The role of idiosyncratic jumps in stock markets

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Abstract

I study how realized idiosyncratic jumps play a role in pricing individual stocks. I find that stocks with high variances associated with positive idiosyncratic jumps tend to have low subsequent returns. To explain the negative premium, I show that positive idiosyncratic jump variances are important predictors for future skewness. Thus, my finding is consistent with investors' preference for unusually large gains over short horizons. I demonstrate the economic significance of my results by highlighting the superior performance of a strategy based on variances associated with positive idiosyncratic jumps compared to strategies based on other variance measures.

JEL classification: G00, G10, G12

Keywords: idiosyncratic jump risk, idiosyncratic risk decomposition, cross-section of stock returns, preference for large gains

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1 Introduction

Merton (1976) asserts that jumps in individual stock prices reflect important new information that is usually firm-specific. Therefore, the presumed assumption is that they represent "idiosyncratic" risk, which can be diversified away and hence should not carry a premium. Similar assumptions of no premium for general idiosyncratic risk are widely imposed in many asset pricing studies, although empirical studies document that idiosyncratic risk matters.[1] In this paper, I study how the uncertainties associated with realized idiosyncratic jumps play a role in pricing individual stocks. This study is motivated by previous studies, which suggests that investors' reactions to extreme gains or losses are significantly different from those to normal innovations in various financial markets.[2] Separating the effects of signed jump risks in individual stock returns is important because it allows me to address investors' asymmetric responses to unusually different market events, as well as to examine the nonlinearity of the idiosyncratic risk effect. The aim of this paper is to provide a better understanding of idiosyncratic jumps, which has substantial implications for not only asset pricing but also for portfolio and risk management.

I establish an inference framework in which idiosyncratic variances can be decomposed into idiosyncratic diffusive and jump components with different signs, and I suggest approaches to separately estimate their associated premiums. I distinguish the impact of these components by capturing their contributions in explaining the cross-section of stock returns and examine how variances associated with positive and negative idiosyncratic jumps affect the results. I measure idiosyncratic risk every month by summing the squared daily return

[1] See Goyal and Santa-Clara (2003) and the references therein for earlier work on the pricing of idiosyncratic risk in aggregate stock market returns, as well as in the cross-section of stock returns.

[2] See Patton and Sheppard (2015) highlight the importance of separating upside and downside volatilities using stock return data and consider their implications for the dynamics of equity markets.

residuals.[3] This measure facilitates the linear decomposition of idiosyncratic risk into various components. For the main analyses, I decompose the idiosyncratic risk measure into three components: idiosyncratic diffusive variance ($IDVAR$), idiosyncratic positive jump variance ($IPJVAR$), and idiosyncratic negative jump variance ($INJVAR$). Similarly, I call the total idiosyncratic risk measure before this decomposition idiosyncratic variance ($IVAR$). I use these decomposed variance measures to identify the most important idiosyncratic variance component that explains individual stock returns in subsequent months.

The main results indicate that only idiosyncratic positive jump variances (i.e.,$IPJVAR$) are cross-sectionally priced and associated with significantly negative risk premiums in subsequent months. By contrast, idiosyncratic diffusive variances (i.e.,$IDVAR$) and idiosyncratic negative jump variances (i.e.,$INJVAR$) are not consistently priced. These results are robust to the inclusion of control variables, such as firm size, book-to-market ratios, momentum, and liquidity measures, which have been documented in the literature as variables affecting expected stock returns. Essentially, one can expect lower returns from individual stocks with higher variances associated with positive idiosyncratic jumps, whereas the other types of idiosyncratic variances do not play significant roles in explaining expected stock returns.

To demonstrate the economic significance of the findings, I discuss the implications for portfolio strategies that are constructed based on the results. Because I find that stocks with higher $IPJVAR$s tend to be associated with significantly lower subsequent returns than stocks with lower $IPJVAR$s, I consider a strategy that takes a short (long) position on stocks with higher (lower) $IPJVAR$s. I call this the $IPJVAR$-sorted portfolio strategy. I also consider similar portfolio strategies for the other variance measures ($INJVAR$, $IDVAR$,

[3]For this estimation, I adopt the approach applied in Schwert (1989) and Paye (2012). This estimation approach is also related to many studies on realized volatility that take the sum of squared intraday returns for daily volatility estimation (e.g., Andersen et al. (2001a)).

and *IVAR*). I implement these four strategies and compare their relative performance. I find that the *IPJVAR*-sorted portfolio outperforms the other portfolios. The Sharpe ratio of the *IPJVAR*-sorted portfolio is the highest among the four portfolios and much higher than that of the next best strategy (*INJVAR*-sorted portfolio). The cumulative excess return of the *IPJVAR*-sorted portfolio is more than 100% higher than that of the *INJVAR*-sorted or the *IVAR*-sorted portfolios. On average, the *IPJVAR*-sorted portfolio offers more than 2% higher annual returns than the *INJVAR*-sorted or *IVAR*-sorted portfolios. The *IPJVAR*-sorted portfolio generates the greatest CAPM alpha as well as other multifactor alphas.

Given the previous studies suggesting that nonnormal market conditions (which tend to be related to jumps) may generate the negative relation I find, I perform a horse race test using skewness, coskewness, illiquidity measures, and maximum returns. I find that the maximum daily return effects of Bali et al. (2011) are closely related to positive idiosyncratic jumps. Using the jump data, I distinguish maximum daily returns for each stock realized in months without and with positive idiosyncratic jumps and show that the maximum daily return effects are mainly driven by positive idiosyncratic jumps.

I also examine how variances associated with positive idiosyncratic jumps are related to future skewness, which has been used as a proxy for lottery-type payoffs in the literature. This examination is motivated by the fact that investors gain unusually large returns over a short horizon when positive jumps occur. I conjecture investors can revise their expectations for lottery-type payoffs (i.e., greater skewness) in light of the high variances associated with positive realized jumps. Since positive jumps with low variances are regarded as pure outliers, their reoccurrences are not expected to be highly likely when positive jump variances are low. Therefore, it is important to consider the positive jump variance component in the prediction for lottery-type payoffs. My empirical analyses show that the skewness tends to be significantly higher for stocks with higher positive idiosyncratic jump variances realized in the previous month. Overall, the findings are consistent with Barberis and Huang (2008), who predict lower expected returns for stocks with skewed payoffs.

I perform multiple robustness checks. The results hold with respect to not only the standard Fama-French three-factor model but also the CAPM, the four-factor model with the momentum factor, the Fama-French five-factor model, the q-factor model of Hou et al. (2015), and the no-factor model. I also conduct various subsample analyses by splitting samples into two or three groups depending on the fraction of zero returns, illiquidity, sample periods or the business cycle (e.g., expansion vs. recession periods) and continue to find similar results.[4] The regression analyses with control variables, such as size and illiquidity measures, further indicate that the evidence cannot be explained by differences in the characteristics of stocks.[5] Market jumps do not play a role in generating the results. In general, no particular common return (or jump) component drives the results.

This study is related to studies that separate jump risks from volatility risks to examine their association with stock returns. Bollerslev et al. (2016) investigate how individual equity prices respond to continuous and jumpy market prices by using decomposed betas and find that betas that are associated with discontinuous and overnight returns entail significant risk premiums, whereas the continuous beta does not. Kelly and Jiang (2014) use a cross-section of crash events for individual firms to identify a common component of left-tail risks and show its strong predictive power for stock returns. Jiang and Yao (2013) find that size and liquidity anomalies and the value effect to a large extent are driven by jumps. Bollerslev

[4] I also confirm that the results are robust to outlier effects by winsorizing data and using log-transformed variance data.

