Jump Risk and Option Returns

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Abstract

We show that the term structure of equity volatility is a strong predictor of jumps in the underlying equity. Our analysis provides a risk-based explanation for some of the largest option-based anomalies from the literature. Returns of option strategies based upon different measures of term structure slope reflect the horizons over which each measure predicts jumps in the underlying. This further supports the theory that premiums associated with term structure are due to jump risk. We further show volatility term structure is a stronger predictor of jumps than existing predictors from the literature.

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1 Introduction

We study the information content embedded in the term structure of equity volatility. Prior studies have shown that volatility term structure signals are associated with large premia across multiple option trading strategies. The purpose of this paper is to understand why these large, seemingly anomalous premia exist. In doing so, we uncover new empirical evidence linking volatility term structure to time varying jump probability of the underlying. We show when term structure slope is low, or downward sloping (short term volatility is high relative to long term volatility), jump probability is high. In fact, volatility term structure is a better predictor of stock jumps than previously proposed indicators in the literature.

We examine two different measures of volatility term structure that have been shown to strongly predict option returns. The first, $SLOPE$, uses option implied volatilities to estimate both short and long-term volatility. Vasquez (2017) shows $SLOPE$ to be a very strong predictor of subsequent option returns. The second measure, $IVRVSLOPE$ uses option implied volatility to estimate short term volatility and uses past realized volatility to estimate long-term volatility. Goyal and Saretto (2009) show that $IVRVSLOPE$ predicts returns of option strategies. While Goyal and Saretto (2009) use $IVRVSLOPE$ as a signal to form portfolios of options, they do not call it a measure of volatility term structure slope. However, we find that realized volatility over the past year is highly correlated with the option-implied volatility of long-term options. Therefore, $IVRVSLOPE$ can be re-cast as a measure of volatility term structure.

The empirical options literature has uncovered many predictors of returns in individual stock options. These predictors include idiosyncratic risk (Cao and Han (2013)), risk-neutral skewness of the underlying (Bali and Murray (2013)), put-call implied-volatility spreads (Doran et al. (2013)), ex-ante skewness of the option (Boyer and Vorkink (2014)), past option-implied volatility (An et al. (2014)), option illiquidity (Christoffersen et al. (2018)), the introduction of credit default swaps on the same firm (Cao et al. (2021)), time between expiration dates (Eisdorfer et al. (2022)), volatility uncertainty (Cao et al. (2023)), default risk (Vasquez and Xiao (2023)), and past option returns (Heston et al. (2023)). Cao et al. (2021) show stock price, profit margin, firm profitability, cash holdings, cash flow variance, share issuance, external financing, and distress risk all help predict option returns. $IVRVSLOPE$ of Goyal and Saretto (2009) and $SLOPE$ of Vasquez (2017) remain two of the strongest and most well-known predictors of option returns. In a recent study, Heston et al. (2023) analyze option return predictors from the literature and show $SLOPE$ and $IVRVSLOPE$ to be "the two strongest predictors" of returns.

Despite the prominence of these two studies and the growing literature on equity option returns, the reason for the term structure's predictive power is not well understood. We contribute to the literature by showing that both volatility term structure measures, $SLOPE$ and $IVRVSLOPE$ predict jumps in the underlying asset and hence returns conditioned on term structures are related to jump risk. In portfolios formed weekly by sorting on term structure slope, we find a significant difference in both total and idiosyncratic jump frequency between the first and last quintiles. Equities in the lowest $SLOPE$ quintile experience more than twice as many jumps as those in the highest $SLOPE$ quintile. Similarly, jump frequency for stocks in the lowest $IVRVSLOPE$ quintile is approximately 3.5 times higher than that of stocks in the highest $IVRVSLOPE$. When comparing term structure slope with previously suggested measures of jump risk, both slope versions do a better job of predicting jumps even after one controls for implied volatility of the underlying. An examination of the time series of term structure slope and jump frequency indicate the differential is not a function of crisis periods.

Goyal and Saretto (2009) and Vasquez (2017) show that anomalous option returns associated with $IVRVSLOPE$ and $SLOPE$ are robust to exposures of common equity pricing factors and risk factors derived from the empirical options literature do not appear to explain much of the straddle returns. Both papers explore the possibility of overreaction as an explanation for the puzzling returns, although neither is able to definitively explain the return premium with known proxies for overreaction. Thus the returns remain a puzzle. In addition, option returns associated with one measure of volatility term structure do not completely explain option returns associated with the other. We show that this is because the two predict jumps at different frequencies.

Using a simple realized jump measure similar to the idiosyncratic jump measure in Kapadia and Zekhnini (2019), we show that both volatility term structure measures outperform well-known jump risk measures from the literature. Stocks with high values of jump risk estimated by $SLOPE$ have a much higher frequency of realized jumps in the following week. The frequency of realized jumps rapidly declines in the next few weeks. We see similar results using $IVRVSLOPE$. Stocks with high jump risk as estimated by $IVRVSLOPE$ are even more likely to experience jumps in the subsequent week. Furthermore, the high frequency of realized jumps predicted by $IVRVSLOPE$ persists for many weeks. The disparity in prediction horizon highlights differences in the types of jump risk each slope measure captures. In addition, we examine alternative realized jump definitions to account for the fact that the jump measure of Kapadia and Zekhnini (2019) and $IVRVSLOPE$ both contain past realized volatility in their definitions.

At four weeks after identification stocks with low $IVRVSLOPE$ experience twice as many jumps as stocks with a high $IVRVSLOPE$, and eight weeks after identification jump frequency differential remains significant. Accordingly, when forming straddle portfolios by sorting on $IVRVSLOPE$, stocks with higher predicted jump frequency realize low straddle returns. Stocks with high $IVRVSLOPE$ which are predicted to have low jump incidence, experience high straddle returns. As the jump prediction persists over a number of weeks, the return pattern in option portfolios exists at both short and long horizons.

The implied volatility term structure slope ($SLOPE$), is defined using long-term and short-term (one month) implied volatility, IV_{LT} and IV_{1M} respectively. $SLOPE$ is given by $SLOPE = (IV_{LT} - IV_{1M})/IV_{LT})$. This ex-ante measure forecasts transitory jump activity. Since $SLOPE$ only predicts jumps in the near future, returns of short maturity option portfolios are increasing with $SLOPE$, as they do with the $IVRVSLOPE$ portfolios. However, for portfolios constructed using three through six month options, returns are *decreasing* in $SLOPE$.

When examining the returns documented in studies like Goyal and Saretto (2009) and Vasquez (2017), it is natural to ask whether the premia associated with volatility based signals are consistent with subsequent realized volatility. In both cases, the authors find that subsequent realized volatility does not appear to be large enough to explain returns to straddles meant to capture variance risk premia. However, because jumps are rare and extreme events, option-based strategies which embed associated risk premia will tend to look large relative to realized volatility. Option straddles offer protection against extreme price movement in the underlying. As a result, buying low (negative) slope straddles is expensive because they hedge jump risk even though jumps are unlikely to be realized.

Goyal and Saretto (2009) posits that the large returns are a result of investor overreaction due to recent stock performance, as stocks with a low slope suffered recent poor performance while stocks with a high slope performed relatively well. We check to see whether the jump patterns are a function of recent stock performance or short term implied volatility, and find that after controlling for both, the pattern remains. Slope predicts jumps in the underlying, and thus, the large and robust premium associated with volatility term structure is consistent with option traders paying a premium to protect against jumps. Furthermore, straddle return patterns across maturities are consistent with the predictability of jumps for each measure of term structure.

The following section describes the data and methodology; Section 3 examines the identification of jumps by each measure of slope; Section 4 examines option returns; Sections 5 and 6 further examine the patterns identified; Section 7 concludes.

2 Data and Methodology

[INSERT FIGURE 1 HERE]

The OptionMetrics Ivy Database is the source for all equity option prices, implied volatilities, related greeks, and realized volatility and implied volatility surfaces which we use as a robustness check for our calculations of annualized realized volatility and slope of the volatility term structure, respectively. Implied volatilities and greeks are computed using a modified Cox et al. (1979) model given that listed equity options are American style. The CRSP database supplies equity prices. Each week we calculate two versions of volatility slope, $SLOPE$ and $IVRVSLOPE$, for each equity. $SLOPE$ is defined as the percentage difference between long-term and short-term implied volatility, $\frac{(IV_{LT}-IV_{1M})}{IV_{LT}}$; $IVRVSLOPE$ is defined as the percentage difference between long-term realized and short-term implied volatility, $\frac{(RV_{LT}-IV_{1M})}{RV_{LT}}$, where RV_{LT} is defined as twelve month realized volatility calculated from the daily closing prices of the underlying equity. For both implied volatility measures we use ATM straddle implied volatilities computed as the average volatility of the put and call options closest to at-the-money which survive the following filters: (1) The underlying equity has a closing price of at least \$10; (2) The option price must not violate arbitrage conditions; (3) The option must have a non-zero bid; (4) The absolute value of the delta must be between 0.35 and 0.65; and (5) The implied volatility must be between 3% and 200%. Short-term implied volatility (IV_{1M}) is defined as the at-the-money (ATM) straddle implied volatility with a maturity closest to one month; long-term implied volatility (IV_{LT}) is the implied volatility of the ATM straddle with the shortest maturity of at least six months. We allow flexibility for the long term maturity since an equity may not have six month options listed due to its calendar listing cycle.[1] Our dataset spans from January, 1996 through December, 2017 and includes 1,648,439 weekly observations on 7,854 equities. Panel A of Table 1 holds the descriptive statistics for both slopes and long and short term measures of volatility. IV_{1M} averages 0.447, higher than both IV_{LT}, 0.426, and RV_{LT}, 0.427, and so slope is negative on average. As long-term realized volatility evolves more slowly than long-term implied volatility, $IVRVSLOPE$ has a higher variance than $SLOPE$. At the 5^{th} percentiles, IV_{1M} is 36.9% higher than RV_{LT} and IV_{1M} is 14.4% higher than IV_{LT}. At the 95^{th} percentiles, IV_{1M} is 19.5% lower than RV_{LT} and 6.3% lower than IV_{LT}. While the slope measures are related mechanically as they include IV_{1M} in their calculation, variation exists when sorting on each measure. Figure 1 displays the percentage of firms within portfolios formed by double sorting independently on $SLOPE$ and $IVRVSLOPE$. While the two most heavily populated portfolios are those for which both slopes are either lowest or highest (Quintile

[1] The options of each equity are assigned to one of three sequential cycles: January, February, and March. Regardless of the cycle, options are listed for the first two monthly expirations. (In addition, equities with the most heavily traded options may list additional expirations.) Beyond the front two months, the expirations listed vary. For example, on the first trading day of the year, January and February options are listed for all equities. The next expirations listed for options of the January cycle are April and July, the first month of the following quarters; for the February cycle, the next listings are May and August, the second month of the following quarters. Those equities in the March cycle find March and June options listed. Thus, in any one month, roughly 33% of equities list a six month option, with the remainder listing a seven or eight month option.

1/Quintile 1 or Quintile 5/Quintile 5), roughly half of equities which fall in Quintile 1 (5) for one slope version are not within Quintile 1 (5) for the other.

