{\sqrt{\sum_{d=1}^{D} r^2_{t,d,j}}\sqrt{\sum_{d=1}^{D} \Delta RV^2_{t,d,j}}} \qquad (13)\\ &\equiv \rho^{r^+\Delta V^+}_{t,j} + \rho^{r^+\Delta V^-}_{t,j} + \rho^{r^-\Delta V^+}_{t,j} + \rho^{r^-\Delta V^-}_{t,j}.\end{aligned}$$

Table 12 evaluates the return predictability of these alternative decompositions using Fama–MacBeth regressions. Both ρ^{r^+} and ρ^{r^-} exhibit significantly negative coefficients in a joint regression of both; but their predictive power disappears once ρ or $\rho^{\Delta V^+}$ is included in the regressions. Similarly, although $\rho^{r^+\Delta V^+}$ and $\rho^{r^-\Delta V^+}$ display statistically significant predictive power in a joint setting of four components, their explanatory content is subsumed by $\rho^{\Delta V^+}$. Overall, the results indicate that the decomposition of ρ based on the sign of variance innovations captures the return-relevant information more effectively than alternative decompositions.

5.2 Firm-Level and Systematic Variance Exposures

The return-variance correlation in equation (3) is a natural alternative to proxy skewness-related risks. Nevertheless, it is also intuitively appealing to scale the relevant information somewhat differently by using covariance–variance ratios instead of realized correlations between returns and variance innovations. This transformation preserves the economic content of the measures while allowing us to interpret them as sensitivities or exposures to firm-level variance shocks. Formally, we compute the total firm-level variance exposure ($\beta_{\Delta V}$), exposure to positive firm-level variance innovations ($\beta_{\Delta V^+}$), and exposure to negative firm-level variance innovations ($\beta_{\Delta V^-}$) as

$$\beta_{\Delta V,t,j} = \frac{\sum_{d=1}^{D} r_{t,d,j}\Delta RV_{t,d,j}}{\sum_{d=1}^{D} \Delta RV_{t,d,j}^2}, \qquad \beta_{\Delta V^+,t,j} = \frac{\sum_{d=1}^{D} r_{t,d,j}\Delta V_{t,d,j}^+}{\sum_{d=1}^{D} \Delta RV_{t,d,j}^2}, \tag{14}$$

$$\beta_{\Delta V^-,t,j} = \frac{\sum_{d=1}^{D} r_{t,d,j}\Delta V_{t,d,j}^-}{\sum_{d=1}^{D} \Delta RV_{t,d,j}^2}.$$

where $\Delta V_{t,d,j}^+ = \max(\Delta RV_{t,d,j}, 0)$ and $\Delta V_{t,d,j}^- = \min(\Delta RV_{t,d,j}, 0)$.

Panel A of Table 13 reports monthly value-weighted quintile portfolio returns formed on the firm-level variance exposures and their decompositions. The results closely mirror the main findings for ρ and $\rho^{\Delta V^+}$. Exposure to firm-level variance innovations, $\beta_{\Delta V}$, is priced negatively in the cross section, with a statistically significant high-minus-low spread of -20 bps per month. The pricing effect becomes stronger for exposure to positive variance innovations, $\beta_{\Delta V^+}$, which generates a statistically significant spread of -35 bps per month, whereas the spread for $\beta_{\Delta V^-}$ is statistically insignificant. These findings indicate that the negative pricing relation is concentrated in sensitivity to increases in firm-level variance.

Equation (14) also clarifies the connection between our analysis and the literature on *systematic* variance risk. Several studies show that stocks with higher exposure to aggregate volatility innovations earn lower average returns (e.g., Ang et al. (2006b) and Detzel, Duarte, Kamara, Siegel, and Sun (2023)), while other work emphasizes that these pricing effects are concentrated in sensitivity to increases in market volatility (e.g., DeLisle, Doran, and Peterson (2011)). Motivated by this literature, we next examine whether the asymmetry documented for firm-level variance exposures also appears for exposures to systematic variance innovations.

Following Ang et al. (2006b), we estimate systematic variance exposures using both squared VIX innovations and innovations in SPY realized variance. Specifically, for each month t and stock j, we estimate the following time-series regression using daily stock returns $r_{t,d,j}$, daily CRSP value-weighted market returns $r_{t,d,M}$, and daily innovations in a systematic variance measure $\Delta X_{t,d}$:

$$r_{t,d,j} = \alpha_{t,j} + \beta_{M,t,j} r_{t,d,M} + \beta_{\Delta X,t,j} \Delta X_{t,d} + \varepsilon_{t,d,j}, \tag{15}$$

where $\Delta X_{t,d}$ corresponds either to innovations in squared VIX or innovations in SPY realized variance. We further decompose systematic variance innovations into positive and negative components to separately estimate exposures to increases and decreases in aggregate variance.

Panel A of Table 13 also reports monthly value-weighted quintile portfolio returns formed on the systematic variance exposures and their decompositions. Consistent with the existing literature, total systematic variance exposure is priced negatively in the cross section. More importantly, decomposing the exposures reveals that the negative pricing effects are concentrated in sensitivity to positive variance innovations. Firms with higher exposure to increases in systematic variance earn significantly lower subsequent returns, whereas exposures to negative variance innovations do not exhibit robust pricing effects.

Panel B of Table 13 reports Fama–MacBeth regressions controlling for the standard firm characteristics used in Table 5. The results confirm that the pricing effects are concentrated in the positive variance-innovation components. In particular, the coefficients on $\beta_{\Delta VIX^{2+}}$ and $\beta_{\Delta V^{+}}$ remain negative and statistically significant across specifications, while the negative innovation components are generally insignificant. Overall, the results show that the asymmetry documented for the realized correlation measures extends naturally to both firm-level and systematic variance exposures.

5.3 Lead–Lag Correlations and Volatility Feedback

The negative return–variance relation may arise from either a leverage channel or volatility feedback. The leverage hypothesis implies that returns lead variance, whereas volatility feedback implies that variance innovations affect contemporaneous or future returns. Motivated by this distinction, we construct realized correlation measures using one-day leads and lags of variance innovations.

Table A.3 in the Appendix reports portfolio-sort and Fama–MacBeth regression results for the lead–lag specifications. Overall, the strongest and most robust effects arise from contemporaneous correlations between returns and positive variance innovations, supporting our focus on contemporaneous return–variance correlations in the main analysis.

5.4 Additional Robustness Results

Appendix A.4 reports several additional robustness analyses. First, we show that the results from portfolio sorts remain qualitatively unchanged under alternative sorting schemes including quartile and decile portfolios. Second, we verify that the results are robust to using the bias-corrected leverage-effect estimator of Aït-Sahalia, Fan, and Li (2013). Third, we show that the predictive power of ρ and $\rho^{\Delta V^+}$ remains statistically significant after controlling for volatility-of-volatility proxied by realized quarticity.

6 Conclusion

We show that cross-sectional variation in the leverage effect helps explain differences in expected stock returns. Consistent with economic priors, our empirical analysis reveals a strong negative relation between the leverage effect and subsequent stock returns that remains robust after controlling for known risk factors and firm characteristics. Our use of the leverage effect attempts to provide a solution to the well-documented low-persistence problems associated with measuring skewness. Our measure exhibits greater persistence and performs better empirically compared to traditional skewness proxies and asymmetric variance measures, while subsuming their explanatory power in multivariate specifications.

Decomposing the leverage effect into upside and downside components shows that only the upside correlation drives the cross-sectional relation, while downside correlations show no systematic association with returns. This finding provides new insight into the structure of asymmetric risk premia in equity markets. Overall, our results demonstrate the relevance of the leverage effect for cross-sectional asset pricing and contribute to the literature on the pricing of asymmetric risk in the cross-section of stock returns.

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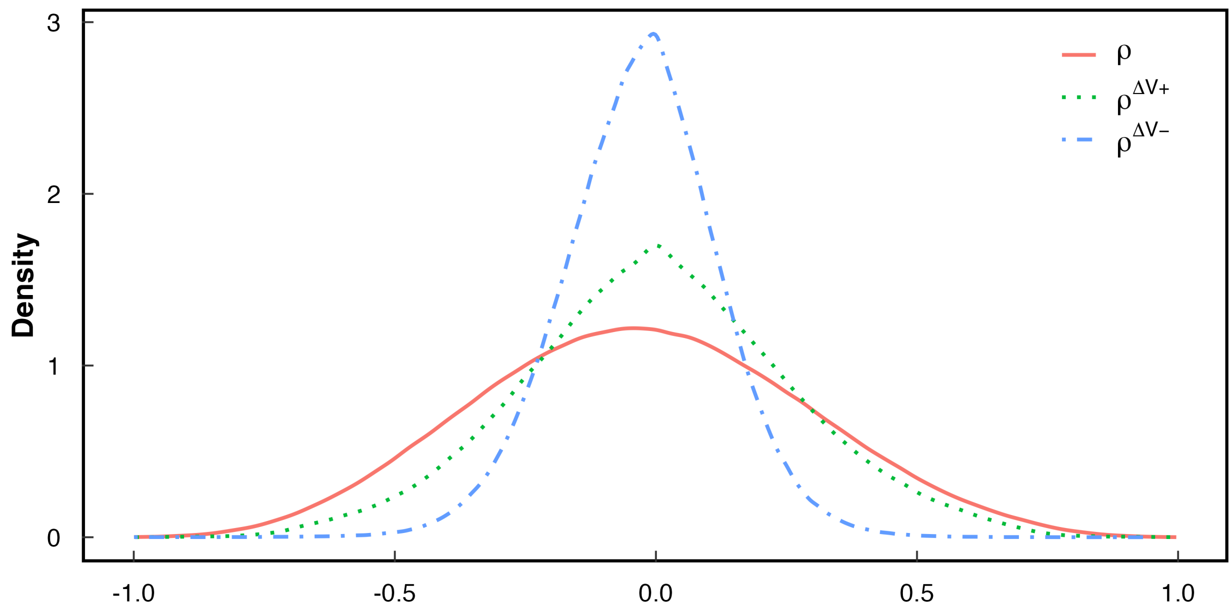
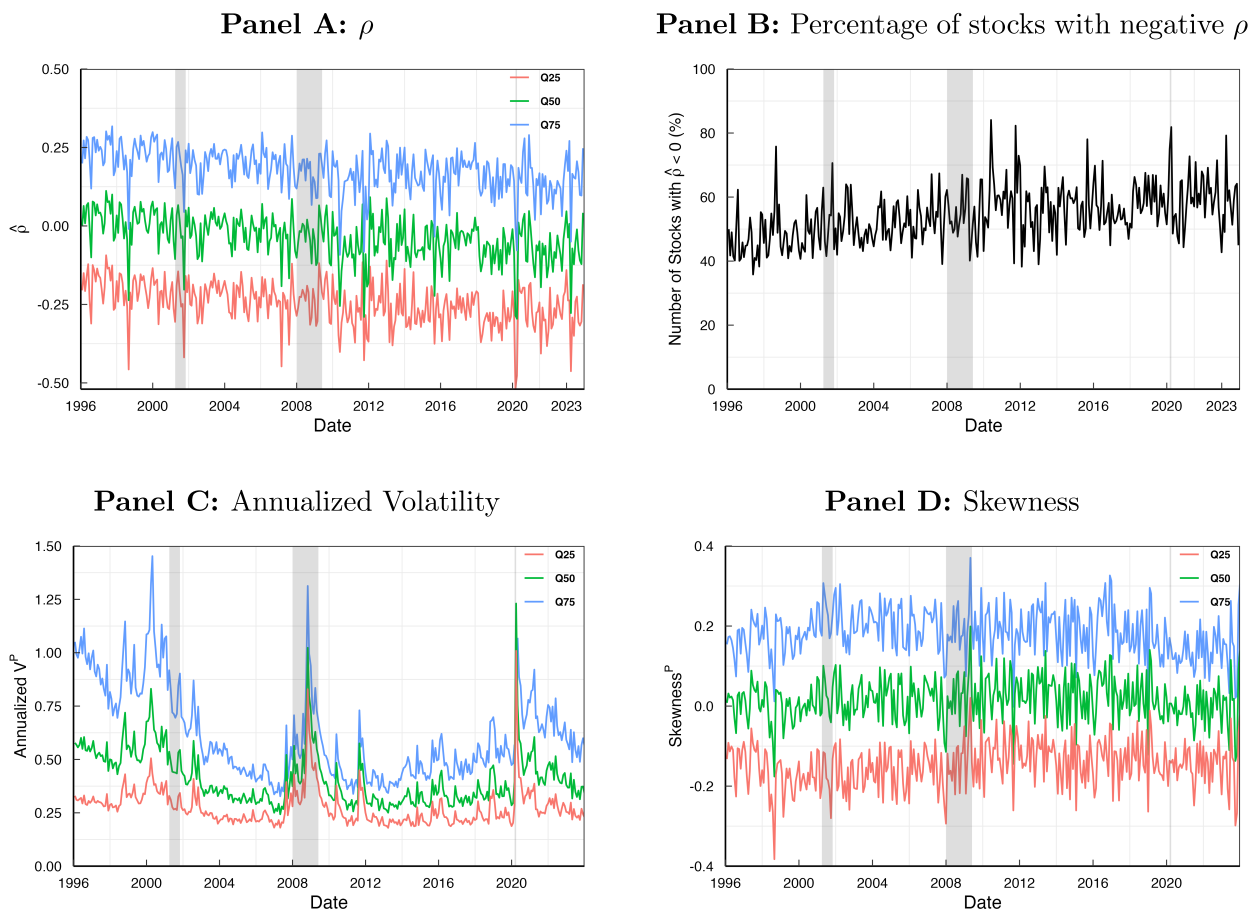
Figure 1: Unconditional Densities of Realized Correlation Measures.