[5] The results show that the expected skewness tends to be higher for stocks with lower prices and sizes. These results also suggest that the findings are inconsistent with risk-based explanations because smaller-sized stocks traded at lower prices are considered riskier, but the results show that they tend to offer unexpectedly lower average returns in the subsequent month than do other stocks.

et al. (2020) study the weekly return predictability of the signed jump variation computed using the difference between the up and down semivariances. I contribute to this literature by focusing on the effects of idiosyncratic jump variances on subsequent stock returns.

A few recent studies focus on idiosyncratic jumps. Yan (2011) shows that expected stock returns are negatively related to average jump sizes and finds that neither idiosyncratic nor systematic jumps explain all of the return predictability of jump sizes. Using both option and stock data, Bégin et al. (2019) find that the contribution of idiosyncratic risk to the equity risk premium arises exclusively from jump risk and report that the idiosyncratic jump risk premium is positive.[6] Kapadia and Zekhnini (2019) also find that idiosyncratic jumps are a key determinant of mean stock returns.[7] The key difference between these studies and mine is that I separate the variances of positive and negative idiosyncratic jumps that are realized in stock markets and identify that the negative relation between realized idiosyncratic variances and subsequent returns stems mainly from positive idiosyncratic jumps. To my knowledge, this paper is the first to demonstrate the importance of separating signed jump variances in studying how idiosyncratic risks are priced in the cross-section of stock returns.

This study is also related to the skewness literature because the presence of positive jumps is a sufficient condition for the increased skewness of stock return distributions. For

[6]Using option market data makes their sample period much shorter and the number of included stocks much smaller than mine: their sample includes 260 firms from 1996 to 2015, while my sample includes more than 3,300 firms from 1963 to 2016. Another important difference is that they did not separately consider positive and negative jumps. Moreover, their estimation method imposes no arbitrage and the condition that the cap-weighted cross-sectional average of both idiosyncratic premiums is zero, whereas my inference method has no such conditions imposed and can allow more flexible market conditions with potential limits to arbitrage.

[7]The main difference between theirs and mine mainly derives from their usage of option market data. Among others, they show the positive mean returns of a trading strategy that buys (sells) stocks in the top (bottom) quintile of jump probability predicted out-of-sample using information on option prices available from 1996. However, my results are based on realized jumps from stock markets and are not inconsistent with their Tables 2 and 4, where they show that positive jumps realized in stock markets tend to lead to low subsequent returns over the next 30 days.

example, using the approach of Bakshi et al. (2003) based on option data, Conrad et al. (2012) document that more ex ante positively (negatively) skewed returns yield subsequent lower (higher) returns. Boyer et al. (2010) find that expected idiosyncratic skewness and returns are negatively correlated. Amaya et al. (2015) find that realized skewness based on high-frequency data captures jumps in returns and has a negative relation with subsequent returns. I contribute to this literature by resolving the empirical challenge of separating signed jump effects from usual volatility effects and by showing the significant role of idiosyncratic jump variances in cross-sectional asset pricing. Moreover, skewness has been used as an empirical proxy for lottery-type returns (Barberis and Huang, 2008; Kumar, 2009). My study refines the understanding of lottery prediction by presenting the significance of realized variances associated with positive idiosyncratic jumps in stock markets.

The remainder of this paper is organized as follows. After explaining the data and inference methods for the impact of idiosyncratic jump variances in Section 2, I present the main results in Section 3. In Section 4, I discuss the relation of the finding with maximum return effects as well as the pricing channels. After multiple robustness checks in Section 5, I conclude in Section 6.

2 Inference methods and data

In this section, I explain how I distinguish idiosyncratic jumps for the variance decomposition and discuss an inference framework used to identify the impact of idiosyncratic jump risk in a cross-section of stock returns. Using the sample, I estimate decomposed variance measures and describe their distributional properties.

2.1. Estimating idiosyncratic diffusive and jump variances

To consider the impact of separate idiosyncratic risks attributable to diffusive and jump components on subsequent stock returns, I must first estimate the decomposed idiosyncratic variances. To construct the estimators, I apply the approach adopted in Schwert (1989) and Paye (2012) to daily return residuals after identifying signed idiosyncratic jumps. Specifically, I estimate the variances by taking the sum of the squared return residuals from different components. Unlike the usual standard deviation measure, this definition facilitates the linear decomposition of idiosyncratic risk.

I begin by considering the estimation of total idiosyncratic variance ($IVAR$). Following Ang et al. (2009), I employ the idea of using return residuals from the Fama and French (1993) three-factor models.[8] I capture the overall idiosyncratic risk for stock i on day d through daily return residuals $\epsilon_{i,d}$, which are expressed in the following formula:

$$\epsilon_{i,d} = r_{i,d} - \alpha_i - \beta_i^{MKT} MKT_d - \beta_i^{SMB} SMB_d - \beta_i^{HML} HML_d, \tag{1}$$

where $r_{i,d}$ is the daily realization of excess return for stock i and day d. MKT_d, SMB_d, and HML_d are risk premiums associated with the market, size, and value factor portfolios, respectively, on day d.[9] After obtaining daily return residuals $\epsilon_{i,d}$ from the regression in equation (1) estimated using daily stock and factor return data during the past month, I categorize these daily return residuals into different groups by applying the jump tests proposed by Lee and Mykland (2008). The $IDVAR$ is estimated using the sum of the squared

[8] Although I use the three-factor model as an example, a similar approach can be applied using other factor models. I perform robustness checks and confirm that the empirical results are robust to the factor model specifications in Section 5.

[9] β_i^{MKT}, β_i^{SMB}, and β_i^{HML} are factor loadings of stock i for the market, size, and value factors, respectively. Following the literature on idiosyncratic volatility, these beta estimates are obtained every month as in Ang et al. (2009).

return residuals from the diffusive component only. Similarly, the *IPJVAR* (*INJVAR*) is estimated using the sum of the squared residuals from the positive (negative) jump component only.