[INSERT TABLE 1 HERE]

Each Tuesday, we sort firms into quintiles based on $SLOPE$ and $IVRVSLOPE$ and record several volatility measures for each firm; Panels B and C of Table 1 hold the means of these measures. Included are IV_{ST}, IV_{LT}, RV_{LT}, RV_{ST}, the one month realized volatility calculated from the daily closing prices of the underlying equity, $Idio$, the one month idiosyncratic volatility calculated using the Fama-French-Carhart model, and two crude measures of the volatility risk premium, $IV_{ST} - RV_{ST}$ and $IV_{ST} - Idio$. For both sets of portfolios, the alternate slope measure also increases across quintiles. For the $SLOPE$ portfolios the average $SLOPE$ increases from -0.226 to 0.103 while $IVRVSLOPE$ rises from -0.301 to 0.054. $IVRVSLOPE$ increases from -0.426 to 0.163 while $SLOPE$ rises from -0.162 to 0.042 in the $IVRVSLOPE$ portfolios. When examining the slope components and other measures we find several commonalities across both sets of portfolios. Both IV_{ST} and IV_{LT} are declining across portfolios, although IV_{ST} has greater variation. For $SLOPE$ ($IVRVSLOPE$) portfolios, IV_{ST} declines from 0.554 (0.556) to 0.371 (0.382) while IV_{LT} drops from 0.451 to 0.410 and 0.481 to 0.394. While RV_{ST} and $Idio$ also decline across both sets of quintiles, the range is smaller than that of IV_{ST}, and so the measures of the volatility risk premium, $IV_{ST} - RV_{ST}$ and $IV_{ST} - Idio$, are decreasing from Quintile 1 to Quintile 5. In Quintile 1, short term implied volatility is 0.097 higher on average than short term realized volatility for $SLOPE$ portfolios; for $IVRVSLOPE$ portfolios short term implied volatility is 0.129 higher. In summary, variation in IV_{ST} drives slope differences across the portfolios and when slope is low, short term implied volatility is elevated both absolutely and relative to all other measures.

We include two measures of skew, $Skew50\Delta$ and $Skew25\Delta$ from Yan (2011), and the left-and right-tailed jump measures, LT and RT, of Bollerslev and Todorov (2011). $Skew50\Delta$ and $Skew25\Delta$ are the one month implied volatility differentials between the 50 (25) delta put and call taken from the implied volatility surface supplied by the OptionMetrics Ivy Database. LT and RT of Bollerslev and Todorov (2011) are defined as $\frac{e^{rt}P}{\tau S}$ and $\frac{e^{rt}C}{\tau S}$, respectively, where P and C are the prices of short-dated 90% and 110% moneyness puts and calls, τ is the time to expiration, and S is the current stock price. Since LT and RT are calculated using short-dated prices there is a mechanical relationship with both measures of slope and both LT and RT are decreasing across quintiles. No relationship between slope and implied skewness is found, as the ratio of LT to RT and both skew measures are roughly consistent across portfolios. We include firm characteristics $Size$, the market capitalization expressed in $millions; BE/ME, the book to market value ratio; and $ILLIQ$, the Amihud (2002) measure of illiquidity. The low slope portfolios hold relatively illiquid, smaller equities while no relationship between BE/ME is found. As portfolios are formed each week, we include turnover, the percentage of firms which change each week within each portfolio. Over 40% of the extreme $SLOPE$ portfolios change compared with a turnover greater than 60% for portfolios two through four. Since by construction long term realized volatility evolves more slowly than long term implied volatility, 28.6% and 29.6% of $IVRVSLOPE$ Quintiles 1 and 5 change while more than half of the middle three portfolio turn over.

Table 1 illustrates that slope differences are driven by an equity's short term implied volatility measure, as long term implied and historic volatility are more stable than short term implied volatility. When slope is low, short term implied volatility is elevated absolutely and relative to both short term realized and idiosyncratic volatility. Since short term option prices are more sensitive to changes in the underlying, slope may provide information about the underlying equity's volatility. Given these dynamics, we next test whether slope provides any information regarding jump frequency in the underlying.

3 Jump Identification

To test whether slope holds any information regarding jump frequency, we first estimate the following regression, where J is the number of jump days for an equity within the weekly holding period.

$$J_{i,t+1} = \beta_0 + \beta_1 SLOPE_{i,t} + \beta_2 IVRVSLOPE_{i,t} + \beta_3 J_{i,t} + \beta_4 Size_{i,t} + \beta_5 BE/ME_{i,t} + \beta_6 ILLIQ_{i,t} +$$

$$\beta_7 SPXSLOPE_t + \beta_8 SPXIVRVSLOPE_t + \beta_9 SPXIV1M_t \quad (1)$$

The results are held in Table 2. Panel A (B) includes $SLOPE$ ($IVRVSLOPE$) as an independent variable. We define a jump as $\frac{|r_i^{tot}|}{\sigma_i} > 3$, where $|r_i^{tot}|$ is the absolute daily return of an equity and σ_i is the daily standard deviation of returns over the past twelve months. Firm variables included are the number of jumps the week prior, $J_{i,t}$; $Size$, the natural log of a firm's market capitalization in billions; BE/ME, a firm's book to market ratio; and $ILLIQ$, the Amihud (2002) illiquidity measure. We also include three market volatility variables: $SPXSLOPE$ and $SPXIVRVSLOPE$, the S&P 500 Index analogues to the slope measures calculated using the realized volatility data and volatility surface provided by OptionMetrics, and $SPXIV1M$, the one month S&P 500 Index ATM implied volatility. Reported here are the fixed-effects model where standard errors are clustered by firm and week; unreported Fama-MacBeth regressions yield similar results. The coefficient estimates for each slope measure are significantly negative. When firm control variables are included, the $SLOPE$ and $IVRVSLOPE$ coefficients are -0.212 and -0.177, with t-statistics of -6.68 and -8.89, respectively. Recalling the mean slopes of the low and high $SLOPE$ ($IVRVSLOPE$) portfolios from Table 1, the regression estimates predict 0.070 (0.104) more jumps per week for the low $SLOPE$ ($IVRVSLOPE$) portfolios, or 3.63 (5.42) jumps per year. Of the firm variables included, only firm size is statistically significant. Somewhat surprisingly, size is positively related to jump frequency.

[INSERT TABLE 2 HERE]

While regression estimates show a negative relationship between volatility slope and jump frequency, it is possible that systemic factors may explain this relationship. Figure 2 displays the slope differentials between Quintile Portfolios 1 and 5 over the sample period. The differences widen in the aftermath of the dot-com bubble and the Financial Crisis. However, they are widest from 2013-2017, a period of low volatility and strong equity performance, and so it does not appear that market factors drive cross-sectional variation in slope. They may, however, impact the jump frequency differential between Quintiles 1 and 5. Figure 3 plots this difference. For $IVRVSLOPE$ portfolios, the jump frequency differential corresponds broadly with market volatility, as they are largest in the early 2000s and 2008-2009. This pattern is evident in the $SLOPE$ portfolios as well, although the differential is also elevated from 2014 to 2017.

[INSERT FIGURE 2 HERE]

[INSERT FIGURE 3 HERE]

Table 2 includes market slope and one month ATM index implied volatility to examine the extent to which market factors explain the jump frequency differential. Consistent with equity slope, index slope is negatively related to jumps. $SPXSLOPE$ is statistically significant when included as a variable with either $SLOPE$ or $IVRVSLOPE$. When $SPXSLOPE$ is at its 10^{th} percentile, approximately 0.020 more jumps per week occur than when $SPXSLOPE$ is at its median level. $SPXIVRVSLOPE$ is significant when included as a variable with $SLOPE$; roughly 0.025 more jumps per week occur when $SPXIVRVSLOPE$ is at its 10^{th} percentile than when it is at its median. We find a positive relationship between one month index implied volatility and jump frequency, although it is significant only when included with $IVRVSLOPE$. A ten percentage point difference in index implied volatility predicts roughly 0.024 more jumps per week. After controlling for market factors though, both equity slope measures remain statistically significant with coefficient estimates similar in magnitude.

[INSERT TABLE 3 HERE]

To place the regression estimates above into context, Panel A of Table 3 examines the difference in daily jump frequency across portfolios. Alternate jump definitions, $J \equiv \frac{|r_i^{tot}|}{\sigma_i} > 2$ and $J \equiv \frac{|r_i^{tot}|}{\sigma_i} > 4$ are also included. Evident across all portfolios is the rarity of jumps; daily jump frequency for the sample is approximately 1.40% which equates to about 3.5 jumps each year. Thus, the regression estimates for the difference in jump frequency between low and high slope portfolios is roughly equivalent to the average number of jumps per year. In sympathy with regression findings, we see a significant decline in jump frequency from Quintile 1 to Quintile 5 across all jump hurdles. For $SLOPE$ portfolios, the daily jump frequency declines from 2.21% to 0.96% when $J > 3$, resulting in a statistically significant frequency differential of 1.25%. On an annual basis, equities in the low slope portfolio experience 5.54 jumps while those in the high slope portfolio have 2.42 jumps. When using alternative jump hurdle levels similar patterns are found. With $J > 2$, the daily jump frequency declines from 7.50% to 4.23% across portfolios, resulting in a 3.27% differential with a t-statistic of 22.04. We find almost three times as many jumps in Quintile 1 than Quintile 5 (0.73% vs. 0.27%) when $J > 4$.

The differentials for $IVRVSLOPE$ portfolios are greater. When $J > 3$, the Quintile 1 portfolio's jump frequency (2.55%) is more than three times greater than that of the Quintile 5 portfolio (0.68%). On an annual basis, this equates to 6.4 jumps for the low slope portfolio and 1.7 jumps for the high slope portfolio. The daily frequency declines from 8.39% to 3.33% when $J > 2$, resulting in a 5.06% differential with a t-statistic of 24.98. We find the Quintile 1 portfolio to have a jump frequency five times larger than that of Quintile 5 when $J > 4$. In both sets of portfolios we find a monotone decline from Quintile 1 to 5 and the Portfolio 1-5 differential is significantly positive across all jump hurdles. In addition, the decrease found between Quintiles 1 and 2 is relatively large for both sets of portfolios, as it accounts for roughly half of the 1-5 differential. This gap between portfolios is similar to the relatively large difference in slopes between Quintiles 1 and 2 seen in Table 1. Finally, the ratio of jumps between the low and high slope portfolios increases as the hurdle increases, and so larger jumps occur relatively more often in the low slope portfolios. The results in Table 3 support the hypothesis that both $SLOPE$ and $IVRVSLOPE$ inversely predict jump frequency in the underlying.

Table 2 shows that equity slope negatively predicts jumps after accounting for market volatility dynamics. To mute the effects of market jumps in portfolio sorts, we examine idiosyncratic jump frequency; Table 3 Panel B holds the results. Idiosyncratic jumps are defined as $\frac{|r_i^{idio}|}{\sigma_i} > J$, where

$|r_i^{idio}|$ represents the daily absolute idiosyncratic returns of an equity estimated using a market model and σ_i is the twelve month daily standard deviation of returns. For both slope measures, idiosyncratic jump frequency declines from Quintile 1 to Quintile 5, the Quintile 1-5 differentials are statistically significant and roughly equivalent to those seen in Panel A. When $J = 3$, the idiosyncratic jump frequency differential for $SLOPE$ portfolios is 1.46% compared to 1.25% total jump differential; for $IVRVSLOPE$ portfolios the idiosyncratic jump differential is 1.91% vs a 1.87% total jump differential. As with total jumps, the relative jump frequency differential increases when the jump hurdle is increased.

[INSERT TABLE 4 HERE]

We find that slope predicts jumps in the underlying after accounting for market dynamics. We next explore whether volatility slope is serving as a proxy for other stock-specific factors. Since Table 1 shows that variation in slope is driven by short term implied volatility, after sorting on both slope measures, we sort independently on one month ATM equity volatility. Panel A of Table 4 sorts on $SLOPE$ and IV_{1m}; Panel B sorts on $IVRVSLOPE$ and IV_{1m}. Interestingly, there is not a strong relationship between implied volatility and jump frequency. The average jump frequency is roughly constant across IV_{1m} Quintiles 2-5 and lowest in IV_{1m} Quintile 1 when ATM implied volatility is lowest. For slope portfolios the jump frequency is lowest when one month implied volatility is lowest; when sorting on $SLOPE$ ($IVRVSLOPE$), the differential is 0.63% (1.46%). Otherwise, the jump frequency differentials are comparable to those seen in the single sorts in Table 3. For IV_{1m} Quintiles 2 through 5 the differentials range from 1.19% to 1.47% for $SLOPE$ and 1.84% to 2.28% for $IVRVSLOPE$ portfolios. In all cases the differentials are statistically significant.