Notes: This figure plots the unconditional densities of the overall realized correlation (ρ) as well as the upside ($\rho^{\Delta V^+}$) and downside ($\rho^{\Delta V^-}$) realized correlations. We use the correlations for all stocks over the entire sample to construct the density. The sample contains all common, non-penny stocks from 1996 to 2023.

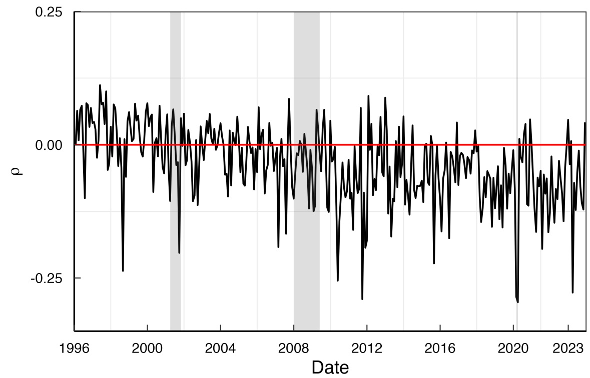
Figure 2: Time-series of Realized Correlation, Volatility, and Skewness.



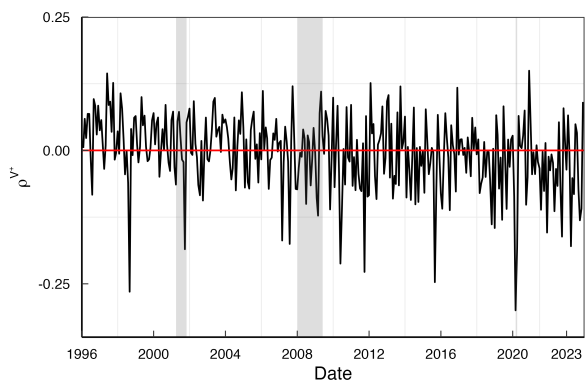
Notes: This figure plots the monthly 25th, 50th, and 75th percentiles of realized correlation (ρ), annualized volatility, and realized skewness in Panels A, C, and D, respectively. Panel B reports the percentage of stocks with negative ρ. ρ is defined as the correlation between daily returns and daily changes in variance within a month. Annualized volatility is computed as the square root of monthly realized variance multiplied by $\sqrt{12}$. Realized skewness is computed as the sum of cubed daily returns scaled by realized variance. The sample includes all common non-penny stocks from 1996 to 2023. NBER recession periods are shaded.

Figure 3: Time Series of Cross-Sectional Median Realized Correlations

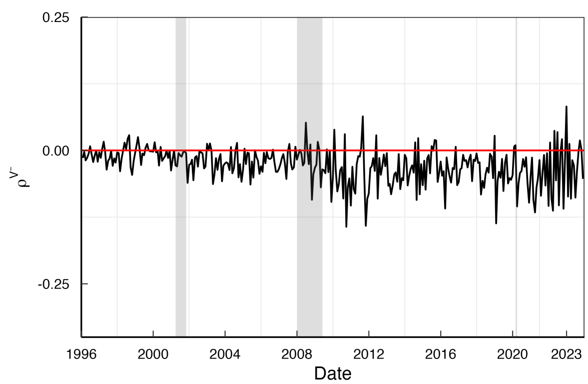
Panel A: ρ



Panel B: $\rho^{\Delta V^+}$

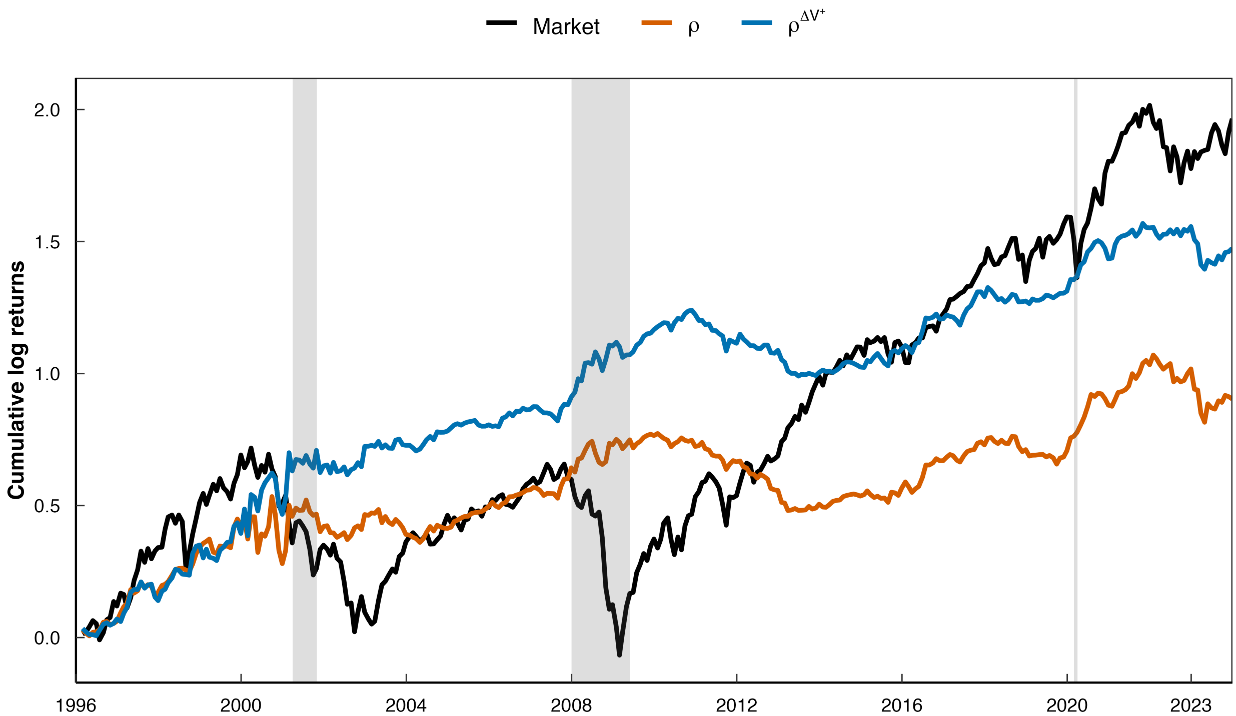


Panel C: $\rho^{\Delta V^-}$



Notes: This figure plots the monthly cross-sectional median values of ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. The solid black line denotes the monthly median, and the horizontal red line marks the zero threshold. ρ is the correlation between daily returns and daily variance changes, while $\rho^{\Delta V^+}$ and $\rho^{\Delta V^-}$ denote the components associated with positive and negative variance innovations, respectively. The sample includes all common non-penny stocks from 1996 to 2023. NBER recession periods are shaded.

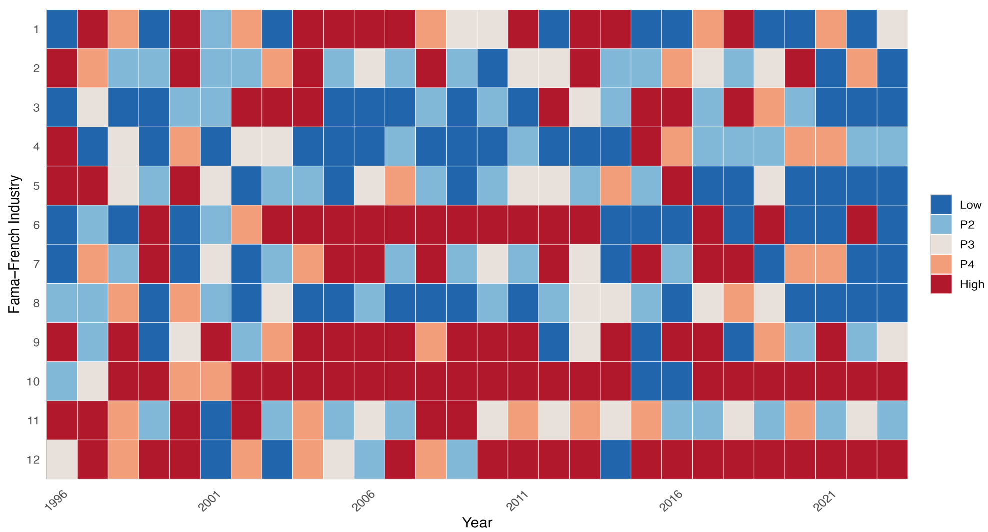
Figure 4: Cumulative Returns of Correlation-Based Long–Short Portfolios



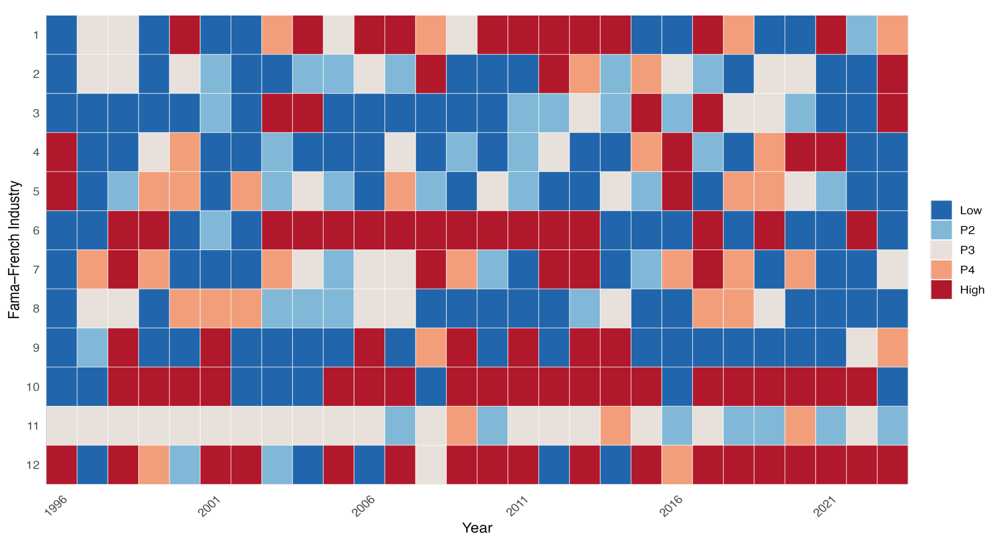
Notes: This figure plots the cumulative log returns of the value-weighted low-minus-high portfolios formed on ρ and $\rho^{\Delta V^+}$, together with the cumulative log return of the market portfolio, from 1996 to 2023. NBER recession periods are shaded.