Formally, I write the following estimators for *IDVAR*, *IPJVAR*, and *INJVAR* for stock i and month m:

$$
\begin{aligned}
\widehat{IDVAR}_{i,m} &= \sum_{i,D_d \subset M_m} \hat{\epsilon}^2_{df,i,d} = \sum_{i,D_d \subset M_m} \epsilon^2_{i,d} I(|T_{i,d}| < \tau), \\
\widehat{IPJVAR}_{i,m} &= \sum_{i,D_d \subset M_m} \hat{\epsilon}^2_{pj,i,d} = \sum_{i,D_d \subset M_m} \epsilon^2_{i,d} I(|T_{i,d}| > \tau) \times I(\epsilon_{i,d} > 0), \text{ and} \\
\widehat{INJVAR}_{i,m} &= \sum_{i,D_d \subset M_m} \hat{\epsilon}^2_{nj,i,d} = \sum_{i,D_d \subset M_m} \epsilon^2_{i,d} I(|T_{i,d}| > \tau) \times I(\epsilon_{i,d} < 0),
\end{aligned}
\tag{2}
$$

where $\epsilon_{i,d}$ is the return residual of stock i on day d from the regression in equation (1). $I(x)$ is an indicator function that equals 1 if x is true. $T_{i,d}$ is the idiosyncratic jump test statistic, whose formal definition is $T_{i,d} \equiv \frac{\epsilon_{i,d}}{\widehat{\sigma_{\epsilon_{i,d}}}}$, where $\widehat{\sigma^2_{\epsilon_{i,d}}} \equiv \frac{1}{K-2} \sum_{c=d-K+2}^{d-1} |\epsilon_{i,c}||\epsilon_{i,c-1}|$, and window size K can be selected for several months.[10] The parameter τ is the rejection criterion, which is based on a standard normal distribution.[11]

To support the empirical analyses using daily data, I perform simulation studies under general assumptions of jump diffusion models.[12] I confirm that jump detection power continues to be higher than 95% using daily data even when there are jumps in stochastic

[10]Following Lee and Mykland (2008), the test uses jump-robust volatility estimators based on bipower variation. Since daily data are much less subject to market microstructure noise compared to ultra-high frequency data, I do not expect such noise to contaminate the results.

[11]I perform normality tests according to the asymptotic distribution of jump test statistics under the null hypothesis of no idiosyncratic jumps. I use a 5% significance level for the two-sided tests. The jump test indicates the idiosyncratic jump arrivals when the absolute value of test statistic is greater than 1.96. I use a rejection criterion based on a standard normal distribution instead of an extreme value distribution, such as a Gumbel distribution, to mitigate small sample problems because of a lack of jump data.

[12]The jump detection test of Lee and Mykland (2008) is developed under the assumption that asset prices follow a jump diffusion model.

volatility. The precision of jump variance estimators mainly depends on the detection power of individual jump tests. In other words, given the high jump detection power, the proposed jump variance estimators based on daily data perform well. Their estimation error does not significantly depend on the actual jump sizes given a fixed sampling frequency. As I examine the impact of large-sized infrequent rare jumps, it is legitimate to use this jump identification approach and make inferences about the (functions of) jump sizes. Detailed simulation results are reported in Appendix A.

2.2 Separating the impact of decomposed idiosyncratic variances

For the actual tests, I set the return horizon to one month to be consistent with the literature on idiosyncratic risk. Then, I examine the relation between the decomposed idiosyncratic variances and the subsequent month's stock return using a series of Fama-MacBeth cross-sectional regressions expressed as follows:

$$r_{i,m} = c + \gamma_{df} IDVAR_{i,m-1} + \gamma_{pj} IPJVAR_{i,m-1} + \gamma_{nj} INJVAR_{i,m-1} + \lambda'_\beta \beta_{i,m} + \lambda'_z z_{i,m-1} + e_{i,m}, \tag{3}$$

where $r_{i,m} = \int_{t \in M_m} (d \log S_{i,t} - r_t dt)$ is stock i's excess return over the risk-free rate r_t in month m and $M_m \in [0,T]$ denotes the time interval for month m:
$M_m = \{s|s \text{ belongs to month } m\}$. $\beta_{i,m}$ is a vector of k factor loadings for stock i over month m.[13] $z_{i,m-1}$ is a vector of firm characteristics for stock i observed over month $m-1$, and $e_{i,m}$ is an error term with $E(e_{i,m}) = 0$. $IDVAR_{i,m-1}$, $IPJVAR_{i,m-1}$, and $INJVAR_{i,m-1}$ are the idiosyncratic diffusive variance, idiosyncratic positive jump variance, and idiosyncratic negative jump variance for stock i for month $m-1$, respectively.

[13] As in Ang et al. (2009), I control for exposures to risk factors by including contemporaneous factor loadings estimated over the current month.

2.3 Data

I perform the empirical analyses using U.S. individual stock return data from the CRSP common stock universe from July 1963 to December 2016. Table 1 reports the descriptive statistics of $IDVAR$, $IPJVAR$, and $INJVAR$, along with the other control variables. The summary statistics for returns in Table 1 are consistent with those of the previous study, such as Hou and Loh (2016), using similar data from different sample periods. Notably, $IPJVAR$ has a standard deviation nearly seven times greater than that of $IDVAR$ and four times greater than that of $INJVAR$. Figure 1 shows the time series patterns of decomposed variance measures. Specifically, I create quintile portfolios sorted according to each idiosyncratic variance measure and present their monthly averages. Compared to the other variance measures, $IPJVAR$ shows the greatest variation over time. The cross-sectional difference appears much greater for the highest quintile portfolios with the greatest idiosyncratic risk than for the other portfolios.

Table 2 reports the summary statistics for detected jumps, in particular, the cross-sectional distribution of positive and negative idiosyncratic jumps in terms of their frequencies and sizes. I find positive idiosyncratic jumps are detected slightly more frequently than negative idiosyncratic jumps. Both absolute jump size magnitudes and standard deviations of positive jumps are again slightly greater than those of negative jumps. These results are consistent with the evidence of positively skewed distributions for individual stock returns. Additional details on the sample selection criteria and other related descriptions of the data are provided in Appendix B.

3 Main results

In this section, I perform analyses using decomposed idiosyncratic variances and report the results of monthly Fama-MacBeth cross-sectional regressions. I use the full unbalanced panel data for the main inference. The dependent variable is multiplied by 100 for a better exposition of the results. For each estimation, the number of observations may differ slightly because of the data availability of the variables examined. The following discussion is based on the results for a one-month holding period. I also obtain consistent results for longer horizons up to one year.

3.1 Separate impact of decomposed idiosyncratic variances

Column (1) of Table 3 shows that the average coefficient on $IVOL$ (idiosyncratic volatility estimated using the typical standard deviation) is -10.643 and statistically significant at 5%, confirming previous evidence of a negative relationship between idiosyncratic volatility and subsequent returns. Note that I use the sum of the squared return residuals from different components instead of the standard deviation when calculating the risk measures. To ensure that the results are not affected by the transformation, I confirm similar results for the total idiosyncratic variance measure ($IVAR$) in column (2). I next examine whether idiosyncratic risk in the absence of jumps (measured by $IDVAR$) is priced. The results in column (3) shows that the average coefficient on $IDVAR$ is insignificant, which indicates that idiosyncratic risk is not priced when there is no jump. I find this result insightful because it suggests that diffusive firm-specific risks are indeed well diversified away during normal times without extreme price movements, as has been assumed in many classical asset pricing studies. In fact, this finding is fairly consistent and robust in my study.

Columns (4) and (5) in Table 3 present results that show how idiosyncratic risk is priced in the presence of jumps. In column (4), the average coefficient on *IPJVAR* is -16.384 and is statistically significant at the 1% level. Compared to the coefficient on the total idiosyncratic variance *IVAR* in column (2), this coefficient has an absolute magnitude that is approximately 2.5 times greater (-6.698 vs. -16.384). A comparison of the results in columns (3) and (4) demonstrates that idiosyncratic risks are priced in the presence of positive jumps and that the negative premium associated with idiosyncratic risk occurs only through positive jumps. I add *INJVAR* to the model considered in column (4) to assess whether uncertainties associated with negative jumps play a role in explaining the evidence, and find that the coefficient for *INJVAR* is positive and insignificant. Even after adding *INJVAR* to the model, the negative coefficient for *IPJVAR* remains significant.[14] The main takeaway from Table 3 is that positive jumps play a critical role in a significant relation between idiosyncratic risk and negative premiums in the subsequent months.