As Goyal and Saretto (2009) notes that low $IVRVSLOPE$ is usually preceded by low returns for the underlying, and since volatility and returns are negatively correlated, we examine whether the prior month's return can explain jump predictability. Similar to above, we sort independently on slope and lagged one month return. Panels C and D hold the results. An inverse relationship between prior returns and jumps exist. In the first Ret_{1m} Quintile, the average jump frequency is 1.70% for $SLOPE$ portfolios and 1.59% for $IVRVSLOPE$ portfolios. The average declines as prior returns increase and when prior returns are highest, jumps occur 1.10% and 1.17% of the time. For each version of slope we find that as prior return increases, jump frequency differential decreases. For $SLOPE$ portfolios the differential declines from 1.31% to 0.91%; for $IVRVSLOPE$ portfolios the differential declines from 2.06% to 1.52%. However, in every instance the difference remains statistically significant.

Although the results from Panels A through D show that slope predicts jumps in the underlying after controlling for one month implied volatility and lagged returns, there is some relationship between these factors and the difference in jumps between low and high slope portfolios. We next examine subsets of our sample to see whether extreme levels of slope, one month implied volatility, or lagged returns drive our findings. Panels E and F of Table 4 hold single sorts on slope after excluding extreme portfolios. Each week we exclude firms which fall in the highest and lowest slope quintiles. In Panel E we also exclude the firms with IV_{1m} falling in Quintile 1 or 5; in Panel F we do the same with lagged one month return. In each instance the differentials are lower but remain statistically significant. When eliminating the extreme IV_{1m} portfolio, the differential falls from 1.25% to 1.13% for $SLOPE$. Removing IV_{1m} portfolios has the largest impact on jump differential for the $IVRVSLOPE$ portfolios, resulting in a decrease from 1.87% to 1.02%. The results are similar when removing extreme Ret_{1m} portfolios. We conclude jump differentials found in Table 4 do not appear to be driven by extreme observations nor are the differentials a function solely of short term implied volatility or prior returns.

[INSERT TABLE 5 HERE]

Until this point the analysis has centered on jump frequency the week after portfolio formation. We next examine the extent to which slope predicts jumps in subsequent weeks. Table 5 displays the jump frequency ($J > 3$) from week $t + 1$ through $t + 9$ for both sets of portfolios. For the $IVRVSLOPE$ portfolios jump frequency differential declines each week after portfolio formation but remains statistically significant. The week after formation average jump frequency decreases from 2.55% in Quintile 1 to 0.68% in Quintile 5 for a differential of 1.87%. The following week the difference declines to 1.44% and in week $t + 3$ it stands at 1.24%. In week $t + 9$ it stands at 0.55% with a t-statistic of 11.05. This persistence is not found in the $SLOPE$ portfolios. After four weeks the difference between low and high $SLOPE$ portfolios is 0.45%, and at six weeks the differential is only 0.11%. Thus while both versions of slope predict jumps the week following portfolio formation, over time the predictive power of $SLOPE$ dissipates and after one month there is no appreciable difference across portfolios. While the differential in the $IVRVSLOPE$ portfolios decline over time, it remains statistically significant after two months.

[INSERT TABLE 6 HERE]

We next compare slope to a number of option-related measures of jump predictability from the literature; Table 6 holds the results. Included are three ratios of implied to realized volatility: $ln(IV_{1M}/RV_{1m})$, the log difference of one month implied and realized volatility; $ln(IV_{1M}/RV_{cond})$, the log difference of one month implied volatility and conditional volatility, from Kapadia and Zekhnini (2019); and $ln(IV_{ST}/RV_{cond})$, the log difference of short term implied volatility and conditional volatility, where short term volatility is the ATM implied volatility of options with the shortest maturity greater than eight days, from Kapadia and Zekhnini (2019). Two measures of skew are included: $Skew50$ and $Skew25$ from Yan (2011), the implied volatility differences in 50 and 25 delta put and call volatilities respectively. We include two measures of implied volatility: $LTRT$, the sum of the Bollerslev and Todorov (2011) tail measures; and IV_{1M}, since it is the common element in the slope measures. For each measure, the jump differential between Quintile 1 and 5 is significant but lower than that of $SLOPE$ (1.24%) and $IVRVSLOPE$ (1.86%). The three ratios which compare a measure of short term implied and realized volatility have the largest jump differentials of the included measures, ranging from -0.55% ($ln(IV_{1m}/RV_{1m})$) to -0.72% $ln(IV_{1m}/RV_{cond})$. (Negative differentials here are consistent with our findings as Quintile 5 portfolios are those with a relatively elevated implied volatility.) The differentials of IV_{1M} and $LTRT$ are similar, -0.23% and -0.26%, which is unsurprising given that $LTRT$ is calculated from short-term options, and these low levels illustrate that the large jump differentials in both slope portfolios are not driven by outright IV_{1M} levels. Finally, the two skew measures produce the smallest differentials of less than 0.20%. Overall, slope best predicts the likelihood of jumps, followed by the measures comparing short-term implied volatility to realized. When $SLOPE$ and $IVRVSLOPE$ are in the lowest quintile, a jump occurs 2.20% and 2.54% of the time as compared to 1.89% for the next best predictor, $ln(IV_{1M}/RV_{cond})$. When slope is high, jumps are relatively unlikely: in the highest quintile jumps occur only 0.96% ($SLOPE$) and 0.68% ($IVRVSLOPE$) compared to 1.17% for the $ln(IV_{1M}/RV_{cond})$ portfolios. The results show slope does a better job of predicting jumps than other measures commonly referenced in the literature.

4 Robustness Checks

[INSERT TABLE 7 HERE]

So far we have identified jumps by comparing an equity's absolute return to its volatility calculated using the prior twelve months of daily returns so that the jump hurdle is relatively more stable. As there is a mechanical relationship between this definition of jumps and the construction of $IVRVSLOPE$, and alternative jump measures exist in the literature, we next examine whether slope's predictive power is robust to other jump definitions. Tables 7 and 8 hold regression estimates of equation (1) and portfolio sorts using three alternate definitions for realized jumps. In each instance a jump is defined as $\frac{|r_i^{tot}|}{\sigma_i} > 3$, and σ_i is either the one month daily standard deviation of returns ($Jump1m$); the conditional volatility, ($JumpCond$), from Kapadia and Zekhnini (2019), defined as:

$$\sigma_{i,t} = \sqrt{(1-\lambda)\sum_{t=1}^{T}(\lambda^t * r_{i,t})},$$

where $\lambda = 0.94$ and T is the entire history of the stock's returns; or ($JumpBipower$) from Lee and Mykland (2008), which employes a bipower variation:

$$\sqrt{1/(K-2)\sum_{t=i-K+2}^{i-1}|r_{i,t} * r_{i,t-1}|}$$

with $K = 16$. Across all definitions, $SLOPE$ and $IVRVSLOPE$ coefficients are significantly negative, albeit smaller in magnitude. $SLOPE$ coefficient estimates are -0.151 for $Jump1m$, -0.183

for $JumpCond$, and -0.218 for $JumpBipower$ compared to -0.212 from Table 2, when estimating volatility using the prior twelve months of returns. $IVRVSLOPE$ coefficient estimates range from -0.077 for $Jump1m$ to -0.126 for $JumpBipower$ compared to -0.177 in Table 2. In contrast to the original regression estimates, J_t has a significantly inverse relation across all definitions. Since realized volatility the week prior has a larger impact on the jump hurdle under these alternate definitions, this may indicate that a strong relationship exists between the level of volatility used to identify jumps and jump frequency. Further examination in the Appendix shows that this is the case.

Table 8 displays portfolio jump frequency using the alternate definitions. Consistent with the earlier findings jump frequency declines across portfolios under the alternate definitions and all Portfolio 1-5 differentials are significant. For $JumpCond$ the frequency differential declines from 2.13% to 1.39% across $SLOPE$ portfolios, resulting in a statistically significant 0.74% differential. A similar decline from 2.19% to 1.26% is seen across the $IVRVSLOPE$ portfolios. Jump frequency differentials are slightly lower when using $Jump1m$ (0.57% for $SLOPE$ portfolios and 0.76% for $IVRVSLOPE$ portfolios) although they remain statistically significant. When employing the definition using bipower variation, jump frequency is above 5% across all portfolios. Nevertheless, the frequency differentials are also significant.

[INSERT TABLE 8 HERE]

5 Option Returns

When equity jump risk is high one would expect low equity option returns as option traders pay a premium to hedge this risk. Indeed, Goyal and Saretto (2009) show that short-term option returns and $IVRVSLOPE$ are positively related; Vasquez (2017) finds that $SLOPE$ is positively related to short-term options. Since an option's sensitivity to jumps in the underlying decreases as option maturity increases, we examine weekly delta-hedged straddles across a range of maturities to see whether the option return patterns exist in longer term options. Table 9 reports the means and

Newey-West standard errors of delta-hedged ATM option straddle portfolios with maturities from one to six months. The methodology employed to identify straddles and form portfolios mirrors the calculation of slope. Each Tuesday, we identify eligible puts and calls with standard monthly expirations for equities with a closing price of at least \$10. As in the calculation of $SLOPE$ and $IVRVSLOPE$, the puts and calls selected are those closest to ATM, do not violate arbitrage conditions and have absolute deltas between 0.35 and 0.65. For each maturity from one to six months, we form ATM straddles for each equity with a valid put and call option. Since options for each maturity are not listed for all but the most liquid options, we do not require ATM straddles for each maturity as a prerequisite for inclusion. The only qualification with regard to maturity is the identification of a valid ATM straddle with a maturity of at least six months so that $SLOPE$ can be calculated. To avoid microstructure issues, the midpoint of the closing bid and ask prices for the call and put are used from the following day to calculate opening prices. Closing straddle prices are similarly calculated the following week. While the straddles have deltas close to 0, we delta hedge the option at the close each day using the deltas reported from OptionMetrics in order to mute directional exposure. Returns for each portfolio are calculated following Frazzini and Pedersen (2012). At trade inception, straddles worth \$1 are held, $V_0 = 1$. At the end of each day, the value of the portfolio is comprised of the value of the option position, the return from the delta hedge, and financing costs:

$$V_t = V_{t-1} + x(F_t - F_{t-1}) - x\Delta_{t-1} r_t^S S_{t-1} + r_t^f (V_{t-1} - xF_{t-1} + x\Delta - t - 1 S_{t-1}) \tag{2}$$

where $x = 1/F_0$, the number of options contracts, F is the option price, r^s is the daily stock return, r^f is the daily risk free rate, and Δ is the option's delta. The return to the position, R_T, is

$$R_T = V_T - V_0 = V_T - 1 \tag{3}$$

Table 9 displays the average returns for portfolios formed by sorting on $SLOPE$ and $IVRVSLOPE$ with maturities closest to one through six months. Newey and West (1987) standard errors with twelve lags and t-statistics are also included. Consistent with Goyal and Saretto (2009) and Vasquez (2017), we find a strong positive relationship between returns and both versions of slope for one month options as returns are monotonically increasing from Quintile 1 to 5. The one month Quintile 1 $SLOPE$ portfolio loses 1.7%, the Quintile 5 portfolio earns 0.7%, resulting in a long-short portfolio loss of 2.4% per week. The $IVRVSLOPE$ return differential across portfolios is greater: the Quintile 1 portfolio loses 2.9% while the Quintile 5 portfolio earns 1.9% per week. The $SLOPE$ and $IVRVSLOPE$ long-short portfolio returns are significantly different than 0 with t-statistics of -10.81 and -14.13 respectively, and on a risk-adjusted basis a portfolio which owns Quintile 5 and shorts Quintile 1 generates Sharpe Ratios of 2.33 and 3.01. Although not as pronounced, these return patterns are seen in the two month portfolios. The Quintile 1 $SLOPE$ portfolio loses 0.8% and the Quintile 5 portfolio loses 0.1%, resulting in a weekly loss of 0.7%. A portfolio which buys the high slope portfolio and sells the low slope portfolio posts a Sharpe Ratio of 1.28. As with the one month portfolios, the difference across $IVRVSLOPE$ portfolios is greater: Quintile 1 loses 1.7%, Quintile 5 earns 0.8%, resulting in a weekly loss if 2.5%. The high-low $IVRVSLOPE$ long-short portfolio posts a 2.60 Sharpe Ratio.