Figure 5: Industry Composition of Correlation-Sorted Portfolios

Panel A: ρ

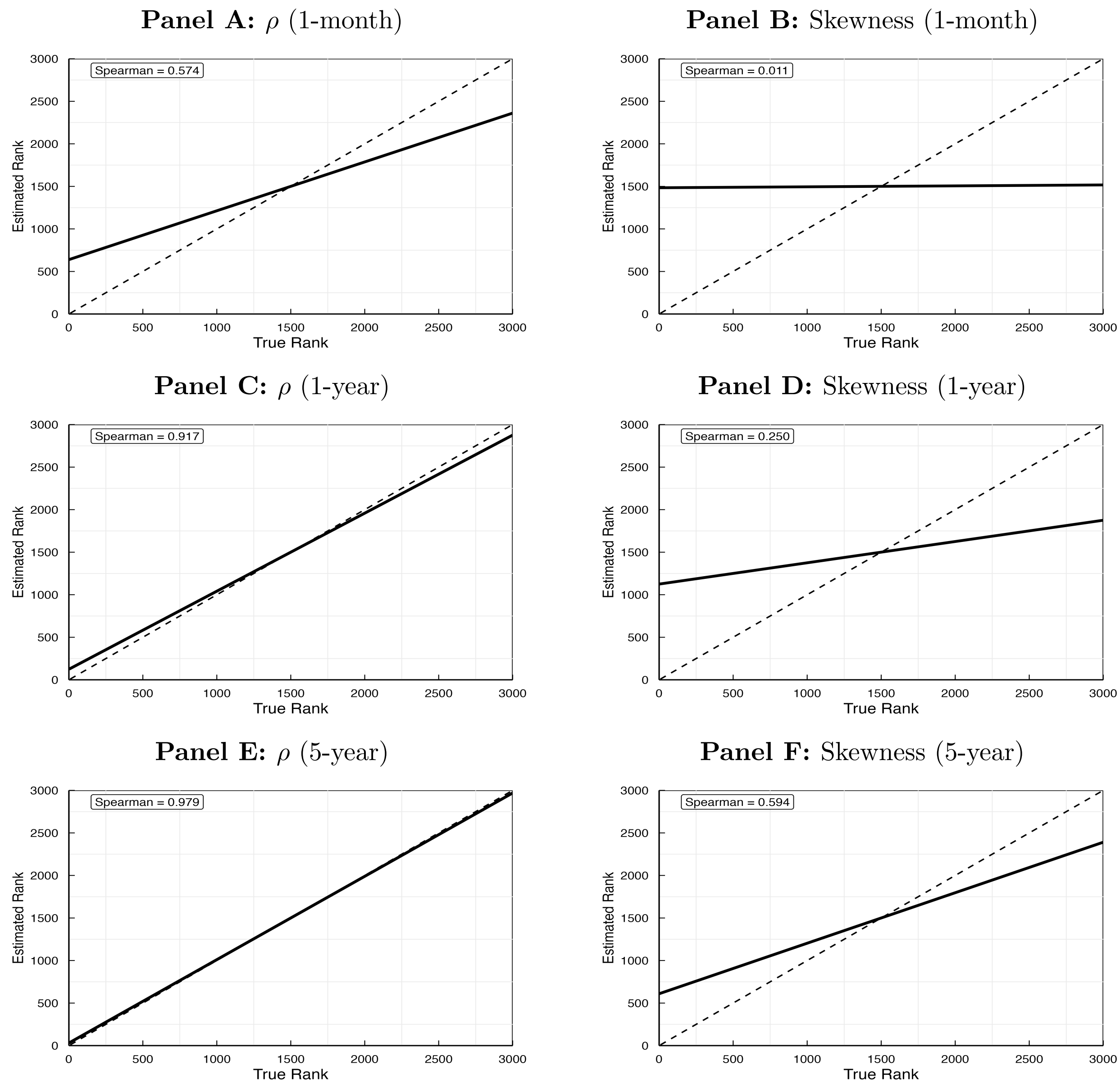


Panel B: $\rho^{\Delta V^+}$



Notes: This figure plots time-series heatmaps based on the 12 Fama–French industries. For each industry-year, we identify the dominant quintile portfolio as the portfolio in which the industry has the largest representation, measured as the fraction of stocks from that industry within the portfolio. Panel A reports the dominant quintile assignments for ρ-sorted portfolios, while Panel B reports the corresponding assignments for $\rho^{\Delta V^+}$-sorted portfolios.

Figure 6: Monte Carlo Evidence on Correlation and Skewness Estimation



Notes: This figure compares the true cross-sectional ranks implied by the cubic variation in Equation (9) with the estimated ranks obtained using ρ and sample skewness. In each simulation, we estimate the relation between true and estimated ranks and evaluate the fitted relation on a common rank grid. The solid line denotes the Monte Carlo mean fitted relation across simulations, while the dashed line is the 45-degree benchmark corresponding to a perfect rank match. Each panel reports the average Spearman rank correlation between true and estimated ranks. Panels A, C, and E report results for ρ estimated over 1-month, 1-year, and 5-year horizons, respectively. Panels B, D, and F report the corresponding results for sample skewness estimated over the same horizons.

Table 1: Descriptive Statistics. This table reports cross-sectional summary statistics and correlations for ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. Each month, we compute the cross-sectional moments and pairwise correlations across stocks and then report their time-series averages. The sample includes all common non-penny stocks from 1996 to 2023.

Panel A: Summary Statistics			
	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$
Mean	-0.031	-0.001	-0.030
Median	-0.036	-0.004	-0.028
Skewness	0.085	0.055	-0.077
Standard Deviation	0.307	0.251	0.146
Panel B: Cross-sectional Correlations			
	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$
ρ	1	0.88	0.59
$\rho^{\Delta V^+}$		1	0.14
$\rho^{\Delta V^-}$			1

Table 2: Predictive Single-Sorted Portfolios. This table reports monthly quintile portfolio returns sorted on ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. The correlation measures are estimated using a one-month window. The sample includes all common non-penny stocks from 1996 to 2023. Newey–West robust t-statistics with three lags are reported in parentheses.

Panel A: Stocks sorted by $\boldsymbol{\rho}$

	Value-Weighted					*Equal-Weighted*				
	Return	t-stat	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$	Return	t-stat	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$
Low	0.98%	(3.73)	−0.45	−0.28	−0.17	1.12%	(3.82)	−0.45	−0.30	−0.15
P2	0.85%	(3.32)	−0.20	−0.11	−0.09	1.07%	(3.53)	−0.20	−0.12	−0.08
P3	0.88%	(3.48)	−0.04	0.00	−0.04	0.97%	(3.29)	−0.04	−0.01	−0.03
P4	0.77%	(2.99)	0.13	0.12	0.01	0.88%	(2.90)	0.13	0.11	0.02
High	0.67%	(2.53)	0.39	0.31	0.08	0.79%	(2.57)	0.41	0.32	0.09
High - Low	−0.31%	(−2.25)	0.84	0.59	0.24	−0.33%	(−3.64)	0.86	0.62	0.24

Panel B: Stocks sorted by $\boldsymbol{\rho^{\Delta V^+}}$

	Value-Weighted					*Equal-Weighted*				
	Return	t-stat	$\rho^{\Delta V^+}$	ρ	$\rho^{\Delta V^-}$	Return	t-stat	$\rho^{\Delta V^+}$	ρ	$\rho^{\Delta V^-}$
Low	1.06%	(3.98)	−0.33	−0.41	−0.07	1.21%	(4.00)	−0.35	−0.40	−0.05
P2	0.99%	(3.86)	−0.13	−0.21	−0.08	1.09%	(3.59)	−0.13	−0.18	−0.05
P3	0.84%	(3.31)	0.00	−0.07	−0.07	1.00%	(3.37)	0.00	−0.04	−0.04
P4	0.73%	(2.78)	0.12	0.08	−0.05	0.80%	(2.73)	0.12	0.11	−0.02
High	0.58%	(2.17)	0.34	0.32	−0.02	0.72%	(2.34)	0.36	0.36	0.01
High - Low	−0.48%	(−3.46)	0.67	0.73	0.06	−0.49%	(−4.49)	0.70	0.76	0.06

Panel C: Stocks sorted by $\boldsymbol{\rho^{\Delta V^-}}$

	Value-Weighted					*Equal-Weighted*				
	Return	t-stat	$\rho^{\Delta V^-}$	ρ	$\rho^{\Delta V^+}$	Return	t-stat	$\rho^{\Delta V^-}$	ρ	$\rho^{\Delta V^+}$
Low	0.77%	(2.92)	−0.23	−0.30	−0.07	0.93%	(3.19)	−0.23	−0.29	−0.05
P2	0.86%	(3.35)	−0.10	−0.15	−0.05	0.97%	(3.28)	−0.10	−0.13	−0.02
P3	0.84%	(3.25)	−0.03	−0.05	−0.02	0.98%	(3.24)	−0.03	−0.02	0.00
P4	0.92%	(3.59)	0.04	0.05	0.00	0.97%	(3.15)	0.04	0.07	0.02
High	0.89%	(3.40)	0.16	0.18	0.02	0.99%	(3.22)	0.17	0.22	0.04
High - Low	0.13%	(0.85)	0.39	0.48	0.08	0.06%	(0.68)	0.41	0.50	0.10

Table 3: Fama–MacBeth Regressions for Return–Variance Correlations. This table reports monthly Fama–MacBeth cross-sectional regressions of stock returns on ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. The sample includes all common non-penny stocks from 1996 to 2023. Newey–West robust t-statistics with three lags are reported in parentheses. $\bar{N}$ denotes the average number of stocks per month, and $\bar{R}^2$ denotes the average R^2 from the monthly cross-sectional regressions.

	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$	R^2	$\bar{N}$
I	-0.44^{***}			0.203%	3575
	(-3.89)				
II		-0.74^{***}		0.295%	3575
		(-4.47)			
III			0.13	0.186%	3575
			(0.65)		
IV		-0.78^{***}	0.34	0.496%	3575
		(-4.54)	(1.58)		
V	0.34	-1.12^{***}		0.496%	3575
	(1.58)	(-3.40)			
VI	-0.78^{***}		1.12^{***}	0.496%	3575
	(-4.54)		(3.40)		

Table 4: Characteristics of Realized Correlation Portfolios. This table reports value-weighted average characteristics of monthly quintile portfolios sorted on ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$, where the correlation measures are estimated using a one-month window. $Size$ is market capitalization in millions of dollars. BM is the logarithm of the book-to-market ratio (Fama and French (1993)). MOM is momentum (Jegadeesh and Titman (1993)), and REV is reversal (Jegadeesh (1990)). $RVOL$ is realized volatility (Andersen et al. (2001)), $IVOL$ is idiosyncratic volatility (Ang et al. (2006b)), and $ILLIQ$ is the illiquidity measure of Amihud (2002) multiplied by 10^6. CSK and CKT denote co-skewness and co-kurtosis, respectively (Harvey and Siddique (2000); Ang et al. (2006a)). MAX and MIN are the maximum and minimum daily returns within a month (Bali et al. (2011)). The sample includes all common non-penny stocks from 1996 to 2023.

Panel A: Stocks sorted by ρ	Size	BM	MOM	REV	RVOL	IVOL	ILLIQ	CSK	CKT	MAX	MIN
Low	7874.834	−0.690	0.247	−0.035	0.124	0.021	0.418	−0.071	1.690	0.037	−0.046
P2	6997.543	−0.645	0.213	−0.002	0.125	0.018	0.519	−0.059	1.700	0.037	−0.036
P3	6026.710	−0.624	0.187	0.015	0.127	0.019	0.608	−0.040	1.640	0.039	−0.034
P4	5374.372	−0.629	0.175	0.033	0.132	0.020	0.691	−0.031	1.550	0.043	−0.033
High	4463.385	−0.648	0.168	0.076	0.141	0.025	0.811	−0.013	1.330	0.058	−0.033
Panel B: Stocks sorted by $\rho^{\Delta V^+}$	Size	BM	MOM	REV	RVOL	IVOL	ILLIQ	CSK	CKT	MAX	MIN
Low	7153.952	−0.716	0.248	−0.069	0.127	0.021	0.392	−0.083	1.600	0.035	−0.050
P2	6750.066	−0.631	0.210	−0.014	0.125	0.018	0.563	−0.050	1.730	0.037	−0.036
P3	5980.245	−0.604	0.184	0.016	0.126	0.019	0.810	−0.038	1.680	0.040	−0.034
P4	5763.608	−0.616	0.176	0.045	0.130	0.019	0.660	−0.029	1.590	0.042	−0.032
High	5091.678	−0.668	0.172	0.111	0.139	0.025	0.622	−0.018	1.350	0.058	−0.031
Panel C: Stocks sorted by $\rho^{\Delta V^-}$	Size	BM	MOM	REV	RVOL	IVOL	ILLIQ	CSK	CKT	MAX	MIN
Low	8117.686	−0.635	0.220	0.054	0.122	0.019	0.473	−0.049	1.730	0.040	−0.034
P2	6966.908	−0.661	0.212	0.033	0.127	0.020	0.446	−0.060	1.660	0.041	−0.038
P3	5990.920	−0.650	0.198	0.022	0.129	0.021	0.648	−0.048	1.580	0.043	−0.039
P4	5368.949	−0.662	0.190	0.005	0.133	0.022	0.652	−0.041	1.530	0.043	−0.039
High	4310.251	−0.629	0.171	−0.026	0.137	0.021	0.827	−0.033	1.450	0.041	−0.039

Table 5: Fama–MacBeth Regressions with Control Variables. This table reports monthly Fama–MacBeth cross-sectional regressions of stock returns on ρ, $\rho^{\Delta V^+}$, $\rho^{\Delta V^-}$, and additional control variables. Definitions of the control variables are provided in the Appendix. The sample includes all common non-penny stocks from 1996 to 2023. Newey–West robust t-statistics with three lags are reported in parentheses. $\bar{N}$ denotes the average number of stocks per month, and $\bar{R}^2$ denotes the average R^2 from the monthly cross-sectional regressions.