These results are confirmed after controlling for the individual stocks' exposure to systematic factors (factor loadings) and other firm characteristics, such as size, book-to-market ratio, momentum, and one-month lagged returns. The coefficients on factor loadings are insignificant, whereas the firm size, book-to-market, and momentum characteristics mostly have strong significance. These results are consistent with the findings of Daniel and Titman (1997) that firm-level characteristics rather than the covariance structure of returns explain the cross-sectional variation in stock returns. The momentum measure is based on Jegadeesh and Titman (1993), whereas the one-month lagged returns are included based on Huang et al. (2009) to capture the one-month return reversal effect. All control variables

[14]The results indicate that if a firm moves from the 50th percentile (0.0015) to the 75th percentile (0.0178) of the cross-sectional *IPJVAR* distribution (holding its other characteristics constant), the decrease in expected returns is approximately 35 bps ($= -21.126 \times (0.0178 - 0.0015)$) per month, which is economically significant.

are observable during month $m-1$ and known at the beginning of month m. Regression coefficients for these controls are reported in Table 3. However, in the subsequent tables, to conserve space, we do not report them because the results are similar. Overall, I conclude that the main findings are robust to different estimation procedures and samples.

3.2 Economic significance of the findings

The findings presented in the previous subsection have many important implications for not only asset pricing but also portfolio and risk management applications. In this subsection, I demonstrate the economic significance of the findings by highlighting portfolio implications with examples. Motivated by the evidence, I suppose that investors can enhance their portfolio performance by incorporating a sorted portfolio strategy. The strategy is proposed to generate a positive return spread from the negative premium. Stocks are sorted every month according to the $IPJVAR$ level. Five quintile portfolios are constructed based on stock rankings. Given the quintile portfolios, investors can implement a strategy that takes short (long) positions on the quintile portfolio with the highest (lowest) $IPJVAR$s. Because I find evidence for a negative premium during the subsequent month, these portfolios are held for one month after the construction and are rebalanced every month. I call this strategy the $IPJVAR$-sorted portfolio.

To compare the relative impact of idiosyncratic positive jump variance on equity portfolio performance to the impact of the other idiosyncratic variances, I also consider strategies for other idiosyncratic variance measures. Instead of sorting stocks according to the $IPJVAR$ level, I construct quintile portfolios by sorting stocks every month according to the levels of $INJVAR$, $IDVAR$, and $IVAR$. Then, short-long strategies are created using the quintile portfolios with the highest and lowest idiosyncratic variance measures. I call those strategies the $INJVAR$-sorted portfolio, the $IDVAR$-sorted portfolio, and the $IVAR$-sorted portfolio.

I analyze the relative performance of the four different strategies from 1964 to 2016. I compute both equal-weighted and value-weighted averages of the returns to the individual stocks held in each portfolio. The performance of the four strategies is presented in Table 4. The performance of the $IPJVAR$-sorted portfolio is the best. Using the equal-weighting scheme, the $IPJVAR$-sorted portfolio provides the highest annualized mean returns of 4.2% compared to 1.92%, -0.22%, and 1.56% for the $INJVAR$-sorted, $IDVAR$-sorted, and $IVAR$-sorted portfolios, respectively. The standard deviation of the $IPJVAR$-sorted portfolio (11.36%) is comparable to that of the $INJVAR$-sorted portfolio (10.32%). The standard deviations of $IDVAR$-sorted and $IVAR$-sorted portfolios are much higher than those of the $IPJVAR$-sorted and $INJVAR$-sorted portfolios. Using the annualized mean returns and standard deviations, the Sharpe ratios are reported in Table 4 as a performance measure. The $IPJVAR$-sorted portfolio has the highest Sharpe ratio of 0.37, which is much higher than the Sharpe ratio of the $INJVAR$-sorted portfolio, the next best strategy. Importantly, the $IPJVAR$-sorted portfolio performs much better than the $IVAR$-sorted portfolio in terms of the Sharpe ratio (i.e., 0.37 for $IPJVAR$ vs. 0.08 for $IVAR$).[15]

I report other performance evaluation measures such as CAPM alphas as well as Fama-French 3-factor, 5-factor, 6-factor plus momentum, and q-factor alphas. The portfolio alpha measures indicate that the $IPJVAR$-sorted portfolio outperforms the other portfolios. Table 4 also shows that the results based on value-weighted average returns are similar to those

[15]Returns to the $IVAR$-sorted portfolio differ slightly from returns to similar portfolios sorted by the idiosyncratic volatility reported in Ang et al. (2006) for three reasons. First, my sample period ends in 2016, whereas their sample period ends in 2000. Second, I use a slightly different definition of idiosyncratic risk, which is the sum of the squared return residuals for my straightforward linear decomposition of idiosyncratic risk, instead of their idiosyncratic volatility estimator, which is the standard deviation of daily return residuals. For a fair comparison, we present the performance of the $IVAR$-sorted portfolio to better illustrate the relative performance. Last, my samples are expected to be different because I require at least one year of observations for each sample firm to satisfy the conditions for idiosyncratic jump tests.

based on equal-weighted average returns.

I also compare the relative performance of the strategies in terms of cumulative excess returns, and present the results in Figure 2. This graph illustrates the better performance of the *IPJVAR*-sorted portfolio. The graph also shows that the *IPJVAR*-sorted portfolio outperforms the other three portfolios throughout the entire sample period and the subsample periods. Furthermore, that portfolio's cumulative return is more than 100% higher than those of the *INJVAR*-sorted and *IVAR*-sorted portfolios, both of which have a similar performance at the end of the investment horizon. The *IDVAR*-sorted portfolio has a cumulative return very close to zero (although slightly negative), which highlights that idiosyncratic diffusive risks are not priced in the market. The results based on cumulative returns are consistent with the results in Table 4 based on Sharpe ratios and cross-sectional regression analyses. Overall, the portfolio analyses emphasize the economic significance of the findings and their substantial implications.

4 Pricing channel for positive jump variance

In this section, I compare the main finding with the evidence of well-established pricing factors that are related to nonnormal market conditions and the "maximum return effect" of Bali et al. (2011). Then, I provide evidence to support my explanation for the main finding based on investors' skewness preference.

4.1 Nonnormal market conditions

Motivated by the previous studies suggesting that nonnormal market conditions may generate a negative relation between lagged volatility and subsequent stock returns, I first check whether and how the main results are affected by variables related to jumps. First, I consider skewness measures because the third moments of return distributions can be related to realized jumps in returns.[16] In column (2) of Table 5, I confirm the evidence that skewness is negatively related to subsequent stock returns. However, $IPJVAR$ continues to be statistically significant, and its negative relationship with subsequent returns remains similar. Therefore, skewness cannot explain stock return variations captured by idiosyncratic positive jump variances, indicating that realized variances associated with positive tails of return distributions influence subsequent returns differently from the skewness measure.[17]

Next, I consider coskewness, which has been considered a determinant of the cross-section of stock returns in previous studies. This measure may be assumed to be related to the effect of priced jump risk on stock returns because jumps may directly influence the magnitude of coskewness. Following Chabi-Yo and Yang (2010), I measure month $m-1$ coskewness using the coefficient from the regression of squared daily individual stock returns on market returns. The results reported in column (3) of Table 5 confirm that coskewness has a significant negative relation with subsequent stock returns.[18] However, the significantly negative association of $IPJVAR$ with subsequent stock returns remains similar. Hence, this systematic return asymmetry does not explain the impact of the positive idiosyncratic jump

[16] Amaya et al. (2015) find a negative relationship between realized total skewness and future stock returns. Conrad et al. (2012) show the negative relationship between ex ante skewness (obtained from option market data) and subsequent stock returns. I use daily return data from month $m-1$ to calculate the month $m-1$ ex post skewness to match the monthly frequency for the regression test. I choose ex post skewness from month $m-1$ because the goal is to gauge whether the jump variance measure delivers different information, even if both measures are calculated using data generated from the same underlying return process. If both measures contain similar information, proving the distinctive role of idiosyncratic jumps would be more difficult in the presence of my skewness measure than in that of any other skewness measures.