[INSERT TABLE 9 HERE]

For maturities greater than two months the return patterns diverge. The Quintile 1 $IVRVSLOPE$ portfolios continue to underperform and the Quintile 5-1 portfolio return differentials are significantly positive: The three month long-short portfolio earns 1.1% weekly, the four and five month portfolio realizes 0.8%, and the six month differential is 0.4%. For the $SLOPE$ portfolios, however, Quintile 1 *outperforms* Quintile 5 for three through six month maturities and returns are *decreasing* across Quintiles. From three through six months, the low $SLOPE$ portfolios outperform weekly by 0.4%, 0.8%, 1.0% and 1.1% and a long-short portfolio which buys the six month low $SLOPE$ and sells the high $SLOPE$ posts a Sharpe ratio of 4.01. While the return pattern documented by Goyal and Saretto (2009) persists across longer maturities, the return pattern documented by Vasquez (2017) is limited to short maturity options.

To see whether market or factor exposures explain these differences in the option portfolio returns, we estimate the following regression:

$$RET^t = \alpha + \beta_1 INDEX_{str}^t + \beta_2 (MKT^2)^t + \beta_3 MKT^t + \beta_4 HML^t$$

$$+\beta_5 SMB^t + \beta_6 MOM^t \tag{4}$$

where RET represents the returns of the $SLOPE$ and $IVRVSLOPE$ Quintile 1-5 long-short portfolios of delta hedged straddles for one and six month maturities. We include the Fama and French (1993) and Carhart (1997) factor returns MKT, HML, SMB, and MOM, along with MKT^2, the square of market returns and $INDEX_{Str}$, the returns of S&P 500 Index one month delta-hedged straddles. In three of the four estimates returns negatively load on Index straddle returns while other factor loadings are largely insignificant. In each estimate intercepts are significant and similar to the long-short portfolio returns. Alphas for one and six month $SLOPE$ portfolios are -2.5% and 1.0% while $IVRVSLOPE$ alphas are -4.9% and -0.4%. Factors do not explain the difference in return patterns for the two sets of portfolios.

6 Conclusion

We study the information content embedded in the term structure of equity volatility. Using two different measures of volatility term structure from the literature, $SLOPE$ and $IVRVSLOPE$, we show that both are strong predictors of jumps in the underlying. Previous studies using each of these measures have found them to predict large and robust returns to option trading strategies. We provide a risk-based explanation for these large premiums that have remained some of the most robust option-based anomalies from the literature. In addition to the risk associated with the underlying assets we also are able to explain why option strategies based upon the two slope measures do not explain each other. $SLOPE$ and $IVRVSLOPE$ differ in the horizons over which they predict jumps. $SLOPE$ is a strong predictor at short horizons while $IVRVSLOPE$ predicts jumps over longer horizons. We show that returns of option strategies using $SLOPE$ and $IVRVSLOPE$ reflect the horizons over which each predicts jumps in the underlying. This further supports the notion that the large premiums associated with each are compensation for jump risk. In addition, we show the ability of both $SLOPE$ and $IVRVSLOPE$ to predict jumps exceeds previously proposed jump predictors from the literature, suggesting they could be used as empirical proxies of jump risk.

References

Amihud, Y. (2002), 'Illiquidity and stock returns: cross-section and time-series effects', *Journal of financial markets* **5**(1), 31–56.

An, B.-J., Ang, A., Bali, T. G. and Cakici, N. (2014), 'The joint cross section of stocks and options', *The Journal of Finance* **69**(5), 2279–2337.

Bali, T. G. and Murray, S. (2013), 'Does risk-neutral skewness predict the cross-section of equity option portfolio returns?', *Journal of Financial and Quantitative Analysis* **48**(4), 1145–1171.

Bollerslev, T. and Todorov, V. (2011), 'Tails, fears, and risk premia', *The Journal of Finance* **66**(6), 2165–2211.

Boyer, B. H. and Vorkink, K. (2014), 'Stock options as lotteries', *The Journal of Finance* **69**(4), 1485–1527.

Cao, J. and Han, B. (2013), 'Cross section of option returns and idiosyncratic stock volatility', *Journal of Financial Economics* **108**(1), 231–249.

Cao, J. J., Vasquez, A., Xiao, X. and Zhan, X. E. (2023), 'Why does volatility uncertainty predict equity option returns?', *The Quarterly Journal of Finance* **13**(01), 2350005.

Cao, J., Jin, Y., Pearson, N. D. and Tang, D. Y. (2021), 'Does the introduction of one derivative affect another derivative? the effect of credit default swaps trading on equity options', *The Effect of Credit Default Swaps Trading on Equity Options (May 19, 2021)* .

Carhart, M. M. (1997), 'On persistence in mutual fund performance', *The Journal of finance* **52**(1), 57–82.

Christoffersen, P., Goyenko, R., Jacobs, K. and Karoui, M. (2018), 'Illiquidity premia in the equity options market', *The Review of Financial Studies* **31**(3), 811–851.

Cox, J. C., Ross, S. A. and Rubinstein, M. (1979), 'Option pricing: A simplified approach', *Journal of financial Economics* **7**(3), 229–263.

Doran, J. S., Fodor, A. and Jiang, D. (2013), 'Call-put implied volatility spreads and option returns', *Review of Asset Pricing Studies* **3**(2), 258–290.

Eisdorfer, A., Sadka, R. and Zhdanov, A. (2022), 'Maturity driven mispricing of options', *Journal of Financial and Quantitative Analysis* **57**(2), 514–542.

Fama, E. F. and French, K. R. (1993), 'Common risk factors in the returns on stocks and bonds', *Journal of* .

Frazzini, A. and Pedersen, L. H. (2012), Embedded leverage, Technical report, National Bureau of Economic Research.

Goyal, A. and Saretto, A. (2009), 'Cross-section of option returns and volatility', *Journal of Financial Economics* **94**(2), 310–326.

Heston, S. L., Jones, C. S., Khorram, M., Li, S. and Mo, H. (2023), 'Option momentum', *The Journal of Finance* **78**(6), 3141–3192.

Kapadia, N. and Zekhnini, M. (2019), 'Do idiosyncratic jumps matter?', *Journal of Financial Economics* **131**(3), 666–692.

Lee, S. S. and Mykland, P. A. (2008), 'Jumps in financial markets: A new nonparametric test and jump dynamics', *The Review of Financial Studies* **21**(6), 2535–2563.

Newey, W. and West, K. (1987), ‘A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix’, *Econometrica* **55**(3), 703–08.

Vasquez, A. (2017), ‘Equity volatility term structures and the cross section of option returns’, *Journal of Financial and Quantitative Analysis* **52**(6), 2727–2754.

Vasquez, A. and Xiao, X. (2023), ‘Default risk and option returns’, *Management Science* .

Yan, S. (2011), ‘Jump risk, stock returns, and slope of implied volatility smile’, *Journal of Financial Economics* **99**(1), 216–233.

Figure 1: Portfolio Composition

Each week firms are sorted into portfolios based on $SLOPE$, as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$, and $IVRVSLOPE$, as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$. This figure charts the percentage of firms which populate both sets of portfolios. The first figure displays the percentage of firms which comprise portfolios sorted on both measures. The next figures display the breakdown of Quintile 1 and 5 portfolios into sorts on the alternative slope measure.

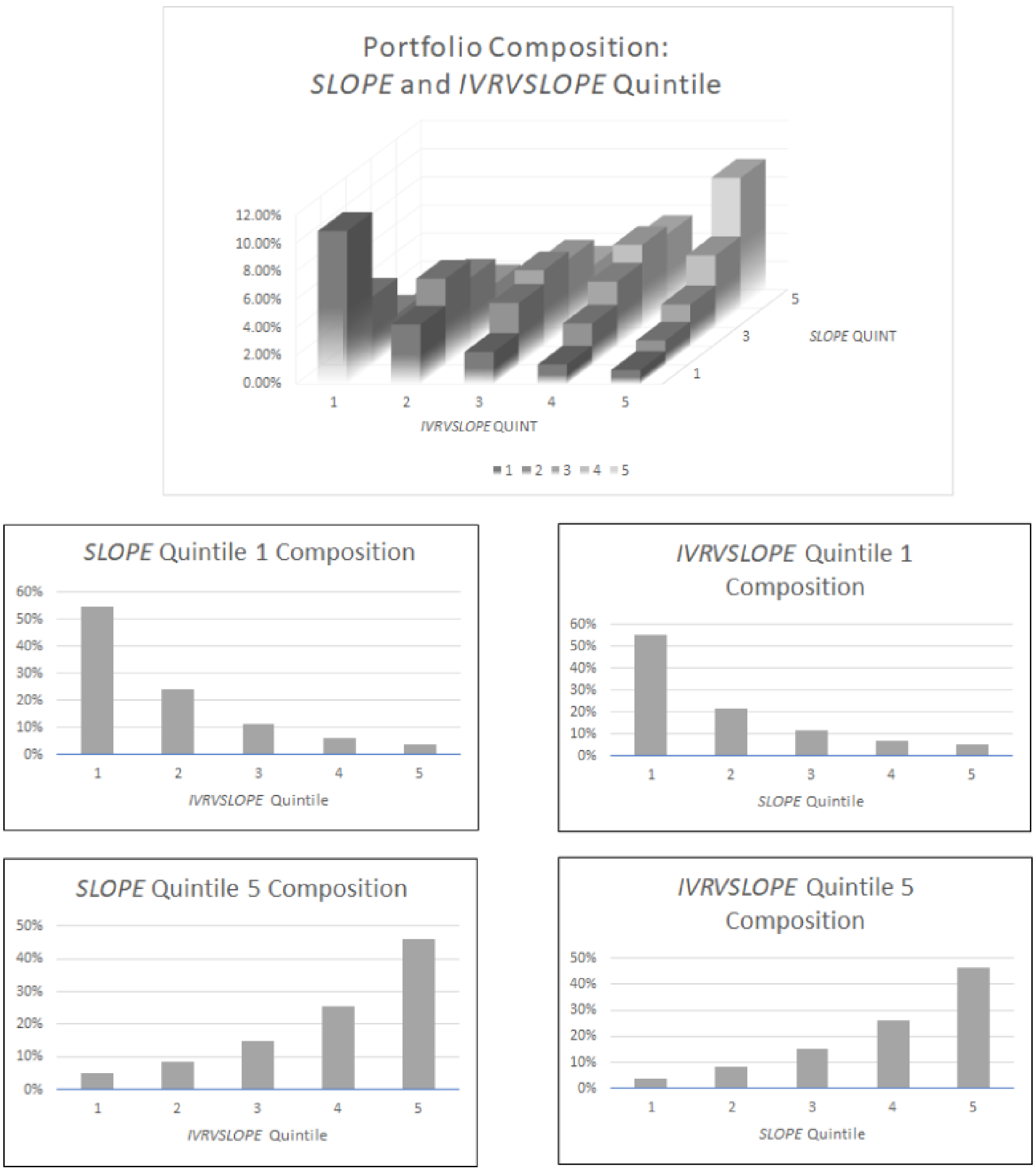


Figure 2: Time Series of Slope Differential

This figure charts the difference in slope between Quintiles 1 and 5 formed each week by sorting on $SLOPE$, as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$ or $IVRVSLOPE$, as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$.