Panel A: Univariate Regressions

ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$	ME	BM	MOM	RVOL	REV	IVOL	ILLIQ	CSK	CKT	MAX	MIN
-0.44^{***}	-0.74^{***}	0.13	-0.02	0.05	0.27	-3.40^{**}	-1.60^{***}	-17.34^{***}	-0.01	-0.33^{*}	0.08	-4.44^{***}	3.74
(-3.89)	(-4.47)	(0.65)	(-0.35)	(0.86)	(1.36)	(-2.47)	(-3.40)	(-2.81)	(-0.70)	(-1.86)	(1.01)	(-3.00)	(1.48)

Panel B: Multivariate Regressions

	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$	ME	BM	MOM	RVOL	REV	IVOL	ILLIQ	CSK	CKT	MAX	MIN	R^2
I	-0.21^{***}			-0.06^{*}	0.02	0.28	-6.63	-1.67^{***}	-9.14	-0.02	-0.29^{**}	0.02	6.39^{**}	-2.40	6.60%
	(-2.71)			(-1.66)	(0.38)	(1.56)	(-1.33)	(-3.38)	(-0.66)	(-1.02)	(-2.12)	(0.46)	(2.56)	(-0.96)	
II		-0.38^{***}	0.06	-0.06^{*}	0.02	0.28	-6.75	-1.45^{***}	-8.99	-0.02	-0.29^{**}	0.03	6.61^{***}	-2.31	6.66%
		(-3.30)	(0.53)	(-1.66)	(0.38)	(1.56)	(-1.35)	(-2.87)	(-0.66)	(-1.02)	(-2.09)	(0.54)	(2.62)	(-0.92)	
III	-0.35^{***}			-0.05	0.02	0.25	-4.03^{***}								4.09%
	(-4.17)			(-1.57)	(0.43)	(1.34)	(-3.29)								
IV	-0.19^{**}			-0.05	0.01	0.26	-3.13	-1.18^{**}	-2.21	-0.02					5.78%
	(-2.48)			(-1.43)	(0.29)	(1.44)	(-0.80)	(-2.52)	(-0.13)	(-1.03)					
V	-0.25^{***}			-0.06^{*}	0.02	0.27	-9.85^{***}				-0.23	0.05	5.50^{*}	-6.65^{***}	5.53%
	(-3.07)			(-1.70)	(0.39)	(1.53)	(-2.72)				(-1.54)	(0.67)	(1.91)	(-2.98)	
VI		-0.72^{***}	0.44^{**}	-0.05	0.02	0.24	-3.97^{***}								4.33%
		(-5.05)	(2.50)	(-1.57)	(0.46)	(1.31)	(-3.24)								
VII		-0.36^{***}	0.10	-0.05	0.01	0.26	-3.13	-0.95^{*}	-2.22	-0.02					5.59%
		(-3.37)	(0.80)	(-1.42)	(0.29)	(1.44)	(-0.80)	(-1.96)	(-0.14)	(-1.04)					
VIII		-0.64^{***}	0.40^{**}	-0.06^{*}	0.02	0.27	-9.81^{***}				-0.23	0.05	6.28^{**}	-5.39^{**}	5.67%
		(-4.86)	(2.56)	(-1.72)	(0.42)	(1.52)	(-2.73)				(-1.54)	(0.73)	(2.22)	(-2.40)	

Table 6: Financial Leverage, Realized Correlation, and Returns. Panel A reports value-weighted average financial leverage characteristics—book leverage (BLEV), market leverage (MLEV), and net book leverage (NBLEV)—across quintile portfolios sorted on ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$. Panel B reports equal-weighted and value-weighted averages of ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$ across the lowest and highest leverage quintiles and for subsamples defined by leverage restrictions (Leverage = 0, Net Leverage = 0, and Net Leverage < 0). Panel C reports Fama–MacBeth cross-sectional regressions of next-month stock returns on ρ, $\rho^{\Delta V^+}$, $\rho^{\Delta V^-}$, and leverage variables. *Controls* equals "✓" if the regression includes the logarithm of size and book-to-market from Fama and French (1993), and "✗" otherwise. Newey–West robust t-statistics with three lags are reported in parentheses. The sample includes all common non-penny U.S. stocks from 1996 to 2023.

Panel A: Financial Leverage in Realized Correlation Portfolios

	Sorted by ρ			Sorted by $\rho^{\Delta V^+}$			Sorted by $\rho^{\Delta V^-}$		
	BLEV	MLEV	NBLEV	BLEV	MLEV	NBLEV	BLEV	MLEV	NBLEV
Low	0.244	0.210	0.104	0.248	0.209	0.110	0.243	0.217	0.104
P2	0.247	0.220	0.109	0.245	0.218	0.106	0.247	0.221	0.108
P3	0.249	0.223	0.112	0.249	0.222	0.112	0.251	0.218	0.112
P4	0.256	0.225	0.122	0.251	0.224	0.114	0.252	0.218	0.115
High	0.255	0.221	0.116	0.257	0.223	0.118	0.256	0.224	0.125
High–Low	0.011	0.011	0.012	0.009	0.013	0.008	0.012	0.007	0.021
	(4.801)	(2.329)	(2.668)	(4.130)	(3.101)	(1.826)	(5.441)	(1.632)	(4.438)

Panel B: Financial Leverage and Realized Correlations

	Equal-Weighted Mean			Value-Weighted Mean		
	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$
$\text{BLEV}_{Bottom-Top}$	0.02	0.01	0.01	−0.01	−0.00	−0.01
	(8.39)	(5.92)	(8.01)	(−1.79)	(−0.80)	(−2.15)
$\text{MLEV}_{Bottom-Top}$	0.01	−0.00	0.01	−0.01	−0.01	−0.00
	(0.51)	(−0.84)	(3.19)	(−1.64)	(−1.59)	(−0.89)
$\text{NBLEV}_{Bottom-Top}$	0.03	0.02	0.01	−0.01	−0.00	−0.01
	(7.79)	(5.84)	(6.66)	(−2.16)	(−0.88)	(−2.68)
Leverage = 0	−0.01	0.02	−0.02	−0.08	−0.02	−0.06
	(−1.50)	(4.14)	(−12.81)	(−12.51)	(−4.73)	(−16.20)
Net Leverage = 0	−0.10	−0.04	−0.06	−0.11	−0.04	−0.07
	(−6.75)	(−3.32)	(−9.36)	(−6.93)	(−3.33)	(−9.29)
Net Leverage < 0	−0.02	0.01	−0.03	−0.10	−0.03	−0.07
	(−4.57)	(2.14)	(−14.70)	(−15.29)	(−6.36)	(−20.11)

Panel C: Financial Leverage and Returns

	Univariate	I	II	III	IV	V	VI	VII	VIII
ρ	−0.44***	−0.47***	−0.47***	−0.48***				−0.48***	
	(−3.90)	(−4.38)	(−4.61)	(−4.79)				(−5.20)	
$\rho^{\Delta V^+}$	−0.74***				−0.83***	−0.87***	−0.86***		−0.88***
	(−4.49)				(−4.98)	(−5.35)	(−5.46)		(−5.71)
$\rho^{\Delta V^-}$	0.13				0.33	0.40*	0.38*		0.39*
	(0.65)				(1.47)	(1.86)	(1.78)		(1.91)
BLEV	−0.49	−0.52			−0.53			−0.57*	−0.57*
	(−1.33)	(−1.44)			(−1.48)			(−1.78)	(−1.79)
MLEV	−0.10		−0.09			−0.09			
	(−0.20)		(−0.19)			(−0.18)			
NBLEV	−0.22			−0.24			−0.25		
	(−0.59)			(−0.66)			(−0.69)		
Controls		✗	✗	✗	✗	✗	✗	✓	✓
R^2		0.67%	1.31%	1.36%	0.97%	1.58%	1.64%	1.99%	2.27%

Table 7: Factor-Adjusted Returns of Long–Short Portfolios. This table reports time-series regressions of monthly value-weighted long–short portfolio returns constructed from ρ and $\rho^{\Delta V^+}$. Panel A reports abnormal returns (α), corresponding to the intercepts from standard asset-pricing factor models, including CAPM, the three-factor model of Fama and French (1993) (FF3), the four-factor model of Carhart (1997) (FFC4), the five-factor model of Fama and French (2015) (FF5), and the augmented q^5 model of Hou et al. (2021). Panel B reports regressions using factors based on firm characteristics, including realized volatility (RVOL), idiosyncratic volatility (IVOL), reversal (REV), and illiquidity (ILLIQ). The sample includes all common non-penny stocks from 1996 to 2023. Newey–West robust t-statistics with three lags are reported in parentheses.

Panel A: Standard Factor Models

	CAPM	FF3	FFC4	FF5	q^5
$\rho^{\Delta V^+}$	-0.46^{***}	-0.46^{***}	-0.43^{***}	-0.44^{***}	-0.46^{***}
	(-3.22)	(-3.20)	(-2.98)	(-3.37)	(-3.17)
ρ	-0.32^{**}	-0.33^{**}	-0.24^{*}	-0.34^{***}	-0.36^{**}
	(-2.14)	(-2.27)	(-1.70)	(-2.63)	(-2.40)

Panel B: Factors on Firm Characteristics

	RVOL	IVOL	REV	ILLIQ
$\rho^{\Delta V^+}$	-0.48^{***}	-0.47^{***}	-0.41^{***}	-0.46^{***}
	(-3.52)	(-3.48)	(-3.09)	(-3.52)
ρ	-0.30^{**}	-0.30^{**}	-0.27^{*}	-0.31^{**}
	(-2.18)	(-2.16)	(-1.91)	(-2.25)

Table 8: Alternative Asymmetric Risk Measures. Panel A reports monthly cross-sectional correlations among ρ, $\rho^{\Delta V^+}$, and alternative asymmetric risk measures. Each month, correlations are computed across stocks and then averaged over time. Panel B reports value-weighted high-minus-low (H–L) returns from univariate quintile portfolio sorts together with the corresponding ex-post H–L realizations of the sorting variables ("Ex-Post"). Newey–West robust t-statistics with three lags are reported in parentheses. The construction of the alternative asymmetric risk measures is described in the Appendix. The sample includes all common non-penny stocks from 1996 to 2023.

Panel A: Cross-Sectional Correlations

	ρ	$\rho^{\Delta V^+}$	RSK_D	RSJ_D	RSK	RSJ
ρ	1.00	0.88	0.48	0.44	0.11	0.08
$\rho^{\Delta V^+}$		1.00	0.67	0.67	0.19	0.17
RSK_D			1.00	0.94	0.21	0.22
RSJ_D				1.00	0.29	0.31
RSK					1.00	0.89
RSJ						1.00

Panel B: Portfolio Sorts and Persistence

		ρ	$\rho^{\Delta V^+}$	RSK_D	RSJ_D	RSK	RSJ
Quintiles	H–L Return	−0.31%	−0.48%	−0.39%	−0.41%	−0.21%	−0.18%
		(−2.25)	(−3.46)	(−2.76)	(−2.64)	(−1.26)	(−0.94)
	Ex-Post	0.05	0.01	−0.04	−0.03	0.03	0.01
		(10.91)	(2.45)	(−2.99)	(−4.29)	(9.31)	(9.07)

Table 9: Predictive Double-Sorted Portfolios. This table reports monthly double-sorted portfolio returns for ρ and $\rho^{\Delta V^+}$ after controlling for RSK and RSJ. The construction of RSK and RSJ is described in the Appendix. The sample includes all common non-penny stocks from 1996 to 2023. Newey–West robust t-statistics with three lags are reported in parentheses.