[17] I consider the expected idiosyncratic skewness of Boyer et al. (2010) but find it to be insignificant in column (7) of Table 5 in the presence of the decomposed idiosyncratic variances in the regression.

[18] The main results are not changed when using an alternative estimation method for coskewness with the coefficient of the regression of daily individual stock returns on squared market returns, as in Harvey and Siddique (2000). Subsection 5.3 presents the robustness of the results to the asset pricing model specifications, which includes this coskewness measure of Harvey and Siddique (2000) as a higher market moment factor.

variances.

I next test whether the results may be related to illiquidity in the corresponding individual stock markets. When liquidity in a market dries up, the market cannot absorb immediate transactions without generating large price changes. Therefore, in theory, more jumps are expected in less liquid markets. I use both Amihud measures and zero returns as proxies for illiquidity.[19] The coefficients for both proxies in columns (4) and (5) are significant. Importantly, this illiquidity effect does not change the finding of the negative relation between *IPJVAR* and stock returns in subsequent months.

Another jump-related variable I consider is the maximum daily return during the previous month. Bali et al. (2011) study the significance of maximum daily returns in explaining a cross-section of stock returns. Column (6) of Table 5 shows a significantly negative relation between the maximum returns over the past month and subsequent stock returns, confirming their finding. They show that adding the maximum daily return to the regression reverses the negative relation between idiosyncratic volatility and expected returns. However, I find that given the decomposed idiosyncratic risk measures, adding maximum returns does not reverse the sign of the coefficients for *IPJVAR*, although its significance disappears. This result is not surprising due to a multicollinearity problem from the well-known mechanical correlation between maximum returns and idiosyncratic risk measures. With existing variables considered in the literature thus far, it is difficult to identify how the maximum effects are related to idiosyncratic jumps.

[19]Following Amihud (2002), I compute the Amihud measure as the month $m-1$ average of daily absolute stock returns divided by the daily dollar trading volume. Following Han and Lesmond (2011), the zero returns variable is the fraction of trading days in month $m-1$ with a zero return. Other liquidity measures are derived from quote data, such as bid-ask spreads. Because employing them for the analyses significantly reduces the sample period, I exclude them from the analyses to maintain the sample period, as maintaining a long sample period is a main reason I use daily data instead of high-frequency data.

4.2 Maximum return effects through positive jumps

In this subsection, I distinguish the role of positive idiosyncratic jumps in the maximum return's ability to predict subsequent returns. In essence, I incorporate the jump data in identifying the source of maximum effects. Note that the maximum daily return data are realized returns from either jump or nonjump components of asset pricing models. In other words, in a month with no jumps, the maximum daily returns are mainly generated from the nonjump components. However, in the presence of jumps in a month, they are likely to result from the (positive) jump component.

To separate the role of jumps in the maximum return effects, I decompose the maximum returns for stock i in month m into those realized without and with positive jumps as follows:

$$\text{Max return}_{i,m} = \text{Max return}_{i,m} \times (1 - IPJ_{i,m}) + \text{Max return}_{i,m} \times IPJ_{i,m}, \tag{4}$$

where $\text{Max return}_{i,m} \times (1 - IPJ_{i,m})$ is the maximum return for stock i in month m realized without positive idiosyncratic jumps and $\text{Max return}_{i,m} \times IPJ_{i,m}$ is that with positive idiosyncratic jumps. Before further analyses, I first check the relation between maximum returns and those returns with positive idiosyncratic jumps (i.e., $\text{Max return}_{i,m}$ and $\text{Max return}_{i,m} \times IPJ_{i,m}$) and find an exceptionally high contemporaneous correlation (greater than 90%) between the two.[20] I also check the R^2s, which represent how much variations in maximum daily returns can be explained by those with or without positive idiosyncratic jumps. With jumps (i.e., using $\text{Max return}_{i,m} \times IPJ_{i,m}$), the (adjusted) R^2 is 81.5%, while it is 0.82% without jumps (i.e., using $\text{Max return}_{i,m} \times (1 - IPJ_{i,m})$). Thus, the initial analyses about maximum returns in relation to jumps suggest that the majority of maximum return

[20] The correlation between $\text{Max return}_{i,m}$ and $\text{Max return}_{i,m} \times (1 - IPJ_{i,m})$ is approximately 9%.

effects are realized through positive idiosyncratic jumps. Using these separated maximum returns, I perform additional regression analyses to examine how maximum daily returns affects the cross-section of subsequent stock returns.

Table 6 shows the estimation results. In column (1), we confirm that stocks with greater maximum daily returns tend to earn significantly lower subsequent stock returns. Using only the maximum returns without positive jumps, however, I show in column (2) that the maximum return effects no longer exist. The results in column (3) indicate that the maximum return effects remain valid only when maximum returns are realized with the presence of positive jumps. The significance of maximum returns without positive jumps is not consistent, as seen in columns (4)-(6). Overall, the results in this section enhance the understanding of maximum return effects on subsequent returns by demonstrating that positive jumps (not mere maximum returns without jumps) are the main source of maximum return effects.

4.3 Skewness prediction with positive idiosyncratic jumps

In this subsection, I study a pricing channel for the main finding. For a potential explanation, I consider the fact that investors can gain unusually large positive returns when positive idiosyncratic jumps occur in asset prices. I conjecture that investors revise their expectation for such unusual gains in light of high variances associated with positive realized jumps. Specifically, I examine how high positive jump variances (along with their arrivals) are related to the lottery-type events considered in Barberis and Huang (2008).[21]

Barberis and Huang (2008) study the asset pricing implication of cumulative prospect theory and build a model in which skewness-loving investors bid up the prices of skewed

[21] Brunnermeier et al. (2007) and Boyer et al. (2010) also produce similar conclusions and predict lower expected returns for stocks with greater idiosyncratic skewness.

securities, leading to low expected returns. They use skewness as a proxy measure for lottery events. To support the explanation for the finding, I test and confirm my hypothesis that positive idiosyncratic jump arrivals and their variances help to predict (positive) skewness in the subsequent month. I use the following regression model to predict the subsequent month's skewness in the cross-section:

$$Skewness_{i,m} = \theta_0 + \theta_1 IPJ_{i,m-1} + \theta_{pj} IPJVAR_{i,m-1} + \delta_x' X_{i,m-1} + e_{i,m}, \tag{5}$$

where $IPJVAR_{i,m-1}$ is the idiosyncratic positive jump variance for stock i for month $m-1$ and $IPJ_{i,m-1}$ is a positive idiosyncratic jump indicator for stock i in month $m-1$, which is one if there is at least one positive jump in month $m-1$ (i.e., $IPJ_{i,m-1} = I[\int_{t \in M_{m-1}} dJ_{i,t}^{(+)} > 0]$).[22]

I focus on studying how positive idiosyncratic jump variances (i.e., *IPJVAR*) realized in month $m-1$ (along with other variance measures) affect the skewness prediction in the subsequent month m.[23] I add the jump arrival indicators $IPJ_{i,m-1}$ to examine whether they matter for skewness prediction. I also include other independent variables that can potentially affect skewness prediction. I select variables employed in prior skewness research, such as Chen et al. (2001) and Boyer et al. (2010). The selected variables include the lagged realized return, stock turnover (volume/shares outstanding), size (log market capitalization), the Amihud measure for illiquidity, stock price, and book-to-market ratio (B/M), all of which are based on observations from month $m-1$.