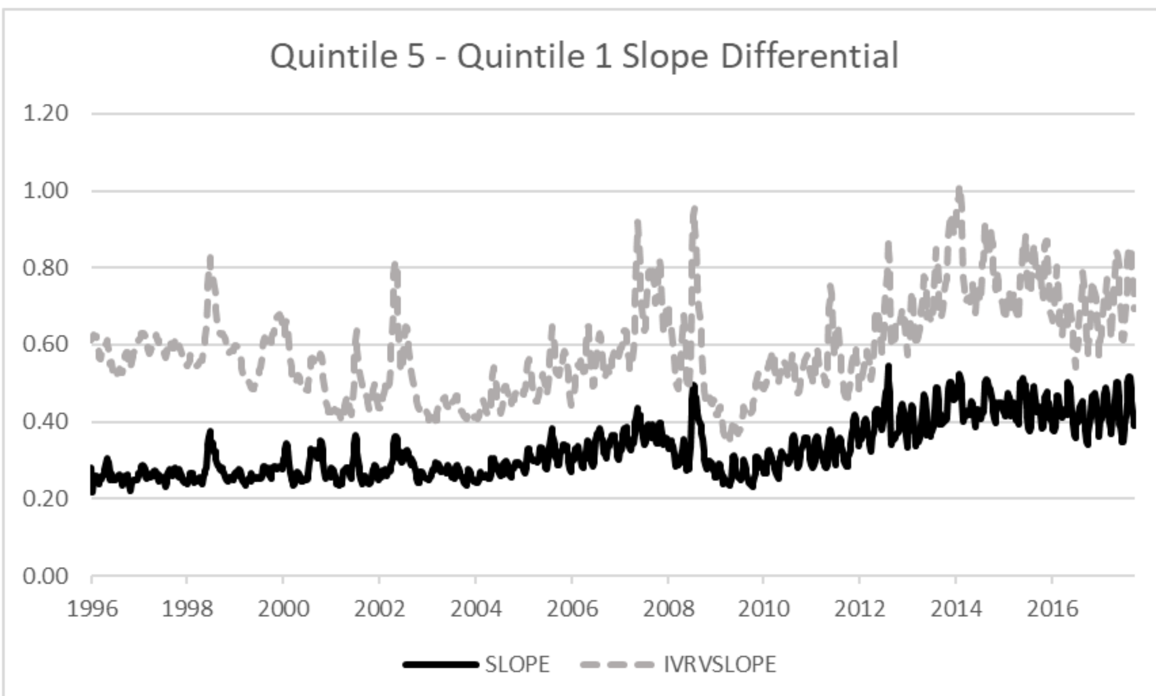


Table 1: Summary Statistics

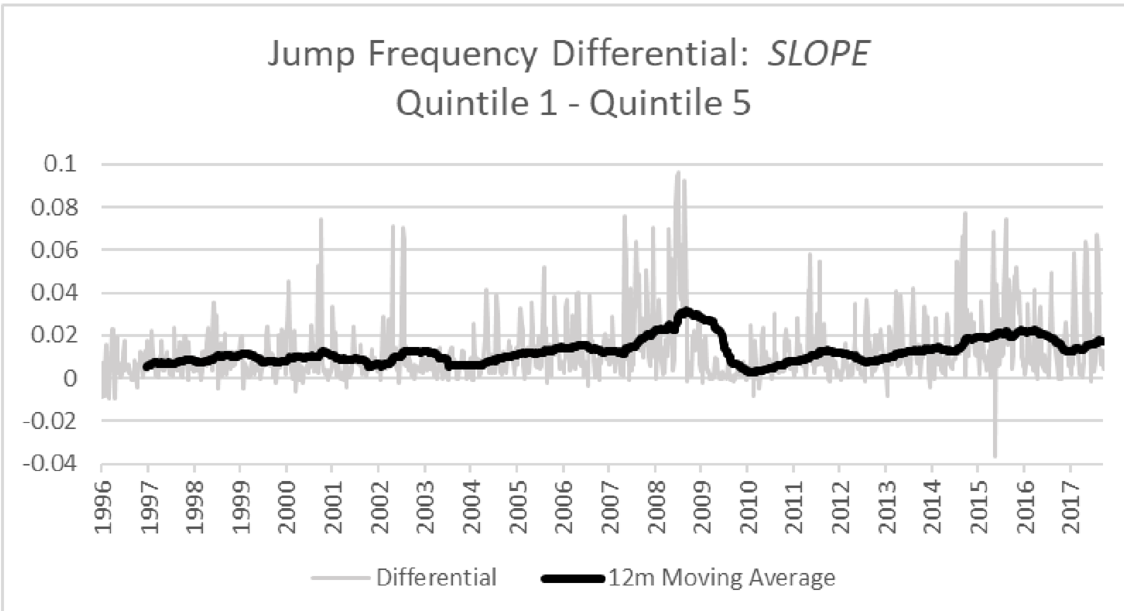
Panel A holds the mean, standard deviation, skewness, kurtosis, 5th, 25th, 50th, 75th, and 95th percentiles of the monthly averages of $SLOPE$, defined by $(IV_{LT} - IV_{1M})/IV_{LT}$; $IVRVSLOPE$, defined by $(RV_{LT} - IV_{1M})/RV_{LT}$, IV_{ST}; IV_{ST}, the implied volatility of the ATM one month straddle; IV_{LT} the implied volatility of an ATM straddle with at least six months; and RV_{ST} and RV_{LT}, the realized volatility of one and twelve months respectively, calculated using daily returns. Panels B and C hold the time series averages of several measures for portfolios sorted on $SLOPE$ and $IVRVSLOPE$. Volatility measures reported are $Idio$, the one month idiosyncratic volatility calculated using the Fama-French-Carhart model; $Skew50\Delta$ and $Skew25\Delta$, the difference between the implied volatility of the 50 or 25 delta put and call respectively; and LT and RT, the left-tailed and right-tailed jump measures from Bollerslev and Todorov (2011). Stock characteristics $Size$, the market capitalization expressed in \$millions; BE/ME, the book to market value; and $ILLIQ$, the Amihud (2002) measure of illiquidity are included. Portfolio Turnover is the average percentage change in composition each week. The period examined spans from 1996 through 2017, and includes 1,648,439 firm-weeks and 7,854 firms.

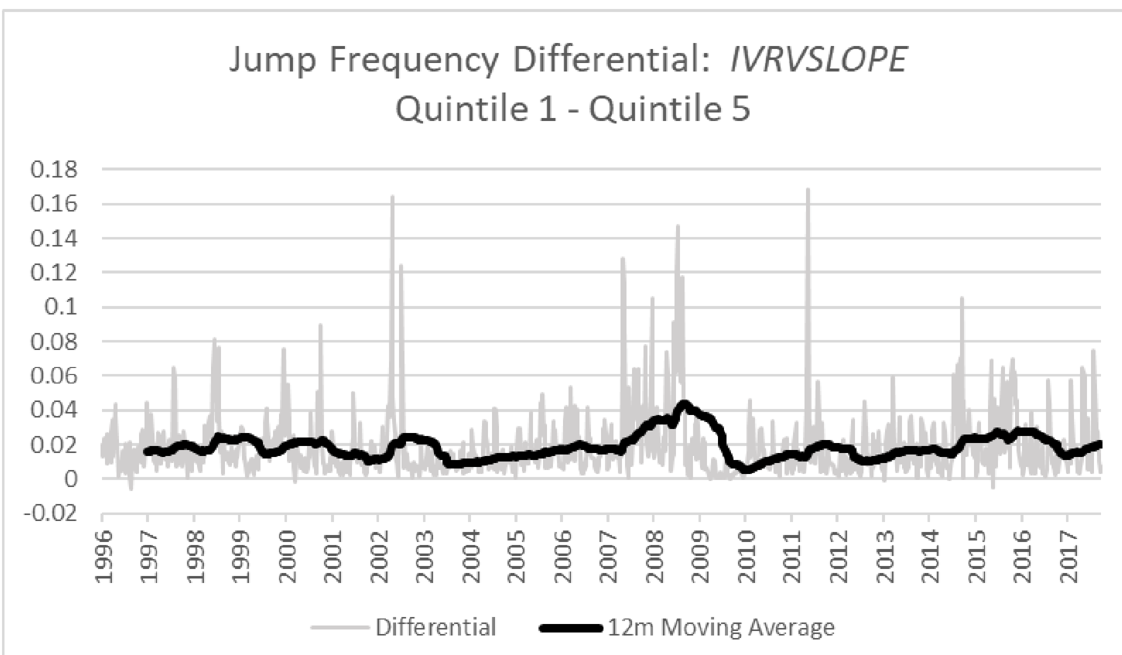
Panel A

	Mean	StDev	Skew	Kurtosis	5%	25%	50%	75%	95%
$SLOPE$	-0.041	0.065	-0.592	4.944	-0.144	-0.078	-0.042	0.001	0.063
$IVRVSLOPE$	-0.082	0.170	-0.452	5.081	-0.369	-0.159	-0.072	0.001	0.195
IV_{ST}	0.447	0.122	1.208	4.050	0.314	0.356	0.409	0.502	0.706
IV_{LT}	0.426	0.099	1.140	3.587	0.320	0.349	0.391	0.466	0.647
RV_{ST}	0.411	0.153	1.586	5.986	0.256	0.299	0.371	0.477	0.726
RV_{LT}	0.427	0.133	0.956	2.886	0.284	0.317	0.393	0.494	0.711

Figure 3: Time Series of Jump Frequency Differential

This figure charts the monthly percentage jump frequency between Quintile Portfolios 1 and 5 formed weekly by sorting on $SLOPE$, defined by $(IV_{LT} - IV_{1M})/IV_{LT}$, and $IVRVSLOPE$, as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$. A jump is defined as $\frac{|r_i^{tot}|}{\sigma} > J$, where $J > 3$. $|r_i^{tot}|$ is the absolute daily return of an equity and σ is the daily volatility calculated using the daily returns of the prior twelve months.





Panel B: Sorted on $SLOPE$

	1	2	3	4	5	All
$SLOPE$	-0.226	-0.079	-0.025	0.023	0.103	-0.041
$IVRVSLOPE$	-0.301	-0.110	-0.050	-0.003	0.054	-0.083
IV_{ST}	0.554	0.471	0.437	0.405	0.371	0.448
IV_{LT}	0.451	0.434	0.423	0.410	0.410	0.426
RV_{ST}	0.457	0.432	0.412	0.390	0.366	0.411
RV_{LT}	0.446	0.440	0.431	0.416	0.402	0.427
$Idio$	0.354	0.334	0.322	0.306	0.297	0.323
$IV_{ST} - RV_{ST}$	0.097	0.039	0.025	0.015	0.005	0.007
$IV_{ST} - Idio$	0.200	0.137	0.115	0.099	0.074	0.125
$Skew50\Delta$	0.014	0.015	0.016	0.017	0.022	0.017
$Skew25\Delta$	0.087	0.089	0.093	0.100	0.107	0.095
LT	0.418	0.312	0.273	0.241	0.220	0.293
RT	0.420	0.308	0.267	0.233	0.209	0.287
$Size$	7771	9509	10609	12279	14427	10890
BM	0.476	0.487	0.485	0.467	0.445	0.472
$ILLIQ$	0.0062	0.0054	0.0051	0.0050	0.0051	0.0054
Portfolio Turnover	0.433	0.645	0.679	0.647	0.437	0.568