	Panel A: RSK **then** ρ							**Panel B:** RSK **then** $\rho^{\Delta V^+}$					
	Low RSK	P2	P3	P4	High RSK	Average		Low RSK	P2	P3	P4	High RSK	Average
Value-Weighted													
Low ρ	1.02%	1.14%	0.92%	0.98%	1.00%	1.01%	Low $\rho^{\Delta V^+}$	1.02%	1.12%	1.13%	1.20%	1.00%	1.09%
P2	0.99%	1.01%	0.83%	0.87%	0.94%	0.93%	P2	1.18%	1.09%	0.76%	0.92%	0.94%	0.98%
P3	1.39%	0.97%	0.76%	0.77%	1.00%	0.98%	P3	1.04%	1.12%	0.69%	0.74%	0.96%	0.91%
P4	0.98%	0.70%	0.75%	0.60%	0.72%	0.75%	P4	1.09%	0.67%	0.79%	0.67%	0.79%	0.80%
High ρ	0.82%	0.84%	0.79%	0.64%	0.61%	0.74%	High $\rho^{\Delta V^+}$	0.86%	0.61%	0.66%	0.59%	0.57%	0.66%
High - Low	−0.19%	−0.30%	−0.13%	−0.34%	−0.39%	−0.27%	High - Low	−0.16%	−0.51%	−0.47%	−0.61%	−0.43%	−0.44%
	(−1.12)	(−1.63)	(−0.72)	(−1.55)	(−2.11)	(−2.12)		(−0.81)	(−2.51)	(−2.69)	(−2.84)	(−2.31)	(−3.53)
Equal-Weighted													
Low ρ	1.27%	1.18%	1.10%	1.02%	0.95%	1.10%	Low $\rho^{\Delta V^+}$	1.34%	1.24%	1.12%	1.16%	1.01%	1.17%
P2	1.20%	1.22%	1.02%	1.03%	0.92%	1.08%	P2	1.25%	1.19%	1.09%	0.94%	0.96%	1.09%
P3	1.17%	0.96%	0.94%	0.98%	0.80%	0.97%	P3	1.15%	1.02%	0.99%	0.99%	0.82%	1.00%
P4	1.06%	0.91%	0.92%	0.74%	0.75%	0.87%	P4	1.02%	0.85%	0.86%	0.72%	0.60%	0.81%
High ρ	0.94%	0.87%	0.85%	0.83%	0.52%	0.80%	High $\rho^{\Delta V^+}$	0.89%	0.83%	0.77%	0.79%	0.55%	0.77%
High - Low	−0.33%	−0.31%	−0.25%	−0.19%	−0.43%	−0.30%	High - Low	−0.45%	−0.41%	−0.35%	−0.36%	−0.46%	−0.41%
	(−3.10)	(−2.70)	(−2.18)	(−1.38)	(−3.53)	(−3.45)		(−3.73)	(−3.26)	(−2.78)	(−2.30)	(−3.44)	(−3.83)

	Panel C: RSJ **then** ρ							**Panel D:** RSJ **then** $\rho^{\Delta V^+}$					
	Low RSJ	P2	P3	P4	High RSJ	Average		Low RSJ	P2	P3	P4	High RSJ	Average
Value-Weighted													
Low ρ	0.95%	1.21%	0.99%	1.02%	0.76%	0.99%	Low $\rho^{\Delta V^+}$	0.98%	1.27%	1.15%	1.15%	0.79%	1.07%
P2	0.85%	1.01%	0.95%	0.82%	0.90%	0.91%	P2	1.10%	1.12%	0.98%	0.87%	1.04%	1.02%
P3	1.12%	1.11%	0.80%	0.69%	0.95%	0.93%	P3	0.66%	1.08%	0.75%	0.62%	0.88%	0.88%
P4	0.82%	0.85%	0.61%	0.72%	0.06%	0.72%	P4	1.13%	0.81%	0.77%	0.85%	0.64%	0.84%
High ρ	0.78%	0.92%	0.75%	0.70%	0.50%	0.73%	High $\rho^{\Delta V^+}$	0.88%	0.77%	0.48%	0.60%	0.47%	0.64%
High - Low	−0.17%	−0.29%	−0.24%	−0.32%	−0.26%	−0.26%	High - Low	−0.10%	−0.50%	−0.67%	−0.56%	−0.32%	−0.43%
	(−0.84)	(−1.72)	(−1.19)	(−1.76)	(−1.39)	(−2.05)		(−0.44)	(−2.69)	(−3.65)	(−2.97)	(−1.74)	(−3.60)
Equal-Weighted													
Low ρ	1.28%	1.21%	1.08%	1.00%	0.97%	1.11%	Low $\rho^{\Delta V^+}$	1.33%	1.27%	1.08%	1.12%	1.05%	1.17%
P2	1.19%	1.17%	1.02%	1.01%	0.92%	1.06%	P2	1.26%	1.18%	1.12%	0.90%	0.97%	1.09%
P3	1.18%	1.02%	0.98%	0.95%	0.78%	0.98%	P3	1.12%	1.11%	1.00%	0.96%	0.74%	0.99%
P4	1.03%	0.96%	0.94%	0.74%	0.76%	0.88%	P4	0.99%	0.84%	0.93%	0.77%	0.59%	0.82%
High ρ	0.89%	0.88%	0.95%	0.76%	0.51%	0.80%	High $\rho^{\Delta V^+}$	0.87%	0.84%	0.83%	0.70%	0.57%	0.76%
High - Low	−0.39%	−0.33%	−0.14%	−0.24%	−0.46%	−0.31%	High - Low	−0.46%	−0.43%	−0.25%	−0.42%	−0.48%	−0.41%
	(−3.63)	(−2.66)	(−1.10)	(−2.11)	(−4.18)	(−3.62)		(−3.92)	(−3.07)	(−1.84)	(−3.06)	(−4.03)	(−4.03)

Table 10: Fama–MacBeth Regressions with Alternative Asymmetric Risk Measures. This table reports monthly Fama–MacBeth cross-sectional regressions of stock returns on ρ, $\rho^{\Delta V^+}$, $\rho^{\Delta V^-}$, realized skewness (RSK and RSK_D), and relative signed jump variation (RSJ and RSJ_D). The construction of the alternative asymmetric risk measures is described in the Appendix. *Controls* equals "✓" if the regression includes the control variables from Table 5, and "✗" otherwise. The sample includes all common non-penny stocks from 1996 to 2023. Newey–West robust t-statistics with three lags are reported in parentheses. $\bar{R}^2$ denotes the average R^2 from the monthly cross-sectional regressions.

Panel A: Univariate Regressions

ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$	RSK$_D$	RSJ$_D$	RSK	RSJ
−0.44***	−0.74***	0.13	−0.16***	−0.55***	−0.42***	−1.06***
(−3.89)	(−4.47)	(0.65)	(−3.42)	(−3.72)	(−4.15)	(−3.05)

Panel B: Multivariate Regressions

	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$	RSK$_D$	RSJ$_D$	RSK	RSJ	Controls	$\bar{R}^2$
I	−0.30***			0.35***	−1.35***			✗	0.92%
	(−2.94)			(3.31)	(−3.53)				
II	−0.40***					−0.38*	−0.22	✗	0.47%
	(−3.57)					(−1.90)	(−0.33)		
III	−0.21***			0.44***	−1.48***			✓	6.81%
	(−2.95)			(4.47)	(−5.04)				
IV	−0.20**					−0.17	−0.06	✓	6.70%
	(−2.55)					(−1.25)	(−0.14)		
V		−0.43***	−0.12	0.34***	−1.27***			✗	0.98%
		(−3.13)	(−0.81)	(3.25)	(−3.27)				
VI		−0.70***	0.25			−0.33*	−0.08	✗	0.70%
		(−4.04)	(1.20)			(−1.66)	(−0.12)		
VII		−0.28***	−0.12	0.44***	−1.45***			✓	6.85%
		(−2.99)	(−1.11)	(4.43)	(−4.89)				
VIII		−0.35***	0.03			−0.15	−0.11	✓	6.76%
		(−2.99)	(0.28)			(−1.11)	(−0.25)		

Table 11: Predicted-rank Portfolios. Panel A reports value-weighted returns from quintile portfolios sorted on the realized correlation measures ρ and $\rho^{\Delta V^+}$ and on their predicted-rank counterparts $\widehat{\rho}$ and $\widehat{\rho}^{\Delta V^+}$. Newey–West robust t-statistics with three lags are reported in parentheses. Panel B reports the time-series correlations between the high-minus-low (H–L) returns of the realized measures and the corresponding predicted-rank portfolios. The sample includes all common non-penny U.S. stocks from 1996 to 2023. Portfolio formation begins in February 1996, and returns are measured beginning in March 1996.

Panel A: Univariate Portfolio Sorts

	Low	P2	P3	P4	High	High–Low
ρ	0.94%	0.84%	0.85%	0.76%	0.67%	−0.27%
	(3.51)	(3.17)	(3.32)	(2.89)	(2.46)	(−1.98)
$\rho^{\Delta V^+}$	1.03%	0.94%	0.80%	0.72%	0.57%	−0.45%
	(3.80)	(3.60)	(3.08)	(2.71)	(2.10)	(−3.25)
$\widehat{\rho}$	0.92%	0.88%	0.86%	0.74%	0.66%	−0.26%
	(3.51)	(3.43)	(3.41)	(2.79)	(2.50)	(−1.84)
$\widehat{\rho}^{\Delta V^+}$	1.05%	0.95%	0.82%	0.72%	0.60%	−0.45%
	(3.99)	(3.62)	(3.25)	(2.76)	(2.27)	(−3.05)

Panel B: Time-series Correlations of High–Low Returns

	ρ & $\widehat{\rho}$	$\rho^{\Delta V^+}$ & $\widehat{\rho}^{\Delta V^+}$
Correlation	93.84%	95.74%

Table 12: Fama–MacBeth Regressions with Alternative Correlation Decompositions. This table reports monthly Fama–MacBeth cross-sectional regressions of stock returns on ρ, $\rho^{\Delta V^+}$, $\rho^{\Delta V^-}$, and the alternative correlation decompositions discussed in Section 5.1. The sample includes all common non-penny stocks from 1996 to 2023. Newey–West robust t-statistics with three lags are reported in parentheses.

	ρ	$\rho^{\Delta V^+}$	$\rho^{\Delta V^-}$	ρ^{r^+}	ρ^{r^-}	$\rho^{r^+\Delta V^+}$	$\rho^{r^+\Delta V^-}$	$\rho^{r^-\Delta V^+}$	$\rho^{r^-\Delta V^-}$
I	-0.44^{***}								
	(-3.89)								
II		-0.78^{***}	0.34						
		(-4.54)	(1.58)						
III				-0.40^{*}	-0.49^{***}				
				(-1.87)	(-2.78)				
IV						-0.66^{**}	0.38	-0.83^{***}	0.23
						(-1.97)	(1.19)	(-2.75)	(0.69)
V	0.34	-1.12^{***}							
	(1.58)	(-3.40)							
VI	-0.35				-0.17				
	(-1.64)				(-0.53)				
VII	-0.08							-1.03^{***}	
	(-0.48)							(-2.73)	
VIII		-0.85^{***}			0.23				
		(-3.33)			(0.86)				
IX		-0.59^{*}						-0.23	
		(-1.82)						(-0.44)	
X					0.45			-1.62^{***}	
					(1.36)			(-3.12)	
XI		-0.60^{*}			0.48			-0.71	
		(-1.87)			(1.44)			(-1.12)	

Table 13: Portfolio Sorts and Fama–MacBeth Regressions for Variance Betas. Panel A reports monthly high-minus-low portfolio returns from univariate portfolio sorts on $\beta_{\Delta V}$, $\beta_{\Delta V+}$, and $\beta_{\Delta V-}$ along with exposures on $\Delta \mathrm{VIX}^2$ and change in realized market variance ΔV_M. Panel B reports Fama–MacBeth cross-sectional regressions of stock returns on the corresponding variance exposure measures. The construction of variables is described in Section 5.2. *Controls* equals "✓" if the regression includes the control variables from Table 5, and "✗" otherwise. The sample includes all common non-penny stocks from 1996 to 2023. Newey–West robust t-statistics with three lags are reported in parentheses. The coefficient on $\beta_{\Delta VIX^2}$ is divided by 1200 in Panel B.