In order to capture lottery-type events, it is worthwhile to differentiate the return asym-

[22] I also consider a negative idiosyncratic jump indicator $INJ_{i,m-1}$ for stock i and month $m-1$, which is one if there is at least one negative jump in month $m-1$ (i.e., $INJ_{i,m-1} = I[\int_{t \in M_{m-1}} dJ_{i,t}^{(-)} > 0]$).

[23] For the empirical analyses, I use the estimates for decomposed variances and realized jumps using daily data in month $m-1$. To be consistent with the main regression method, I estimate both coefficients and standard errors for this cross-sectional regression using the Fama-MacBeth procedure.

metry generated by normal returns from that generated by extreme positive returns (i.e., positive jumps), both of which can be captured by typical skewness measures. To distinguish the two, I consider an additional dependent variable, which is skewness observed only when there are positive jumps. I use this variable because positive jumps share similar properties with lottery-type returns, such as representing large positive returns with low probabilities.

Table 7 reports the estimation results. In all specifications, I find that the key variable $IPJVAR$ is an important predictor for future skewness, showing that stocks with higher $IPJVAR$s tend to exhibit significantly higher skewness in subsequent months. This finding is robust to the inclusion of all other predictors under consideration. The coefficients for positive idiosyncratic jump indicator (IPJ) is also consistently positive, which suggests that positive jump arrivals are also important skewness predictors. Diffusive variance effects become insignificant and the magnitudes of negative jump variance effects become weaker once the subsequent skewness measures captures the presence of positive idiosyncratic jumps.

Important observations were obtained from including other independent variables as well. I find that the lagged return over the previous month is another significant variable. However, its associated coefficients are significantly negative, suggesting that stocks with higher lagged monthly returns tend to have lower skewness in the subsequent month. This observation is consistent with the intuition that large returns with low variances from the past can be considered outliers and are less expected to occur again in the future. This result emphasizes the important role of positive jump variances. I find that coefficients for the size variable are significantly negative, indicating that greater skewness is expected for relatively smaller-sized stocks. Another notable variable is stock price. If investors prefer lottery-type returns, they are typically expected to look for low-priced stocks. Consistent with the typical characteristics of lotteries, I find that greater skewness is expected for stocks with lower stock prices.[24] Book-to-market ratios are included to determine whether being a growth or value firm is related to a skewness prediction. I find these ratios positively affect skewness in subsequent months.[25]

4.4 Discussion

The evidence shown in the previous subsection is consistent with Barberis and Huang (2008), whose model predicts lower expected returns for individual stocks that are likely to exhibit lottery-type returns with greater skewness. They suggest a heterogeneous-holdings equilibrium with different groups of investors. One group of investors takes large undiversified positions in stocks with greater skewness, making it more likely that their wealth distribution will be positively skewed because they find it desirable. Accordingly, for stocks with greater skewness, these investors are willing to pay higher prices, ultimately accepting lower returns. If there are many such investors in the markets, the corresponding stock prices will be pushed up, which can explain my main findings.[26] When Barberis and Huang (2008) consider the effect of fat tails in individual stock return distributions, they address that investors' estimates about lottery events derive from the physical return distribution. Realized positive jump variance data provide legitimate input for such estimates because they are identified in this study as important predictors for future skewness in stock markets.

Skewness measures are often used to capture unusually large gains in stock markets. Empirical challenges recognized in Boyer et al. (2010) are that ex ante skewness is difficult

[24]Kumar (2009) considers three stock characteristics to identify stocks that may be perceived as lotteries: stock-specific or idiosyncratic volatility, idiosyncratic skewness, and stock prices.

[25]I do not consider the cross effects from other firms because my robustness checks in Subsection 5.5 indicate that these negatively priced idiosyncratic jumps do not exhibit significant commonality in their arrivals.

[26]I can also relate my findings with Brunnermeier et al. (2007) and Boyer et al. (2010), who predict lower expected returns for stocks with greater expected idiosyncratic skewness.

to measure when studying the impact of skewness and that separating its effect from usual volatility effects is difficult. Notably, my approach used in this paper allows me to resolve the measurement difficulty by incorporating positive idiosyncratic jumps when making inferences about idiosyncratic skewness. I also resolve the second challenge of separating volatility effects by using jump/nonjump return data, ultimately demonstrating the exclusive role of positive idiosyncratic jump variances in cross-sectional asset pricing.

Lastly, stocks with a greater skewness are not necessarily expected to offer higher average stock returns in subsequent periods. The evidence generally suggests that this type of stock tends to show high volatility generated from both signed returns and to exhibit extremely negative returns, which can negatively affect average stock returns over subsequent periods. Therefore, the results in this section are not inconsistent with lower subsequent (average) returns for stocks with higher realized variances associated with positive idiosyncratic jumps.

5 Robustness tests

In this section, I check whether the main finding is robust to microstructure effects, outliers, sample period selection, estimation approaches, asset pricing model specifications, and missed jump factors, among others.[27]

5.1 Microstructure effects and outliers

In estimating the jump variances, there can be potential concerns due to biases that arise from market microstructure effects or outliers. In this subsection, I first perform subsample

[27]Additional robustness checks are included in Appendix C. The robustness checks in this section are based on regression methods that are also used in the main analyses. As an alternative approach, sorting analyses can be used, and the overall results are consistent.

analyses to check how zero returns affect the results. I create two subsamples based on the median level (14%) of the fraction of trading days in month $m-1$ with zero returns. The results are reported in columns (2) and (3) of Table 8 after reporting in column (1) the full sample results shown in Table 3. The coefficient signs of $IPJVAR$ continue to be negative and significant at the 5% level. The coefficient magnitudes tend to be greater for the subsample with more zero returns. The coefficient signs for $INJVAR$ are inconsistent and change depending on the fraction of zero returns in the data. In addition, I perform subsample analyses with the Amihud illiquidity measure for any concerns related to illiquidity in the markets. I create two subsamples based on the median level (10%) of the Amihud measure. I continue to find that the main results are robust regardless of the level of illiquidity in the stock markets. The results are in columns (4) and (5).[28]

To remove the effect of a bid-ask bounce, I perform the test by skipping a month between measuring jump variances and predicting returns. I continue to find that the main results are robust, as shown in column (6). I mitigate the concern about outlier effects by winsorizing the independent variables, as well as by taking logs of the variances. I winsorize all independent variables at the levels of 1% and 99% and rerun the regressions. I continue to find that the results are robust in columns (7) and (8).