Panel C: Sorted on $IVRVSLOPE$

	1	2	3	4	5	All
$IVRVSLOPE$	-0.426	-0.146	-0.045	0.040	0.163	-0.083
$SLOPE$	-0.162	-0.062	-0.026	0.004	0.042	-0.041
IV_{ST}	0.556	0.460	0.431	0.410	0.382	0.448
IV_{LT}	0.481	0.431	0.416	0.407	0.394	0.426
RV_{ST}	0.427	0.412	0.409	0.408	0.402	0.411
RV_{LT}	0.399	0.408	0.420	0.437	0.471	0.427
$Idio$	0.347	0.323	0.317	0.314	0.313	0.323
$IV_{ST} - RV_{ST}$	0.129	0.048	0.022	0.002	-0.02	0.037
$IV_{ST} - Idio$	0.209	0.137	0.114	0.096	0.069	0.125
$Skew50\Delta$	0.017	0.015	0.015	0.016	0.020	0.017
$Skew25\Delta$	0.079	0.087	0.094	0.102	0.111	0.095
LT	0.424	0.303	0.269	0.246	0.221	0.293
RT	0.426	0.298	0.263	0.239	0.211	0.287
$Size$	6900	9577	11066	12441	14463	10890
BM	0.470	0.466	0.468	0.469	0.488	0.472
$ILLIQ$	0.0078	0.0056	0.0047	0.0043	0.0046	0.0054
Portfolio Turnover	0.286	0.514	0.565	0.528	0.295	0.438

Table 2: Jump Panel Regressions

This table examines the extent to which $SLOPE$ and $IVRVSLOPE$ predict jumps in the underlying equity by estimating the following regression:

$$J_{i,t+1} = \beta_0 + \beta_1 SLOPE_{i,t} + \beta_2 IVRVSLOPE_{i,t} + \beta_3 J_{i,t} + \beta_4 Size_{i,t} + \beta_5 BE/ME_{i,t} + \beta_6 ILLIQ_{i,t} +$$

$$\beta_7 SPXSLOPE_t + \beta_8 SPXIVRVSLOPE_t + \beta_9 SPXIV1M_t$$

The regression is estimated using a fixed-effects model where standard errors are clustered by firm and week. $SLOPE$ is the equity implied volatility term structure slope; $IVRVSLOPE$ is the equity implied/realized volatility slope as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$. J is the number of total jumps in a week, where a jump is defined as $\frac{|r_i^{tot}|}{\sigma_i} > 3$, $|r_i^{tot}|$ is the absolute daily returns of an equity and σ_i is the twelve month daily standard deviation of returns. $Size$ is the natural log of the market capitalization in \$billions; BE/ME is the book to market value; and $ILLIQ$ is the Amihud (2002) illiquidity measure. $SPXSLOPE$ and $SPXIVRVSLOPE$ are the S&P 500 Index counterparts of the slope measures. $SPXIV1M$ is the one month ATM implied volatility of the S&P 500 Index. The period examined spans from 1996 through 2017, and includes 1,648,439 firm-weeks and 7,854 firms.

PANEL A: SLOPE

	(1)	(2)	(3)	(4)	(5)
$SLOPE$	-0.196***	-0.212***	-0.207***	-0.212***	-0.209***
	(-6.72)	(-6.68)	(-6.93)	(-6.86)	(-6.91)
J_t		0.031	0.029	0.028	0.030
		(1.85)	(1.79)	(1.66)	(1.86)
$Size$		0.011***	0.016***	0.013***	0.014***
		(3.43)	(4.36)	(3.90)	(3.70)
BE/ME		-0.007	-0.004	0.005	-0.008
		(-1.29)	(-0.71)	(0.96)	(-1.49)
$ILLIQ$		0.051	0.064	0.069	0.033
		(0.32)	(0.42)	(0.47)	(0.21)
$SPXSLOPE$			-0.110*		
			(-2.29)		
$SPXIVRVSLOPE$				-0.059***	
				(-4.36)	
$SPXIV1M$					0.122
					(1.14)
R^2	0.013	0.017	0.019	0.020	0.017

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

PANEL B: $IVRVSLOPE$

	(1)	(2)	(3)	(4)	(5)
$IVRVSLOPE$	-0.165***	-0.177***	-0.175***	-0.180***	-0.180***
	(-8.95)	(-8.89)	(-9.44)	(-8.69)	(-9.46)
J_t		0.015	0.012	0.015	0.012
		(0.98)	(0.86)	(0.98)	(0.86)
$Size$		0.003	0.008*	0.003	0.008**
		(1.03)	(2.55)	(0.94)	(2.62)
BE/ME		0.006	0.008	0.004	0.004
		(1.18)	(1.60)	(0.88)	(0.83)
$ILLIQ$		-0.029	-0.016	-0.033	-0.066
		(-0.19)	(-0.10)	(-0.21)	(-0.41)
$SPXSLOPE$			-0.107*		
			(-2.55)		
$SPXIVRVSLOPE$				0.008	
				(0.56)	
$SPXIV1M$					0.239*
					(2.44)
R^2	0.031	0.033	0.035	0.033	0.035

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Portfolio Jump Frequency

This table displays the frequency of realized jumps in portfolios formed by sorting each week on $SLOPE$ and $IVRVSLOPE$, where $SLOPE$ is the implied volatility term structure slope as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$ and $IVRVSLOPE$ is the implied/realized volatility slope as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$.

Panel A displays the frequency of jumps realized in each portfolio, where a jump is defined as $\frac{|r_i^{tot}|}{\sigma_i} > 3$, $|r_i^{tot}|$ is the absolute daily returns of an equity and σ_i is the twelve month daily standard deviation of returns. Panel B displays the frequency of idiosyncratic jumps realized in each portfolio, where an idiosyncratic jump is defined as $\frac{|r_i^{idio}|}{\sigma_i} > J$, $|r_i^{idio}|$ are the daily absolute idiosyncratic returns of an equity and σ_i is the 12 month daily standard deviation of returns. Displayed are the average daily frequency, Newey-West standard errors with 12 lags and t-statistics of the Quintile 1 - Quintile 5 Portfolios. The period examined spans from 1996 through 2017, and includes 1,648,439 firm-weeks and 7,854 firms.

Panel A: Total Jumps

SLOPE

$J = 2$	1	2	3	4	5	1-5
Jump Pct.	7.50%	6.05%	5.31%	4.78%	4.23%	3.27%
St. Error	0.0018	0.0017	0.0016	0.0015	0.0014	0.0015
t-stat						22.04
$J = 3$	1	2	3	4	5	1-5
Jump Pct.	2.21%	1.54%	1.29%	1.10%	0.96%	1.25%
St. Error	0.0008	0.0007	0.0007	0.0006	0.0006	0.0008
t-stat						14.81
$J = 4$	1	2	3	4	5	1-5
Jump Pct.	0.73%	0.47%	0.37%	0.32%	0.27%	0.45%
St. Error	0.0004	0.0003	0.0003	0.0003	0.0003	0.0004
t-stat						10.74

IVRVSLOPE

$J = 2$	1	2	3	4	5	1-5
Jump Pct.	8.39%	6.37%	5.34%	4.44%	3.33%	5.06%
	0.0019	0.0017	0.0016	0.0015	0.0013	0.0020
						24.98
$J = 3$	1	2	3	4	5	1-5
Jump Pct.	2.55%	1.66%	1.26%	0.97%	0.68%	1.87%
	0.0009	0.0008	0.0007	0.0006	0.0005	0.0012
						16.04
$J = 4$	1	2	3	4	5	1-5
Jump Pct.	0.87%	0.50%	0.35%	0.26%	0.18%	0.69%
	0.0005	0.0004	0.0003	0.0002	0.0002	0.0006
						11.40

PANEL B: Idiosyncratic Jumps

SLOPE

$J=2$	1	2	3	4	5	1-5
Jump Pct.	7.31%	5.73%	4.98%	4.47%	3.95%	3.36%
St. Error	0.0033	0.0030	0.0027	0.0026	0.0024	0.0014
t-stat						24.50
$J=3$	1	2	3	4	5	1-5
Jump Pct.	2.42%	1.64%	1.32%	1.13%	0.96%	1.46%
St. Error	0.0014	0.0011	0.0010	0.0009	0.0008	0.0008
t-stat						18.35
$J=4$	1	2	3	4	5	1-5
Jump Pct.	0.90%	0.56%	0.43%	0.36%	0.29%	0.61%
St. Error	0.0006	0.0005	0.0004	0.0003	0.0003	0.0004
t-stat						14.27

IVRVSLOPE

$J=2$	1	2	3	4	5	1-5
Jump Pct.	7.98%	5.93%	4.99%	4.26%	3.31%	4.67%
St. Error	0.0014	0.0014	0.0014	0.0014	0.0014	0.0017
t-stat						27.88
$J=3$	1	2	3	4	5	1-5
Jump Pct.	2.64%	1.73%	1.33%	1.05%	0.73%	1.91%
St. Error	0.0006	0.0005	0.0004	0.0005	0.0005	0.0008
t-stat						20.34
$J=4$	1	2	3	4	5	1-5
Jump Pct.	1.00%	0.59%	0.43%	0.32%	0.20%	0.79%
St. Error	0.0003	0.0002	0.0002	0.0002	0.0002	0.0004
t-stat						15.69

Table 4: Portfolio Jump Frequencies: Controlling for Other Factors

This table examines volatility slope as a predictor of jumps ($J > 3$) after controlling for other factors. Panels A and B hold the results of sorting independently on one month implied volatility, IV_{1m}, and $SLOPE$, as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$, and $IVRVSLOPE$, as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$. Panels C and D hold the results of sorting independently on the prior month return in the underlying, Ret_{1m}, and $SLOPE$ and $IVRVSLOPE$. Panel E and F sort on volatility slope after eliminating extreme portfolios. Panel E removes firms in the highest and lowest volatility slope quintile and IV_{1m} quintiles; Panel F removes firms in the highest and lowest volatility slope quintile and Ret_{1m}. The period examined spans from 1996 through 2017, and includes 1,648,439 weekly observations on 7,854 firms.

Panel A: Sorting on $SLOPE$ and IV_{1m}

	$SLOPE$					
IV_{1m}	1	2	3	4	5	1-5
Quintile 1						
Jump Pct.	1.65%	1.66%	1.41%	1.23%	1.02%	0.63%
St. Error	0.0009	0.0009	0.0009	0.0008	0.0007	0.0007
t-stat						8.75
Quintile 2						
Jump Pct.	2.17%	1.72%	1.39%	1.15%	0.98%	1.19%
St. Error	0.0009	0.0009	0.0007	0.0006	0.0006	0.0009
t-stat						12.95
Quintile 3						
Jump Pct.	2.30%	1.64%	1.33%	1.12%	0.96%	1.34%
St. Error	0.0009	0.0007	0.0007	0.0006	0.0006	0.0009
t-stat						14.75
Quintile 4						
Jump Pct.	2.38%	1.53%	1.21%	1.03%	0.92%	1.47%
St. Error	0.0009	0.0007	0.0007	0.0006	0.0006	0.0009
t-stat						16.69
Quintile 5						
Jump Pct.	2.14%	1.25%	1.04%	0.88%	0.79%	1.35%
St. Error	0.0009	0.0007	0.0007	0.0006	0.0006	0.0010
t-stat						12.88

Panel B: Sorting on $IVRVSLOPE$ and IV_{1m}

			$IVRVSLOPE$			
IV_{1m}	1	2	3	4	5	1-5
Quintile 1						
Jump Pct.	2.25%	1.74%	1.37%	1.11%	0.79%	1.46%
St. Error	0.0012	0.0009	0.0008	0.0007	0.0006	0.0026
t-stat						5.53
Quintile 2						
Jump Pct.	2.59%	1.81%	1.39%	1.06%	0.74%	1.84%
St. Error	0.0011	0.0009	0.0007	0.0006	0.0005	0.0014
t-stat						13.55
Quintile 3						
Jump Pct.	2.70%	1.81%	1.36%	1.04%	0.68%	2.03%
St. Error	0.0010	0.0008	0.0007	0.0006	0.0005	0.0012
t-stat						16.32
Quintile 4						
Jump Pct.	2.83%	1.76%	1.23%	0.87%	0.55%	2.28%
St. Error	0.0010	0.0008	0.0007	0.0006	0.0005	0.0012
t-stat						18.50
Quintile 5						
Jump Pct.	2.37%	1.21%	0.85%	0.60%	0.36%	2.00%
St. Error	0.0009	0.0007	0.0006	0.0005	0.0004	0.0014
t-stat						14.15