Panel A: Univariate Portfolio Sorts

	Firm-Level			Systematic Variance					
	Total	Decompositions		Total		Decompositions			
	$\beta_{\Delta V}$	$\beta_{\Delta V^+}$	$\beta_{\Delta V^-}$	$\beta_{\Delta VIX^2}$	$\beta_{\Delta V_M}$	$\beta_{\Delta VIX^{2+}}$	$\beta_{\Delta VIX^{2-}}$	$\beta_{\Delta V_M^+}$	$\beta_{\Delta V_M^-}$
Low	0.93%	1.03%	0.85%	0.99%	0.93%	1.04%	0.79%	0.92%	0.79%
	(3.73)	(4.12)	(3.41)	(3.38)	(2.81)	(3.59)	(2.60)	(3.07)	(2.36)
P2	0.90%	0.99%	0.82%	0.85%	0.91%	0.93%	0.86%	1.02%	0.87%
	(3.30)	(3.45)	(2.98)	(3.46)	(3.62)	(3.99)	(3.49)	(4.24)	(3.50)
P3	0.96%	0.82%	0.81%	0.89%	0.89%	0.86%	0.92%	0.93%	0.88%
	(3.42)	(2.97)	(2.70)	(3.80)	(3.87)	(3.46)	(3.74)	(3.96)	(3.86)
P4	0.69%	0.79%	0.87%	0.88%	0.84%	0.81%	0.89%	0.73%	0.90%
	(2.43)	(2.80)	(3.20)	(3.23)	(3.38)	(3.05)	(3.42)	(2.71)	(3.57)
High	0.73%	0.68%	0.90%	0.60%	0.61%	0.53%	0.77%	0.58%	0.78%
	(2.90)	(2.68)	(3.61)	(1.74)	(1.84)	(1.53)	(2.30)	(1.76)	(2.47)
High–Low	−0.20%	−0.35%	0.05%	−0.39%	−0.32%	−0.51%	−0.03%	−0.34%	−0.02%
	(−1.83)	(−3.25)	(0.46)	(−1.84)	(−1.91)	(−2.42)	(−0.13)	(−1.79)	(−0.08)

Panel B: Fama-MacBeth Regressions

	$\beta_{\Delta V}$	$\beta_{\Delta V^+}$	$\beta_{\Delta V^-}$	$\beta_{\Delta VIX^2}$	$\beta_{\Delta V_M}$	$\beta_{\Delta VIX^{2+}}$	$\beta_{\Delta VIX^{2-}}$	$\beta_{\Delta V_M^+}$	$\beta_{\Delta V_M^-}$	Controls	R^2
Univariate	−0.46***	−0.18***	0.13	−0.73**	0.22	−0.72***	−0.12	−0.63	0.97		
	(−3.95)	(−4.25)	(0.49)	(−1.98)	(0.23)	(−2.81)	(−0.38)	(−1.14)	(1.20)		
I	−0.42***			−0.66*						✗	0.53%
	(−3.64)			(−1.90)							
II	−0.44***				0.00					✗	0.48%
	(−3.41)				(0.60)						
III		−0.75***	0.35			−0.75***	0.07			✗	1.04%
		(−3.87)	(1.31)			(−3.07)	(0.23)				
IV		−0.72***	0.30					−0.05	0.10	✗	1.01%
		(−3.96)	(1.08)					(−0.96)	(1.23)		
V	−0.23***			−0.52*						✓	6.77%
	(−2.87)			(−1.79)							
VI	−0.23***				0.11					✓	6.77%
	(−2.66)				(1.41)						
VII		−0.30**	−0.15			−0.60**	−0.04			✓	6.96%
		(−2.40)	(−1.19)			(−2.45)	(−0.14)				
VIII		−0.28**	−0.13					0.05	0.06	✓	6.96%
		(−2.16)	(−1.07)					(1.13)	(1.20)		

Appendix

This appendix provides supplementary details on the Monte Carlo simulation design, dataset construction, and additional empirical results. Section A.1 provides details on the Monte Carlo simulations. Section A.2 describes the TAQ data cleaning procedures implemented to ensure data quality. Section A.3 outlines the computation of realized measures and other firm-level characteristics used in the main tests. Section A.4 provides additional robustness results.

A.1 Monte Carlo Simulations

In each Monte Carlo simulation $j \in \{1, \ldots, 1000\}$, we simulate a cross-section of $N =$ 3,000 assets. At the start of simulation j, we draw an asset-specific leverage parameter ρ_i independently across assets from a uniform distribution on $[-0.95, 0.95]$. Given ρ_i, asset i's latent log price $S_{t,i}$ and variance $V_{t,i}$ follow Heston (1993)'s stochastic-volatility model,

$$dS_{t,i} = \Big(\mu - \tfrac{1}{2}V_{t,i}\Big)dt + \sqrt{V_{t,i}}\, dK_{t,i}, \tag{A.1.1}$$

$$dV_{t,i} = \kappa(\theta - V_{t,i})dt + \sigma\sqrt{V_{t,i}}\, dB_{t,i}, \tag{A.1.2}$$

with instantaneous correlation $d\langle K_i, B_i\rangle_t = \rho_i\, dt$. We set $\{\mu, \kappa, \theta, \sigma\}$ as $\{0.05, 5, 0.1, 0.5\}$ following Aït-Sahalia et al. (2013). We simulate the model at intraday frequency using an Euler discretization with full truncation to enforce variance nonnegativity. Specifically, within each trading day d, we use $n = 390$ equally spaced intervals (one-minute sampling) with calendar step $D = 1/252$ and $\Delta t = D/n$. Letting $V_{t,i}^{+} \equiv \max(V_{t,i}, 0)$, the updates are

$$V_{t+\Delta t,i} = \max\Big\{V_{t,i} + \kappa(\theta - V_{t,i}^{+})\Delta t + \sigma\sqrt{V_{t,i}^{+}}\sqrt{\Delta t}\, B_{t,i},\, 0\Big\}, \tag{A.1.3}$$

$$S_{t+\Delta t,i} = S_{t,i} + (\mu - \tfrac{1}{2}V_{t,i}^{+})\Delta t + \sqrt{V_{t,i}^{+}}\sqrt{\Delta t}\, K_{t,i}. \tag{A.1.4}$$

We model the observed price $S_{t,i}^{\text{obs}}$ as a noisy measurement of the latent price process. To capture market microstructure noise, we form an observed log price $S_{t,i}^{\text{obs}} = S_{t,i} + \varepsilon_{t,i}$ with $\varepsilon_{t,i} \sim \mathcal{N}(0, \sigma_{\varepsilon}^2)$ and $\sigma_{\varepsilon} = 0.0005$.

For each asset i, we simulate $h \in \{22, 252, 1260\}$ trading days, corresponding to annualized horizons $T = h/252$, for estimation of ρ and skewness. In order to estimate ρ and skewness, we form 1-minute returns and aggregate within day d to obtain the daily return $r_{d,i}$. Daily realized variance $RV_{d,i}$ is estimated as the sum of squared 1-minute returns over each day d. Then, for each horizon T, we estimate

$$\rho_i(T) = \mathrm{Cor}(r_{d,i}, \Delta RV_{d,i}), \qquad \text{where} \qquad \Delta RV_{d,i} = RV_{d,i} - RV_{d-1,i}. \tag{A.1.5}$$

and skewness as the standardized third central moment of daily returns,

$$\mathrm{Skew}_i(T) = \frac{\frac{1}{T}\sum_{d=1}^{T}\left(r_{d,i} - \bar{r}_i(T)\right)^3}{\left(\frac{1}{T}\sum_{d=1}^{T}\left(r_{d,i} - \bar{r}_i(T)\right)^2\right)^{3/2}}, \tag{A.1.6}$$

where $\bar{r}_i(T)$ denotes the sample mean of daily returns over the T-year window.

We evaluate how well the estimators recover the cross-sectional sorting of the true cubic variation in Equation (9). At the end of each simulation j, we compute cross-sectional ranks of the true cubic variation implied by Equation (9) and the corresponding ranks of the estimated ρ and skewness for each horizon following Equations (A.1.5) and (A.1.6). We then run a cross-sectional regression of the true rank on the estimated rank within replication j and use the fitted relation to map a common rank grid into predicted true ranks. Finally, we aggregate these fitted mappings across replications.

A.2 TAQ Data Filters

We construct the sample by excluding all trade records that meet any of the following criteria:

- Occur outside of standard trading hours (9:30 AM to 4:00 PM);
- Have a trade price or size less than or equal to zero;
- Have a correction indicator ($CORR$) other than 0, 1, or 2;
- Have a sale condition ($COND$) other than @, *, E, F, @E, @F, *E, or *F.

We then partition each trading day into 78 five-minute intervals and assign each trade to an interval based on its time stamp. Within each interval, we use the last observed trade to determine the closing price of the bucket. If no trade occurs in a given interval, its closing price is set equal to that of the most recent non-empty interval.

A.3 Variable Construction

This section explains the calculation of additional variables used in the empirical analysis.

- Realized Variance (RV): We denote by $r_{t,d,j}^{(k)}$ the intraday log-return of asset j on day d in month t, where k indexes the 5-minute interval within the trading day. We then compute the daily realized variance ($RV_{t,d,j}$) as the summation of 5-minute squared log-returns,

$$RV_{t,d,j} = \sum_{k=1}^{78} (r_{t,d,j}^{(k)})^2.$$

  The monthly realized variance is the sum of the daily realized variances over month t,

$$RV_{t,j} = \sum_{d=1}^{D} RV_{t,d,j},$$

  where D is the total number of trading days in month t.

- Realized Skewness (RSK and RSK_D): Following Amaya et al. (2015), the daily realized skewness using high-frequency returns is defined as:

$$RSK_{t,d,j} = \frac{\sqrt{78}\sum_{k=1}^{78}(r_{t,d,j}^{(k)})^3}{RV_{t,d,j}^{3/2}}$$

  The monthly realized skewness using high-frequency returns is then:

$$RSK_{t,j} = \frac{1}{D}\sum_{d=1}^{D} RSK_{t,d,j}.$$

We also compute the realized skewness over a month using daily returns by:

$$RSK_{D,t,j} = \frac{\sqrt{D}\sum_{d=1}^{D} r_{t,d,j}^3}{\left(\sum_{d=1}^{D} r_{t,d,j}^2\right)^{3/2}}$$

where $r_{t,d,j}$ is the daily return of stock j on day d, in month t.

- Realized Signed Jump Variation (RSJ and RSJ$_D$): Following Bollerslev et al. (2020), the daily relative signed jump variation using high-frequency returns is the sum of squared positive returns minus the sum of squared negative returns over day d:

$$RSJ_{t,d,j} = \frac{\sum_{k=1}^{78}(r_{t,d,j}^{(k)})^2\mathbf{1}_{(r_{t,d,j}^{(k)}>0)} - \sum_{k=1}^{78}(r_{t,d,j}^{(k)})^2\mathbf{1}_{(r_{t,d,j}^{(k)}<0)}}{RV_{t,d,j}}.$$

  The monthly relative signed jump variation using high-frequency returns is

$$RSJ_{t,j} = \frac{1}{D}\sum_{d=1}^{D} RSJ_{t,d,j}.$$

  We also compute the realized signed jump variation over a month using daily returns by:

$$RSJ_{D,t,j} = \frac{\sum_{d=1}^{D}(r_{t,d,j})^2\mathbf{1}_{(r_{t,d,j}>0)} - \sum_{d=1}^{D}(r_{t,d,j})^2\mathbf{1}_{(r_{t,d,j}<0)}}{\sum_{d=1}^{D}(r_{t,d,j})^2}.$$

- Size (ME): Following Fama and French (1993), we compute size as the product of month-end close price and the number of shares outstanding. Following the literature, we take its natural logarithm.

- Book-to-market ratio (BM): Following Fama and French (1993), the book-to-market variable of stock j in June of year t is computed as the book value of common equity in year $t-1$ divided by market value of equity in December of year $t-1$. Following the literature, we take its natural logarithm.

- Momentum (MOM): Following Jegadeesh and Titman (1993), the momentum variable at the end of month t is the gross product of monthly returns from month $t-12$ to month $t-1$.

- Reversal (REV): Following Jegadeesh (1990) and Lehmann (1990), the reversal variable in month t is defined as the return of month t.