5.2 Sample periods and business cycles

In this subsection, I discuss robustness checks conducted with several subsamples according to business cycles and sample periods. The results are in Table 9. First, I report the results for the entire sample period in column (1), confirming the robustness of the results

[28]I also perform double sorting analyses using the fraction of trading days with zero returns and the Amihud illiquidity measure and confirm that the alphas of double-sorted portfolios are all significant at the 1% level.

to the controls including jump-related variables. Next, I split the sample period depending on the business cycle. Using the NBER's U.S. business cycle expansion and contraction records, I generate a subsample called "Expansion" ("Recession") for the period of expansion (recession) starting from the trough (peak) and ending at the peak (trough) of a business cycle. Columns (2) and (3) present the results depending on the business cycle. Overall, I confirm the prior results that regardless of the business cycle. I notice that the magnitude of the coefficient for *IPJVAR* is greater for the "Recession" sample than for the "Expansion" sample, which can be interpreted as investors' stronger preference for stocks with larger positive jump variances, during a recession than during an expansion, thus creating a greater negative premium.

I next test whether the results are robust to the sample period selection. For the "First" ("Second") sample, I use data during the first (second) half of the sample period from 1963 to 1990 (1991 to 2016) and report the results in column (4) (column (5)). I find that the overall results are consistent. The magnitude of the coefficient for *IPJVAR* for the "First" sample is more than four times greater than that for the "Second" sample, although the statistical significance is similar. I examine a time trend of the finding by further splitting the sample period according to the years of observations: 1963 to 1979, 1980 to 1999, and 2000 to 2016. The results are presented in columns (6)-(8). The coefficient magnitude (-30.993) for IPJVAR for the sample from 1963 to 1979 is approximately twice as large as that (-16.230) for the sample from 1980 to 1999 and more than six times larger than that (-4.547) for the sample from 2000 to 2016. The decreasing coefficient magnitudes can be linked to the finding of Han and Kumar (2013), which indicates that retail investors tend to hold individual stocks with lottery features.[29]

[29] This explanation is consistent with evidence of a steady increase in the proportion of U.S. public equities managed by institutions over the past six decades and the gradual shift in their holdings from larger to smaller

5.3 Asset pricing model specification

In the main analyses, I follow previous studies to assume that the Fama-French three-factor model captures systematic risk and that the daily return residuals are a realization of idiosyncratic risk. One may question the robustness of the results to the specific choice of the factor model specification. In this subsection, I examine whether the findings hold regardless of how the factor model is specified. Overall, I prove that the results hold with respect to not only the Fama-French three-factor model used in the main analyses but also other models, such as the CAPM, the q-factor models of Hou et al. (2015), the four-factor model including the momentum factor, and the five-factor model of Fama and French (2015), as well as the no-factor model. I also consider the four- and five-factor models with higher market moments to incorporate the systematic nonlinear factor, which may be missed in linear factor models.[30]

The results are in Table 10. The regression for the results in column (1) does not include a systematic factor. Because no assumptions are imposed on the factor structure, I can at least avoid concerns about model misspecifications in this no-factor model. I continue to find a significantly negative coefficient for *IPJVAR*. Unlike the main result, I find a significantly positive coefficient for *INJVAR*, indicating that negative jump variances are positively related to subsequent stock returns.[31] Columns (2)-(5) present the results with respect to the CAPM, the q-factor model, the four-factor model including the momentum factor, and the five-factor model. In the regression for the results in columns (6)-(7), I include

stocks over time. See additional details in Blume and Keim (2012).

[30]Fama-French factor returns are obtained from Ken French's online data library, while the q-factor returns are obtained directly from the author of Hou et al. (2015).

[31]This result in column (1) for the no-factor model is consistent with evidence of an overall negative relation between the signed jump variations and subsequent stock returns documented in Bollerslev et al. (2020). They calculate a jump variation measure using intraday return data without filtering out systematic factor return components.

the coskewness factor of Harvey and Siddique (2000), which I did not consider in the main analyses. I also consider factor models with short-term reversals or the first five principal components.[32] Overall, I continue to find the results are robust to the model specification.

5.4 Missed market jumps

The decomposed idiosyncratic variance measures may include market jumps because I do not explicitly incorporate them in the factor models. However, this approach may raise the question of whether there exists a systematic market jump component that is missed in the model but that influences the results. I perform a test to rule out such a possibility.

To facilitate this test, I create a market jump indicator that is set to one on a day when a jump exists in the overall market portfolio and zero otherwise. To empirically detect jump arrivals in the overall market portfolio, I apply jump detection tests to the daily market return series during the sample period and identify their arrivals. The daily market returns are calculated by taking the average of the return data for all individual stocks in the sample. Panel A of Table 11 presents the summary statistics of the realized market jumps. I find that the total number of positive (negative) market jumps during the sample period is 646 (805). The average numbers of positive (negative) jumps per year, month, and day are approximately 11.49 (14.32), 0.95 (1.19), and 0.047 (0.059), respectively.[33]

Here, I note that market jumps become identifiable only when a sufficient number of individual stock jumps exist in a day because the market return is essentially the average of individual component stock returns. Hence, if there is a positive idiosyncratic jump in a

[32]To save space, the estimation results based on principal components and short-term reversal factors are not reported, because they essentially provide similar results.

[33]Notably, unlike in idiosyncratic jumps, the number of positive market jumps is lower than the number of negative market jumps. Additionally, the absolute magnitudes of positive market jump sizes tend to be smaller than those of negative market jump sizes, which is different from the properties observed for idiosyncratic jumps.

stock and its arrival coincides with a market jump arrival on the same day, one can presume that the positive idiosyncratic jump is associated with the market jump and further speculate that such an association is related to the findings. In this subsection, I check this possibility by examining whether part of the *IPJVAR* variable related to market jumps is indeed the priced component in the previous regression analyses.

To test the aforementioned hypothesis, I decompose the variable *IPJVAR* into two components: one attributable to those positive jumps whose arrivals coincide with market jump arrivals and the other attributable to positive jumps whose arrivals do not coincide with market jump arrivals.[34] Using these further decomposed *IPJVAR*s, along with other variables, I again run the cross-sectional regression to identify the components that remain important and significant for pricing. Column (2) of Table 12 reports the estimation results from this test. The table shows that the coefficient for $IPJVAR^M$ related to market jumps is insignificant, whereas the coefficient for $IPJVAR^{NM}$ unrelated to market jumps is significant and negative. These results confirm that market jumps are not the main channel for the main finding.

[34]Formally, these further decomposed IPJVAR estimators for stock i in month m are expressed as follows:

$$\begin{aligned} \widehat{IPJVAR}^{M}_{i,m} &= \sum_{i,D_d\subset M_m} \epsilon^2_{i,d} I(T_{i,d} > \tau) \times I(T_{market,d} > \tau), \text{ and} \\ \widehat{IPJVAR}^{NM}_{i,m} &= \sum_{i,D_d\subset M_m} \epsilon^2_{i,d} I(T_{i,d} > \tau) \times I(T_{market,d} < \tau), \end{aligned} \tag{6}$$

where $\widehat{IPJVAR}^{M}$ ($\widehat{IPJVAR}^{NM}$) is based on positive idiosyncratic jumps whose arrivals (do not) coincide with market jump arrivals and $T_{market,d}$ is the jump test statistic applied to market returns on day d. All other notations are the same as those denoted in Section 2.