Panel C: Sorting on $SLOPE$ and Ret_{1m}

			$SLOPE$			
Ret_{1m}	1	2	3	4	5	1-5
Quintile 1						
Jump Pct.	2.55%	1.79%	1.55%	1.36%	1.24%	1.31%
St. Error	0.0010	0.0008	0.0008	0.0007	0.0007	0.0010
t-stat						12.53
Quintile 2						
Jump Pct.	2.26%	1.68%	1.44%	1.26%	1.06%	1.21%
St. Error	0.0009	0.0008	0.0008	0.0007	0.0006	0.0008
t-stat						14.70
Quintile 3						
Jump Pct.	2.17%	1.55%	1.30%	1.13%	1.00%	1.16%
St. Error	0.0009	0.0008	0.0007	0.0006	0.0006	0.0008
t-stat						15.24
Quintile 4						
Jump Pct.	1.96%	1.42%	1.18%	1.03%	0.91%	1.05%
St. Error	0.0008	0.0007	0.0007	0.0006	0.0006	0.0008
t-stat						13.29
Quintile 5						
Jump Pct.	1.68%	1.21%	0.98%	0.86%	0.77%	0.91%
St. Error	0.0007	0.0007	0.0006	0.0005	0.0005	0.0006
t-stat						14.94

Panel D: Sorting on Implied/Realized Volatility Slope and Ret_{1m}

	Implied/Realized Volatility Slope					
Ret_{1m}	1	2	3	4	5	1-5
Quintile 1						
Jump Pct.	2.88%	1.78%	1.38%	1.08%	0.82%	2.06%
St. Error	0.0011	0.0008	0.0007	0.0007	0.0006	0.0013
t-stat						15.74
Quintile 2						
Jump Pct.	2.60%	1.75%	1.37%	1.06%	0.78%	1.82%
St. Error	0.0010	0.0008	0.0007	0.0006	0.0006	0.0012
t-stat						15.62
Quintile 3						
Jump Pct.	2.44%	1.72%	1.26%	1.04%	0.73%	1.71%
St. Error	0.0010	0.0008	0.0007	0.0006	0.0005	0.0010
t-stat						16.50
Quintile 4						
Jump Pct.	2.31%	1.58%	1.20%	0.94%	0.68%	1.63%
St. Error	0.0009	0.0008	0.0007	0.0006	0.0005	0.0009
t-stat						17.22
Quintile 5						
Jump Pct.	2.07%	1.40%	1.06%	0.79%	0.55%	1.52%
St. Error	0.0008	0.0007	0.0006	0.0005	0.0004	0.0009
t-stat						16.67

Panel E: Eliminating Extreme Portfolios: IV_{1m}

	1	2	3	4	5	1-5
Slope	2.09%	1.48%	1.27%	1.13%	0.96%	1.13%
St. Error	0.0008	0.0007	0.0007	0.0006	0.0005	0.0008
t-stat						14.76
IV RV Slope	2.02%	1.48%	1.27%	1.12%	0.99%	1.02%
St. Error	0.0008	0.0007	0.0007	0.0006	0.0006	0.0007
t-stat						14.09

Panel F: Eliminating Extreme Portfolios: Ret_{1m}

	1	2	3	4	5	1-5
Slope	1.98%	1.50%	1.27%	1.12%	1.03%	0.95%
St. Error	0.0008	0.0007	0.0007	0.0006	0.0006	0.0006
t-stat						14.73
IV RV Slope	2.27%	1.60%	1.25%	1.00%	0.76%	1.51%
St. Error	0.0009	0.0007	0.0007	0.0006	0.0005	0.0009
t-stat						17.57

Table 5: Predicting Jumps Over Time

This table displays the frequency of realized jumps in portfolios created by sorting on $SLOPE$, the implied volatility term structure slope as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$ or $IVRVSLOPE$ the implied/realized volatility slope as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$. Jumps are defined as $\frac{|r_i^{tot}|}{\sigma_i} > J$, where $J = 3$, $|r_i^{tot}|$ are the absolute daily returns of an equity and σ_i is the twelve month daily standard deviation of returns. The frequency of jumps are displayed for one $(t + 1)$, through nine $(t + 9)$ weeks after portfolio formation. The period examined spans from 1996 through 2017, and includes 1,648,439 weekly observations on 7,854 firms.

	$SLOPE$					
	1	2	3	4	5	1-5
$JumpPct_{t+1}$	2.21%	1.54%	1.29%	1.10%	0.96%	1.25%
t-stat						14.81
$JumpPct_{t+2}$	1.87%	1.51%	1.32%	1.17%	1.04%	0.83%
t-stat						11.87
$JumpPct_{t+3}$	1.75%	1.49%	1.33%	1.21%	1.10%	0.66%
t-stat						11.27
$JumpPct_{t+4}$	1.64%	1.46%	1.34%	1.25%	1.19%	0.45%
t-stat						9.12
$JumpPct_{t+5}$	1.54%	1.41%	1.36%	1.31%	1.28%	0.26%
t-stat						6.44
$JumpPct_{t+6}$	1.45%	1.40%	1.35%	1.34%	1.35%	0.11%
t-stat						2.77
$JumpPct_{t+7}$	1.39%	1.39%	1.36%	1.36%	1.40%	-0.01%
t-stat						-0.25
$JumpPct_{t+8}$	1.38%	1.36%	1.36%	1.37%	1.42%	-0.03%
t-stat						-1.06
$JumpPct_{t+9}$	1.38%	1.35%	1.35%	1.38%	1.43%	-0.05%
t-stat						-1.66

	$IVRVSLOPE$					
	1	2	3	4	5	1-5
$JumpPct_{t+1}$	2.55%	1.66%	1.26%	0.97%	0.68%	1.87%
t-stat						16.04
$JumpPct_{t+2}$	2.20%	1.62%	1.29%	1.04%	0.75%	1.44%
t-stat						16.17
$JumpPct_{t+3}$	2.06%	1.61%	1.32%	1.08%	0.81%	1.24%
t-stat						15.73
$JumpPct_{t+4}$	1.93%	1.58%	1.34%	1.14%	0.88%	1.04%
t-stat						15.07
$JumpPct_{t+5}$	1.85%	1.54%	1.37%	1.18%	0.96%	0.88%
t-stat						14.62
$JumpPct_{t+6}$	1.77%	1.53%	1.35%	1.23%	1.00%	0.77%
t-stat						13.36
$JumpPct_{t+7}$	1.71%	1.51%	1.37%	1.25%	1.05%	0.66%
t-stat						12.43
$JumpPct_{t+8}$	1.67%	1.50%	1.36%	1.28%	1.08%	0.59%
t-stat						11.71
$JumpPct_{t+9}$	1.65%	1.48%	1.39%	1.27%	1.10%	0.55%
t-stat						11.05

Table 6: Comparing with Other Jump Prediction Measures

This table displays the jump frequency and standard errors of portfolios created weekly by sorting on various measures: $SLOPE$, the implied volatility term structure slope as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$; $IVRVSLOPE$, the implied/realized volatility slope as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$; $ln(IV_{1m}/RV_{1m})$ and $ln(IV_{1m}/RV_{cond})$, the log difference in one month implied and realized volatility where RV_{cond} is defined as the exponentially weighted moving average $\sqrt{(1-\lambda)\sum_{t=1}^{T}(\lambda^t * r_{i,t})}$, with $\lambda = 0.94$; $ln(IV_{ST}/RV_{cond})$, the log difference in short term implied and annualized conditional volatility where short term volatility is the ATM implied volatility of options with the shortest maturity greater than eight days; $LTRT$, the average of left-tailed and right-tailed jump measures from Bollerslev and Todorov (2011); $Skew50$, the difference in 30 day 50 delta put and call implied volatility as defined in Yan (2011); and $Skew25$, the difference in 30 day 25 delta put and call implied volatility. Newey-West standard errors with 12 lags are displayed. The period examined spans from 1996 through 2017, and includes 1,648,439 weekly observations on 7,854 firms.

	1	2	3	4	5	1-5
$SLOPE$	2.20%	1.55%	1.28%	1.11%	0.96%	1.24%
St. Error	0.0018	0.0016	0.0015	0.0013	0.0012	0.0008
t-stat						14.80
$IVRVSLOPE$	2.54%	1.66%	1.26%	0.97%	0.68%	1.86%
St. Error	0.0021	0.0017	0.014	0.0012	0.0010	0.0012
t-stat						16.04
$ln(IV_{1m}/RV_{1m})$	1.22%	1.26%	1.36%	1.50%	1.77%	-0.55%
St. Error	0.0015	0.0015	0.0015	0.0015	0.0015	0.0005
t-stat						-11.91
$ln(IV_{1m}/RV_{cond})$	1.17%	1.23%	1.32%	1.50%	1.89%	-0.72%
St. Error	0.0015	0.0015	0.0015	0.0015	0.0015	0.0005
t-stat						-15.11
$ln(IV_{ST}/RV_{cond})$	1.21%	1.23%	1.30%	1.47%	1.81%	-0.60%
St. Error	0.0015	0.0015	0.0015	0.0015	0.0015	0.0005
t-stat						-12.34
$Skew50$	1.51%	1.39%	1.37%	1.33%	1.33%	0.19%
St. Error	0.0017	0.0016	0.0015	0.0015	0.0015	0.0003
t-stat						5.48
$Skew25$	1.48%	1.39%	1.35%	1.33%	1.39%	0.10%
St. Error	0.0016	0.0016	0.0015	0.0015	0.0015	0.0004
t-stat						2.71
$LTRT$	1.21%	1.32%	1.40%	1.43%	1.47%	-0.26%
St. Error	0.0014	0.0013	0.0014	0.0015	0.0017	0.0007
t-stat						-3.76
IV_{1M}	1.25%	1.39%	1.46%	1.51%	1.48%	-0.23%
St. Error	0.0014	0.0015	0.0015	0.0014	0.0016	0.0007
t-stat						-3.39

Table 7: Robustness Test: Panel Regressions, Alternate Jump Definitions

This table examines the extent to which $SLOPE$ and $IVRVSLOPE$ predict jumps in the underlying equity, where $SLOPE$ is the implied volatility term structure slope as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$ and $IVRVSLOPE$ is the implied/realized volatility slope as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$. The table reports the estimates of the following regression:

$$J_{i,t+1} = \beta_0 + \beta_1 SLOPE_{i,t} + \beta_2 IVRVSLOPE_{i,t} + \beta_3 J_{i,t} + \beta_4 Size_{i,t} + \beta_5 BE/ME_{i,t} + \beta_6 ILLIQ_{i,t}$$

where J is the number of jumps in a week. A jump is defined as $\frac{|r_i^{tot}|}{\sigma_i} > 3$. $|r_i^{tot}|$ is the absolute daily return of an equity and σ_i is either the one month daily standard deviation of returns ($Jump1m$); the conditional volatility, ($JumpCond$), from Kapadia and Zekhnini (2019); or the bipower variation, ($JumpBipower$) from Lee and Mykland (2008). $Size$ is the market capitalization in \$billions; BE/ME is the book to market value; and $ILLIQ$ is the Amihud (2002) illiquidity measure. The regressions are estimated using a fixed-effects model where standard errors are clustered by firm and week. The period examined spans from 1996 through 2017, and includes 1,648,439 firm-weeks and 7,854 firms.