- Idiosyncratic Volatility (IVOL): Following Ang et al. (2006b), the idiosyncratic volatility variable of the stock j is calculated as the standard deviation of residuals obtained from the following regression ran in month t:

$$r_{j,d} - r_{f,d} = \alpha_j + \beta_j(r_{M,d} - r_{f,d}) + \theta_j SMB_d + \gamma_j HML_d + \epsilon_{j,d}$$

where $r_{j,d}$ is the return of stock j on day d, $r_{M,d}$ is the market portfolio return on day d, SMB_d and HML_d are daily size and book-to-market factors of Fama and French (1993).

- Illiquidity (ILLIQ): Following Amihud (2002), the illiquidity variable of stock j in month t is:

$$ILLIQ_{t,j} = \frac{1}{D}\sum_{d=1}^{D}\left(\frac{|r_{t,d,j}|}{volume_{t,d,j} \times price_{t,d,j}}\right)$$

where $r_{t,d,j}$, $volume_{t,d,j}$, $price_{t,d,j}$ are daily return, volume, and close price of stock j on day d, and D is the total number of trading days in month t.

- Coskewness (CSK): Following Harvey and Siddique (2000) and Ang et al. (2006a), the coskewness of stock j in month t is computed using daily returns by:

$$CSK_{j,t} = \frac{\frac{1}{D}\sum_{d=1}^{D}(r_{t,d,j} - \bar{r}_{t,j})(r_{M,t,d} - \bar{r}_{M,t})^2}{\sqrt{\frac{1}{D}\sum_{d=1}^{D}(r_{t,d,j} - \bar{r}_{t,j})^2}\left(\frac{1}{D}\sum_{d=1}^{D}(r_{M,t,d} - \bar{r}_{M,t}\right)},$$

where $r_{t,d,j}$ and $r_{M,t,d}$ are daily returns of stock j and market on day d, $\bar{r}_{t,j}$ and $\bar{r}_{M,t}$ are corresponding daily average returns over month t, and D is the total number of trading days in month t.

- Cokurtosis (CKT): Following Ang et al. (2006a), the cokurtosis of stock j in month t

is computed using daily returns by:

$$CKT_{j,t} = \frac{\frac{1}{D}\sum_{d=1}^{D}(r_{t,d,j} - \bar{r}_{t,j})(r_{M,t,d} - \bar{r}_{M,t})^3}{\sqrt{\frac{1}{D}\sum_{d=1}^{D}(r_{t,d,j} - \bar{r}_{t,j})^2}\left(\frac{1}{D}\sum_{d=1}^{D}(r_{M,t,d} - \bar{r}_{M,t})\right)^{3/2}},$$

where $r_{t,d,j}$ and $r_{M,t,d}$ are daily returns of stock j and market on day d, $\bar{r}_{t,j}$ and $\bar{r}_{M,t}$ are corresponding daily average returns over month t, and D is the total number of trading days in month t.

- Maximum and Minimum daily return (MAX and MIN, respectively): Following Bali et al. (2011), $MAX_{t,j}$ and $MIN_{t,j}$ are defined as the largest and smallest total daily return of stock j over month t.

A.4 Additional Robustness Results

A.4.1 Alternative Portfolio Sorts

Table A.4 reports robustness tests using alternative portfolio formation procedures. Specifically, we repeat the portfolio-sort analysis from the main text using quartile and decile portfolios in place of the baseline quintile sorts.

At the end of each month, stocks are sorted into portfolios based on the lagged values of ρ and $\rho^{\Delta V^+}$ estimated over the previous month. We then compute value-weighted and equal-weighted portfolio returns in the following month together with high-minus-low return spreads. Across specifications, the return predictability associated with ρ and $\rho^{\Delta V^+}$ remains economically and statistically significant. In particular, the negative relation between $\rho^{\Delta V^+}$ and subsequent stock returns remains monotonic and robust across alternative portfolio partitions under both value- and equal-weighting.

A.4.2 Bias-Corrected Estimation Procedure

Table A.5 evaluates the robustness of the realized correlation measure to alternative estimation procedure for the leverage effect. In particular, we implement the bias-corrected estimator proposed by Aït-Sahalia et al. (2013), which adjusts for finite-sample and microstructure-related biases in the estimation of return–variance dependence using high-frequency data.

Following Aït-Sahalia et al. (2013), we construct ρ^{BC} in three steps using a three-year rolling window of daily returns and realized variance for each stock. First, we compute the preliminary bias-corrected correlation $\hat{\rho}_m$ for each horizon $m \in [1, 252]$ by applying the multiplicative correction factor $2\sqrt{(m^2 - 2m/3)}/(2m-1)$ to the sample correlation between m-day returns and m-day changes in realized volatility, and identify m^* as the horizon corresponding to the minimum corrected correlation. Second, we run simple linear regressions on $\{m, \hat{\rho}_m\}$ for $m \in [m^*, m^* + k]$ across different values of k, and select k^* that yields the largest R^2. Third, we run a final regression on $\{m, \hat{\rho}_m\}$ for $m \in [m^*, m^* + k^*]$, where the intercept provides our estimate of ρ^{BC}.

The results remain qualitatively unchanged. ρ^{BC} continues to exhibit statistically significant negative relations with future stock returns.

A.4.3 Volatility-of-Volatility

Table A.6 examines whether the predictive power of the realized correlation measures is subsumed by volatility-of-volatility. Following the high-frequency volatility literature, we proxy volatility-of-volatility using realized quarticity computed from intraday returns.

For stock j on day d in month t, realized quarticity is defined as

$$RQ_{t,d,j} = \sum_{k=1}^{78} \left(r_{t,d,j}^{(k)} \right)^4, \tag{A.4.1}$$

where $r_{t,d,j}^{(k)}$ denotes the k-th five-minute intraday return. Monthly realized quarticity is then computed by averaging daily realized quarticity measures within each month.

We augment the Fama–MacBeth regressions from the main text by including realized quarticity as an additional control variable:

$$r_{i,t+1} = \alpha_t + \beta_t \rho_{i,t} + \gamma_t RQ_{i,t} + \delta_t' X_{i,t} + \varepsilon_{i,t+1}, \tag{A.4.2}$$

where $X_{i,t}$ denotes the vector of firm-level controls used in the baseline specifications.

The estimated coefficients on ρ remain negative and statistically significant across specifications, indicating that the predictive content of the realized correlation measures is distinct from variation associated with volatility-of-volatility.

Table A.1: Alternative Asymmetric Variance Proxies: Robustness Across Portfolio Sorts. This table reports value-weighted high-minus-low (H–L) returns from various univariate sorts on each variable, along with the ex-post H–L realization of the sorting variable ("Ex-Post"). For both rows, Newey-West robust t-statistics with 3 lags are reported in parentheses. The construction of the alternative asymmetric variance proxies is described in the Appendix. ρ_M is the correlation between daily return and daily change in SPY variance over a month. The sample includes all common stocks excluding penny stocks from 1996–2023.

Portfolio Sorts and Persistence		ρ	$\rho^{\Delta V^+}$	RSK_D	RSJ_D	RSK	RSJ	ρ_M	CSK
Deciles	Return	−0.19%	−0.47%	−0.25%	−0.33%	−0.11%	−0.16%	−0.19%	−0.43%
		(−1.16)	(−2.95)	(−1.63)	(−1.69)	(−0.53)	(−0.85)	(−0.85)	(−1.86)
	Ex-Post	0.06	0.01	−0.02	−0.02	0.05	0.02	0.04	0.02
		(10.50)	(1.39)	(−1.12)	(−3.16)	(10.18)	(10.51)	(6.60)	(1.38)
Quintiles	Return	−0.31%	−0.48%	−0.39%	−0.41%	−0.21%	−0.18%	−0.14%	−0.27%
		(−2.25)	(−3.46)	(−2.76)	(−2.64)	(−1.26)	(−0.94)	(−0.81)	(−1.43)
	Ex-Post	0.05	0.01	−0.04	−0.03	0.03	0.01	0.03	0.02
		(10.91)	(2.45)	(−2.99)	(−4.29)	(9.31)	(9.07)	(6.14)	(2.25)
Quartiles	Return	−0.23%	−0.46%	−0.39%	−0.38%	−0.15%	−0.19%	−0.26%	−0.20%
		(−1.82)	(−3.58)	(−3.02)	(−2.53)	(−1.02)	(−1.09)	(−1.59)	(−1.17)
	Ex-Post	0.05	0.01	−0.05	−0.03	0.03	0.01	0.03	0.02
		(10.89)	(2.73)	(−3.69)	(−4.30)	(9.34)	(8.68)	(5.83)	(2.22)
30% Top-Bottom	Return	−0.20%	−0.37%	−0.38%	−0.36%	−0.21%	−0.30%	−0.23%	−0.14%
		(−1.73)	(−3.17)	(−2.97)	(−2.60)	(−1.73)	(−2.06)	(−1.62)	(−0.93)
	Ex-Post	0.04	0.01	−0.04	−0.02	0.02	0.01	0.02	0.01
		(10.99)	(3.27)	(−3.29)	(−4.43)	(8.07)	(8.02)	(6.12)	(2.03)

Table A.2: Predictive Double-Sorted Portfolios ($\mathbf{RSK}_D$ and $\mathbf{RSJ}_D$). This table reports predictive monthly double-sorted portfolio returns of ρ and $\rho^{\Delta V^+}$ controlling for RSK_D and RSJ_D. The computations of RSK_D and RSJ_D are defined in the Appendix. The sample contains all common and non-penny stocks from 1996 to 2023. Standard errors are corrected using Newey-West with 3 lags. Robust t-statistics are presented in parentheses.

Panel A: RSK_D **then** ρ

	Low RSK_D	P2	P3	P4	High RSK_D	Average
Value-Weighted						
Low ρ	0.91%	1.04%	0.90%	0.80%	0.57%	0.84%
P2	1.11%	1.19%	0.89%	0.98%	0.65%	0.97%
P3	0.89%	1.16%	1.05%	0.49%	0.67%	0.85%
P4	1.15%	0.96%	0.85%	0.63%	0.67%	0.85%
High ρ	0.91%	0.71%	0.61%	0.56%	0.65%	0.69%
High - Low	0.01%	−0.33%	−0.29%	−0.24%	0.07%	−0.16%
	(0.01)	(−1.79)	(−1.32)	(−1.10)	(0.39)	(−1.21)
Equal-Weighted						
Low ρ	1.14%	1.14%	1.14%	0.91%	0.77%	1.02%
P2	1.29%	1.30%	1.03%	0.82%	0.75%	1.04%
P3	1.16%	1.16%	1.03%	0.85%	0.76%	0.99%
P4	1.16%	1.11%	0.95%	0.69%	0.78%	0.94%
High ρ	1.08%	1.05%	0.77%	0.74%	0.60%	0.85%
High - Low	−0.06%	−0.09%	−0.37%	−0.17%	−0.17%	−0.17%
	(−0.59)	(−0.82)	(−3.28)	(−1.51)	(−1.36)	(−2.26)

Panel B: RSK_D **then** $\rho^{\Delta V^+}$

	Low RSK_D	P2	P3	P4	High RSK_D	Average
Value-Weighted						
Low $\rho^{\Delta V^+}$	1.04%	1.19%	0.97%	0.91%	0.63%	0.95%
P2	1.15%	1.22%	0.91%	0.99%	0.60%	0.97%
P3	0.94%	0.97%	0.78%	0.48%	0.66%	0.77%
P4	0.94%	1.11%	0.94%	0.50%	0.69%	0.83%
High $\rho^{\Delta V^+}$	0.83%	0.83%	0.60%	0.52%	0.56%	0.67%
High - Low	−0.21%	−0.36%	−0.37%	−0.38%	−0.06%	−0.28%
	(−1.13)	(−1.93)	(−1.82)	(−1.85)	(−0.31)	(−2.38)
Equal-Weighted						
Low $\rho^{\Delta V^+}$	1.23%	1.21%	1.18%	1.00%	0.79%	1.08%
P2	1.20%	1.26%	1.10%	0.90%	0.73%	1.04%
P3	1.19%	1.16%	1.00%	0.75%	0.70%	0.96%
P4	1.19%	1.17%	0.85%	0.71%	0.83%	0.95%
High $\rho^{\Delta V^+}$	1.01%	0.95%	0.79%	0.67%	0.61%	0.80%
High - Low	−0.22%	−0.26%	−0.39%	−0.33%	−0.18%	−0.28%
	(−1.98)	(−2.47)	(−3.62)	(−2.95)	(−1.40)	(−3.85)

Panel C: RSJ_D **then** ρ

	Low RSJ_D	P2	P3	P4	High RSJ_D	Average
Value-Weighted						
Low ρ	0.91%	1.00%	0.97%	0.66%	0.59%	0.83%
P2	1.20%	1.17%	0.92%	0.89%	0.68%	0.97%
P3	0.99%	1.15%	0.92%	0.62%	0.66%	0.87%
P4	1.18%	1.02%	0.69%	0.69%	0.72%	0.86%
High ρ	0.99%	0.69%	0.66%	0.53%	0.69%	0.71%
High - Low	0.08%	−0.31%	−0.31%	−0.14%	0.10%	−0.11%
	(0.43)	(−1.82)	(−1.38)	(−0.63)	(0.50)	(−1.50)
Equal-Weighted						
Low ρ	1.16%	1.11%	1.10%	0.94%	0.70%	1.00%
P2	1.34%	1.27%	0.99%	0.78%	0.70%	1.01%
P3	1.24%	1.20%	1.09%	0.82%	0.69%	1.01%
P4	1.23%	1.12%	0.89%	0.70%	0.77%	0.94%
High ρ	1.11%	1.04%	0.86%	0.69%	0.60%	0.86%
High - Low	−0.05%	−0.07%	−0.24%	−0.26%	−0.09%	−0.14%
	(−0.50)	(−0.64)	(−2.02)	(−2.23)	(−0.75)	(−1.82)

Panel D: RSJ_D **then** $\rho^{\Delta V^+}$

	Low RSJ_D	P2	P3	P4	High RSJ_D	Average
Value-Weighted						
Low $\rho^{\Delta V^+}$	1.1%	1.06%	0.94%	0.77%	0.62%	0.90%
P2	1.10%	1.21%	1.00%	0.93%	0.71%	0.99%
P3	1.07%	0.95%	0.86%	0.62%	0.62%	0.82%
P4	0.97%	1.02%	0.78%	0.50%	0.59%	0.77%
High $\rho^{\Delta V^+}$	0.91%	0.79%	0.62%	0.54%	0.70%	0.71%
High - Low	−0.19%	−0.27%	−0.33%	−0.23%	0.08%	−0.19%
	(−1.02)	(−1.36)	(−1.84)	(−1.04)	(0.45)	(−1.79)
Equal-Weighted						
Low $\rho^{\Delta V^+}$	1.25%	1.15%	1.12%	0.97%	0.69%	1.04%
P2	1.22%	1.24%	1.10%	0.84%	0.73%	1.03%
P3	1.33%	1.19%	1.03%	0.78%	0.65%	1.00%
P4	1.18%	1.17%	0.82%	0.61%	0.76%	0.91%
High $\rho^{\Delta V^+}$	1.10%	0.99%	0.87%	0.74%	0.62%	0.86%
High - Low	−0.15%	−0.17%	−0.25%	−0.24%	−0.07%	−0.18%
	(−1.44)	(−1.53)	(−2.10)	(−2.14)	(−0.55)	(−2.35)

Table A.3: Realized Correlation with Lagged/Leading Variance Change. This table reports predictive value-weighted returns from monthly quintile portfolios based on different realized correlation estimates in Panel A and monthly Fama-MacBeth cross-sectional predictive regressions in Panel B. The computations of realized correlation estimates with lead/lag relationships between return and variance innovations are documented in Section 5.3. *Controls* is "✓" if regression includes other controls from Table 5, "✗" otherwise. The sample contains all common and non-penny stocks from 1996 to 2023. Standard errors are corrected using Newey-West with 3 lags. Robust t-statistics are presented in parentheses.

Panel A: Univariate Portfolio Sorts

	Low	P2	P3	P4	High	High–Low
$\text{Cor}(R_t, \Delta V_{t-1})$	0.88%	0.84%	0.92%	0.84%	0.79%	−0.09%
	(3.43)	(3.31)	(3.68)	(3.24)	(2.91)	(−0.66)
$\text{Cor}(R_{t-1}, \Delta V_t)$	0.73%	0.86%	0.87%	0.95%	0.96%	0.23%
	(2.50)	(3.39)	(3.44)	(3.86)	(3.79)	(1.68)
$\text{Cor}(R_t, \max(\Delta V_{t-1}, 0))$	1.03%	0.87%	0.93%	0.76%	0.74%	−0.29%
	(3.95)	(3.30)	(3.69)	(2.93)	(2.88)	(−2.11)
$\text{Cor}(R_t, \min(\Delta V_{t-1}, 0))$	0.79%	0.82%	0.82%	0.90%	0.98%	0.18%
	(3.17)	(3.31)	(3.23)	(3.31)	(3.44)	(1.38)
$\text{Cor}(R_{t-1}, \max(\Delta V_t, 0))$	0.92%	0.91%	0.79%	0.91%	0.85%	−0.07%
	(3.21)	(3.43)	(3.10)	(3.79)	(3.38)	(−0.47)
$\text{Cor}(R_{t-1}, \min(\Delta V_t, 0))$	0.59%	0.78%	0.95%	0.94%	1.00%	0.41%
	(2.17)	(2.96)	(3.66)	(3.61)	(3.98)	(3.41)

Panel B: Fama-MacBeth Regressions

	Univariate	I	II	III	IV	V	VI
ρ	-0.44^{***}					-0.22^{**}	-0.21^{***}
	(−3.89)					(−2.49)	(−2.66)
$\text{Cor}(R_t, \Delta V_{t-1})$	0.07	0.16^{**}				0.08	
	(0.74)	(2.38)				(1.14)	
$\text{Cor}(R_{t-1}, \Delta V_t)$	0.18^{**}		−0.00				
	(2.10)		(−0.01)				
$\text{Cor}(R_t, \max(\Delta V_{t-1}, 0))$	-0.44^{**}			−0.06			
	(−2.23)			(−0.55)			
$\text{Cor}(R_t, \min(\Delta V_{t-1}, 0))$	0.77^{***}			0.45^{***}			0.38^{***}
	(3.45)			(3.56)			(3.38)
$\text{Cor}(R_{t-1}, \max(\Delta V_t, 0))$	−0.26				−0.02		
	(−0.96)				(−0.17)		
$\text{Cor}(R_{t-1}, \min(\Delta V_t, 0))$	0.43^{***}				0.03		
	(2.75)				(0.29)		
Controls		✓	✓	✓	✓	✓	✓
R^2		6.49%	6.49%	6.55%	6.55%	6.68%	6.68%

Table A.4: Predictive Single-Sorted Portfolios (Deciles and Quartiles). This table reports predictive monthly portfolio returns based on ρ, $\rho^{\Delta V^+}$, and $\rho^{\Delta V^-}$ for decile sorts in Panel A and for quartile sorts in Panel B. The sample contains all common and non-penny stocks from 1996 to 2023. Standard errors are corrected using Newey-West with 3 lags. Robust t-statistics are presented in parentheses.

Panel A: Deciles

	Stocks sorted by ρ				**Stocks sorted by $\rho^{\Delta V^+}$**				**Stocks sorted by $\rho^{\Delta V^-}$**			
	Value-Weighted		Equal-Weighted		Value-Weighted		Equal-Weighted		Value-Weighted		Equal-Weighted	
Low	0.97%	(3.52)	1.12%	(3.77)	1.14%	(4.15)	1.21%	(3.98)	0.74%	(2.62)	0.87%	(2.99)
P2	1.00%	(3.75)	1.12%	(3.83)	0.97%	(3.60)	1.22%	(3.98)	0.79%	(3.11)	0.99%	(3.39)
P3	0.73%	(2.76)	1.12%	(3.69)	0.96%	(3.68)	1.11%	(3.60)	0.94%	(3.58)	0.96%	(3.24)
P4	1.03%	(3.87)	1.03%	(3.37)	1.00%	(3.77)	1.07%	(3.53)	0.81%	(3.06)	0.98%	(3.29)
P5	0.89%	(3.49)	0.96%	(3.25)	0.85%	(3.14)	1.00%	(3.34)	0.81%	(3.17)	0.98%	(3.24)
P6	0.86%	(3.25)	0.98%	(3.29)	0.80%	(3.22)	1.01%	(3.38)	0.89%	(3.20)	0.98%	(3.23)
P7	0.80%	(2.99)	0.92%	(3.03)	0.72%	(2.65)	0.84%	(2.89)	0.97%	(3.76)	1.02%	(3.36)
P8	0.74%	(2.81)	0.84%	(2.75)	0.78%	(2.94)	0.77%	(2.55)	0.91%	(3.48)	0.92%	(2.92)
P9	0.60%	(2.14)	0.84%	(2.69)	0.52%	(1.87)	0.75%	(2.45)	0.86%	(3.23)	0.99%	(3.16)
High	0.77%	(2.98)	0.74%	(2.43)	0.66%	(2.55)	0.70%	(2.24)	0.92%	(3.41)	0.99%	(3.26)
High - Low	−0.19%	(−1.16)	−0.38%	(−3.32)	−0.48%	(−3.01)	−0.51%	(−3.78)	0.18%	(1.00)	0.12%	(1.12)

Panel B: Quartiles

	Stocks sorted by ρ				**Stocks sorted by $\rho^{\Delta V^+}$**				**Stocks sorted by $\rho^{\Delta V^-}$**			
	Value-Weighted		Equal-Weighted		Value-Weighted		Equal-Weighted		Value-Weighted		Equal-Weighted	
Low	0.94%	(3.59)	1.11%	(3.78)	1.07%	(4.09)	1.19%	(3.92)	0.82%	(3.16)	0.94%	(3.23)
P2	0.91%	(3.56)	1.02%	(3.42)	0.92%	(3.52)	1.05%	(3.50)	0.81%	(3.16)	0.97%	(3.26)
P3	0.81%	(3.12)	0.94%	(3.10)	0.77%	(3.05)	0.89%	(3.06)	0.90%	(3.41)	0.98%	(3.21)
High	0.70%	(2.69)	0.79%	(2.61)	0.60%	(2.29)	0.73%	(2.38)	0.91%	(3.59)	0.98%	(3.20)
High - Low	−0.24%	(−1.83)	−0.32%	(−3.91)	−0.46%	(−3.60)	−0.47%	(−4.71)	0.08%	(0.59)	0.05%	(0.57)

Table A.5: Fama-MacBeth Regressions of Bias-Corrected Correlation. This table reports monthly Fama-MacBeth cross-sectional predictive regressions of stock returns on monthly ρ, $\rho^{\Delta V^+}$, and ρ^{BC}. ρ and $\rho^{\Delta V^+}$ are the monthly correlations between daily stock returns and, respectively, daily variance innovations and positive variance innovations. ρ^{BC} is the bias-corrected estimate of the leverage effect following Aït-Sahalia et al. (2013), with details in Section A.4.2. *Controls* is "✓" if regression includes other controls from Table 5, "✗" otherwise. The sample contains all common and non-penny stocks from 1996 to 2023. Due to the three-year estimation window for ρ^{BC}, the regression sample begins in 1999. Standard errors are corrected using Newey-West with 3 lags. $\bar{R}^2$ is the average R^2 of the monthly cross-sectional predictive regressions. Robust t-statistics are presented in parentheses.

	ρ	$\rho^{\Delta V^+}$	ρ^{BC}	Controls	$\bar{R}^2$
Univariate	-0.40^{***}	-0.73^{***}	-0.29^{***}		
	(-3.50)	(-4.29)	(-2.78)		
I			-0.17^{**}	✓	6.87%
			(-2.24)		

Table A.6: Volatility-of-Volatility. This table reports monthly Fama-MacBeth cross-sectional predictive regressions on *RQ* and ρ. *RQ* is realized quarticity, computed by summing the fourth powers of intraday returns within each day and then averaging the daily values over the month. ρ is the realized correlation of daily returns and daily change in realized variance over the month. *Controls* is "✓" if regression includes other controls from Table 5, "✗" otherwise. The sample contains all common and non-penny stocks from 1996 to 2023. Standard errors are corrected using Newey-West with 3 lags. Robust t-statistics are presented in parentheses.

	I	II	III	IV
ρ			-0.43^{***}	-0.25^{***}
			(-3.78)	(-3.19)
RQ	-0.74^{***}	-0.44^{***}	-0.72^{***}	-0.44^{***}
	(-4.51)	(-2.85)	(-4.42)	(-2.89)
Controls	✗	✓	✗	✓
R^2	0.20%	6.68%	0.41%	6.77%