	$Jump1m$		$JumpCond$		$JumpBipower$	
	(1)	(2)	(3)	(4)	(5)	(6)
$SLOPE$	-0.151***		-0.183***		-0.218***	
	(-5.79)		(-6.74)		(-5.00)	
$IVRVSLOPE$		-0.077***		-0.103***		-0.126***
		(-4.90)		(-6.45)		(-4.79)
J_t	-0.045***	-0.044***	-0.053***	-0.054***	-0.028***	-0.028***
	(-7.93)	(-7.78)	(-9.45)	(-9.53)	(-3.78)	(-3.88)
$Size$	0.003	-0.000	0.009	0.004	-0.015	-0.020*
	(0.70)	(-0.05)	(1.93)	(0.99)	(-1.55)	(-2.26)
BE/ME	-0.001	0.005	-0.004	0.004	-0.027*	-0.018
	(-0.19)	(0.88)	(-0.72)	(0.74)	(-2.52)	(-1.66)
$ILLIQ$	0.137	0.102	0.151	0.104	-0.154	-0.212
	(0.69)	(0.52)	(0.76)	(0.53)	(-0.44)	(-0.60)
R^2	0.007	0.006	0.010	0.010	0.004	0.004

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Robustness Test: Portfolio Jump Frequency, Alternate Jump Definitions

This table examines the extent to which $SLOPE$ and $IVRVSLOPE$ predict jumps in the underlying equity, where $SLOPE$ is the implied volatility term structure slope as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$ and $IVRVSLOPE$ is the implied/realized volatility slope as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$. This table displays the frequency of realized jumps and volatility in portfolios. A jump is defined as $\frac{|r_i^{tot}|}{\sigma_i} > 3$. $|r_i^{tot}|$ is the absolute daily return of an equity and σ_i is either the one month daily standard deviation of returns ($Jump1m$); the conditional volatility, ($JumpCond$), from Kapadia and Zekhnini (2019); or the bipower variation, ($JumpBipower$) from Lee and Mykland (2008). Displayed are the average daily frequency, Newey-West standard errors with 12 lags and t-statistics of the Quintile 1 - Quintile 5 Portfolios. The period examined spans from 1996 through 2017, and includes 1,648,439 firm-weeks and 7,854 firms.

SLOPE

Jump1m	1	2	3	4	5	1-5
Jump Pct.	2.13%	1.70%	1.57%	1.53%	1.56%	0.57%
St. Error	0.0006	0.0004	0.0005	0.0005	0.0005	0.0006
t-stat						9.36
JumpCond	1	2	3	4	5	1-5
Jump Pct.	2.13%	1.66%	1.49%	1.42%	1.39%	0.74%
St. Error	0.0006	0.0005	0.0005	0.0005	0.0005	0.0006
t-stat						12.80
JumpBipower	1	2	3	4	5	1-5
Jump Pct.	5.79%	5.22%	5.06%	5.04%	5.17%	0.62%
St. Error	0.0010	0.0008	0.0008	0.0008	0.0009	0.0010
t-stat						6.46

IVRVSLOPE

Jump1m	1	2	3	4	5	1-5
Jump Pct.	2.20%	1.79%	1.60%	1.48%	1.44%	0.76%
St. Error	0.0005	0.0005	0.0004	0.0004	0.0005	0.0004
t-stat						17.15
JumpCond	1	2	3	4	5	1-5
Jump Pct.	2.19%	1.74%	1.52%	1.38%	1.26%	0.93%
St. Error	0.0006	0.0005	0.005	0.0005	0.0005	0.0004
t-stat						22.08
JumpBipower	1	2	3	4	5	1-5
Jump Pct.	5.97%	5.39%	5.10%	4.92%	4.91%	1.06%
St. Error	0.0009	0.0008	0.0008	0.0008	0.0008	0.0006
t-stat						15.52

Table 9: Option Portfolio Returns

This table reports the mean returns, Newey West standard errors with 12 lags and t-statistics of ATM straddle portfolios with one through six month maturities created weekly by sorting on the $SLOPE$, as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$ in Panel A, or $IVRVSLOPE$, as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$ in Panel B. Each Tuesday straddle portfolios are formed based on slope; on Wednesday straddles are entered, delta-hedged daily, and exited the following Wednesday. The period examined spans from 1996 through 2017, and includes 1,648,439 weekly observations on 7,854 firms.

Panel A: $SLOPE$

	1	2	3	4	5	1-5
1m Return	-0.017	-0.006	-0.005	-0.003	0.007	-0.024
St. Error	0.0022	0.0023	0.0024	0.0024	0.0027	0.0022
t-stat	-7.41	-2.41	-2.08	-0.73	2.74	-10.81
2m	-0.008	-0.004	-0.004	-0.003	-0.001	-0.007
	0.0016	0.0017	0.0014	0.0016	0.0017	0.0012
	-4.96	-2.10	-2.69	-1.93	-0.37	-5.99
3m	0.001	0.001	-0.001	-0.002	-0.003	0.004
	0.0015	0.0014	0.0013	0.0012	0.0013	0.0008
	0.70	0.42	-0.88	-1.39	-2.46	5.67
4m	0.005	0.002	-0.000	-0.002	-0.003	0.008
	0.0013	0.0011	0.0012	0.0012	0.0012	0.0006
	3.85	2.19	-0.27	-1.55	-2.75	13.81
5m	0.007	0.004	0.002	-0.000	-0.003	0.010
	0.0011	0.0010	0.0010	0.0010	0.0010	0.0006
	6.14	3.74	1.81	-0.07	-2.57	15.88
6m	0.008	0.004	0.002	-0.001	-0.003	0.011
	0.0011	0.0009	0.0009	0.0010	0.0009	0.0006
	7.03	4.15	1.68	-0.58	-3.44	18.81

Panel B: $IVRVSLOPE$

	1	2	3	4	5	1-5
1m Return	-0.029	-0.011	-0.004	0.004	0.019	-0.048
St. Error	0.0022	0.0023	0.0024	0.0024	0.0025	0.0034
t-stat	-13.33	-4.85	-1.68	1.53	7.46	-14.13
2m	-0.017	-0.007	-0.004	0.000	0.008	-0.025
	0.0017	0.0014	0.0017	0.0016	0.0017	0.0020
	-10.00	-5.34	-2.14	0.15	4.84	-12.19
3m	-0.007	-0.003	-0.001	0.001	0.004	-0.011
	0.0015	0.0014	0.0013	0.0014	0.0014	0.0014
	-5.08	-2.13	-0.94	0.78	2.99	-8.45
4m	-0.004	-0.001	0.001	0.002	0.004	-0.008
	0.0012	0.0012	0.0011	0.0011	0.0013	0.0012
	-3.18	-0.57	0.42	1.33	3.38	-6.94
5m	-0.002	0.001	0.002	0.003	0.006	-0.008
	0.0010	0.0010	0.0009	0.0010	0.0011	0.0011
	-1.62	1.10	2.31	2.52	4.91	-6.28
6m	0.000	0.001	0.002	0.002	0.004	-0.004
	0.0010	0.0010	0.0009	0.0010	0.0011	0.0010
	0.07	0.81	1.57	2.31	3.55	-3.73

Table 10: Factor Regressions

This table reports the estimates of the following regression:

$$RET^t = \alpha + \beta_1 INDEX^t_{str} + \beta_2 MKT^2 + \beta_3 MKT^t + \beta_4 HML^t + \beta_5 SMB^t + \beta_6 MOM^t$$

where RET represents the returns of the long-short 1-5 one and six month maturity ATM straddle portfolios formed by sorting weekly on the $SLOPE$, as defined by $(IV_{LT} - IV_{1M})/IV_{LT}$, or $IVRVSLOPE$ as defined by $(RV_{LT} - IV_{1M})/RV_{LT}$. $INDEX_{Str}$ is the return of the S&P 500 Index one or six month ATM straddle delta-hedged daily, depending on the maturity of the long-short portfolio; MKT^2 are the weekly market returns, and MKT, HML, SMB, and MOM are the weekly Fama and French (1993) and Carhart (1997) factor returns. The period examined spans from 1996 through 2017, and includes 1,648,439 weekly observations on 7,854 firms.

	$SLOPE$				$IVRVSLOPE$			
	1m		6m		1m		6m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$INDEX_{str}$	-0.116***	-0.105***	-0.017	-0.021	-0.147***	-0.130***	-0.069***	-0.064***
	(-6.66)	(-7.03)	(-0.87)	(-1.34)	(-8.71)	(-7.24)	(-3.34)	(-3.40)
MKT^2		-2.492		0.576		-3.196		-0.382
		(-1.30)		(0.54)		(-1.48)		(-0.27)
MKT		0.084		0.026		0.133		0.015
		(1.43)		(0.76)		(1.76)		(0.35)
SMB		-0.121		-0.072		-0.086		-0.015
		(-1.31)		(-1.71)		(-0.59)		(-0.32)
HML		0.129		0.102*		0.045		0.020
		(1.19)		(2.31)		(0.38)		(0.43)
MOM		0.112		0.068*		0.054		-0.012
		(1.79)		(2.25)		(0.79)		(-0.41)
α	-0.026***	-0.025***	0.011***	0.011***	-0.051***	-0.049***	-0.004***	-0.004***
	(-12.44)	(-11.86)	(18.18)	(14.51)	(-15.95)	(-14.56)	(-5.48)	(-4.15)
R^2	0.099	0.106	0.001	0.012	0.102	0.108	0.021	0.019

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX A

Table 5 examines the extent to which $SLOPE$ and $IVRVSLOPE$ predict jumps in the underlying using alternate definitions of jump. In the initial examination a longer history is used to calculate volatility so that the measure is more stable and less sensitive to recent periods. Table A below seeks to explore the mechanical relationship between the volatility measure used to identify jumps and jump frequency. Each week the sample is sorted into quintiles according to the daily standard deviation of returns using the prior twelve months, σ_{12}; the prior month,, σ_1; a measure of conditional volatility, σ_C; and realized bipower variation, σ_B. In each instance the jump frequency differential between low and high volatility portfolios is statistically significant. When sorting on σ_{12} the low volatility portfolio has a weekly jump frequency of 1.63% as compared to 0.89% for the high volatility portfolio, resulting in a differential of 0.74%. Recall from Table 5 that the differential between low and high $IVRVSLOPE$ portfolios is 1.91%, and so sorting solely on the volatility measure only partially explains this differential.

When sorting on the volatility measures calculated using shorter periods, the differential between the low and high volatility portfolios is greater. When sorting on conditional volatility the jump frequency differential, 1.47% is roughly double that of low and high twelve month volatility portfolio differential. The differentials for the low and high one month and bipower variation volatility portfolios are greater, at 2.13% and 5.88% respectively. The measure of volatility used to identify jumps in each instance has a mechanical relationship to jump frequency, but this relationship is weakest when using the prior twelve months, and only partially explains the differential when sorting on $IVRVSLOPE$.

Table 11: Examination of Jump Frequency and Volatility Measure

This table displays the frequency of realized jumps in portfolios created weekly by sorting on the volatility measure employed. Each week, portfolios of equities are formed by sorting on the daily standard deviation of returns. The daily standard deviation of returns are calculated using the daily returns over the prior twelve months, σ_{12}; the prior one month, σ_1; a conditional volatility measure, σ_C; and realized bipower variation, σ_B. The period examined spans from 1996 through 2017, and includes 1,648,439 weekly observations on 7,854 firms.

σ_{12}	1	2	3	4	5	1-5
Jump Pct.	1.63%	1.56%	1.52%	1.37%	0.89%	0.74%
St. Error	0.0017	0.0015	0.0014	0.0014	0.0013	0.0172
t-stat						9.92
σ_1	1	2	3	4	5	1-5
Jump Pct.	2.70%	2.03%	1.71%	1.26%	0.57%	2.13%
St. Error	0.0007	0.0006	0.0004	0.0004	0.0003	0.0175
t-stat						37.11
σ_C	1	2	3	4	5	1-5
Jump Pct.	2.20%	1.88%	1.70%	1.41%	0.73%	1.47%
St. Error	0.0007	0.0006	0.0005	0.0005	0.0004	0.0154
t-stat						27.29
σ_B	1	2	3	4	5	1-5
Jump Pct.	8.27%	5.89%	4.92%	4.05%	2.39%	5.88%
St. Error	0.0013	0.0010	0.0008	0.0008	0.0005	0.0307
t-stat						57.19