5.5 Common idiosyncratic jumps

In this subsection, I examine whether the evidence is driven by individual stock jumps that occur simultaneously with other stock-specific jumps, which I call "common idiosyncratic jumps." I consider these common jumps separately because they are different from the market jumps in the previous subsection but could be regarded as a missing systematic jump factor that could influence the pricing of the idiosyncratic jumps.

Given the unbalanced panel data, the total number of stocks available each day in the sample is expected to change over time. Therefore, I measure commonality with the percentage of common jumps instead of the raw number of common jumps per day. By taking the ratio of the number of stocks experiencing positive (negative) jumps to the total number of stocks each day, I compute the percentage of positive (negative) common jumps per day as a measure of commonality of positive (negative) jumps. Panel B of Table 11 shows the distributional statistics for the percentage of common positive jumps per day. I find that the commonality of these positive idiosyncratic jumps is far from system-wide and not even close to the market level.[35] Based on the empirical distribution of the percentage of common jumps, I set thresholds for the commonality measure.

To separate the impact of common and uncommon jump components, I decompose *IPJVAR* into two parts: one due to positive idiosyncratic jumps whose arrivals coincide with common jump arrivals (i.e., $IPJVAR^C$) and the other due to those whose arrivals do not coincide with common jump arrivals (i.e., $IPJVAR^U$).[36] With the further decomposed *IPJ-*

[35] Additionally, the significance level used for two-sided jump tests is set at 5%, which means that for the positive jump detection, approximately 2.5% of spurious jumps may exist because of the false positives resulting from type I errors.

[36] Formally, these further decomposed IPJVARs for stock i in month m can be expressed as follows:

$$\widehat{IPJVAR}^C_{i,m} = \sum_{i,D_d \subset M_m} \epsilon^2_{i,d} I(T_{i,d} > \tau) \times I(\frac{\sum_{i=1}^{K_d} I(T_{i,d} > \tau)}{K_d} > \omega), \text{ and}$$

*VAR*s, I test whether the common (or uncommon) jump component is associated with the negative risk premium. Columns (3)-(5) of Table 12 report the test results. In the regression for the results in column (3), the threshold ω for commonality is set at 20% to indicate common jump arrivals.[37] The results show that only the coefficient for $IPJVAR^U$ remains statistically significant and negative. Using other values of the ω threshold, I continue to observe similar results in columns (4)-(5). Thus, the pricing channel for my finding is mainly through the uncommon idiosyncratic jump components of *IPJVAR*s.

6 Conclusion

Motivated by investors' different reactions to extreme gains or losses over short horizons from those to normal innovations in financial markets, I examine how uncertainties associated with realized idiosyncratic jumps play a role in explaining the cross-section of stock returns. Evidence of the distinctive role of idiosyncratic jumps, with different signs, is sparse in the literature. I set up a general inference framework in which idiosyncratic variances can be decomposed into diffusive and signed jump components and suggest approaches for separating their associated premiums. Using stock market data, I provide evidence that positive idiosyncratic jump variances exclusively drive the negative relation between idiosyncratic volatility and subsequent stock returns.

The results indicate that only positive jump variances are consistently associated with

$$\widehat{IPJVAR}^{U}_{i,m} = \sum_{i,D_d \subset M_m} \epsilon^2_{i,d} I(T_{i,d} > \tau) \times I(\frac{\sum_{i=1}^{K_d} I(T_{i,d} > \tau)}{K_d} < \omega), \tag{7}$$

where K_d is the total number of stocks available on day d, and ω is a chosen threshold of commonality for defining common jump arrivals. All other notations are the same as those denoted in Section 2.

[37] In other words, the common jump arrival indicator becomes one when more than 20% of the sample stocks experience positive idiosyncratic jumps simultaneously in a day.

negative premiums. Idiosyncratic diffusive risks are not priced, suggesting that they are well diversified away during normal times with no jumps, as assumed in traditional asset pricing models. Unlike negative market jumps that typically require positive risk premiums, negative idiosyncratic jumps do not show a consistent pricing pattern. My findings imply that investors can enhance their portfolio performance by incorporating the negative premium. I demonstrate this implication by considering strategies with a positive return spread from taking short (long) positions on stocks with higher (lower) idiosyncratic positive jump variances. The strategy based on idiosyncratic positive jump variances outperforms the others.

I perform a horse race test using various jump-related variables and discover that the maximum daily return effects are closely related to the finding. Using idiosyncratic jump data, I show that the maximum daily return effects are mainly driven by positive idiosyncratic jumps. The findings are consistent with theoretical models for pricing individual stocks that tend to exhibit skewed payoffs. To demonstrate the role of the positive jump variances in setting investors' expectations, I show that positive jumps with high realized variances are significant predictors for future skewness. This evidence suggests that some investors take positions in stocks with high positive jump variances, ultimately willing to accept lower returns.

Given the findings and related implications, one may question why these low returns are not arbitraged away by investors who would exploit investment opportunities. One can answer this question based on the results in the skewness prediction analysis that the chances of observing unusually large positive idiosyncratic jumps tend to be higher for relatively smaller-sized stocks with lower prices, for which greater limits to arbitrage, such as higher transaction costs, exist. I leave this interesting issue for future research with more detailed analyses using trading data.

References

Amaya, D., Christoffersen, P., Jacobs, K., Vasquez, A., 2015. Does realized skewness predict the cross-section of equity returns? Journal of Financial Economics 118, 135 – 167.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Andersen, T., Bollerslev, T., Dobrev, D., 2007. No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and i.i.d. noise: Theory and testable distributional implications. Journal of Econometrics 138, 125–180.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Ebens, H., 2001a. The distribution of realized stock return volatility. Journal of Financial Economics 61, 43–76.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259–299.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: Internationa and further u.s. evidence. Journal of Financial Economics 91, 1–23.

Bakshi, G., Kapadia, N., Madan, D., 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. Review of Financial Studies 16, 101–143.

Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427–446.

Barberis, N., Huang, M., 2008. Stocks as lotteries: The implications of probability weighting for security prices. American Economic Review 98, 2066–2100.

Blume, M., Keim, D., 2012. Institutional investors and stock market liquidity: Trends and relationships. Available at SSRN .

Bollerslev, T., Li, S.Z., Todorov, V., 2016. Roughing up beta: Continuous versus discontinuous betas and the cross section of expected stock returns. Journal of Financial Economics 120, 464–490.

Bollerslev, T., Li, S.Z., Zhao, B., 2020. Good volatility, bad volatility, and the cross section of stock returns. Journal of Financial and Quantitative Analysis 55, 751–781.

Boyer, B., Mitton, T., Vorkink, K., 2010. Expected idiosyncratic skewness. Review of Financial Studies 23, 169–202.

Brunnermeier, M.K., Gollier, C., Parker, J.A., 2007. Optimal beliefs, asset prices, and the preference for skewed returns. American Economic Review 97, 159–165.

Bégin, J.F., Dorion, C., Gauthier, G., 2019. Idiosyncratic Jump Risk Matters: Evidence from Equity Returns and Options. The Review of Financial Studies 33, 155–211.

Chabi-Yo, F., Yang, J., 2010. Default risk, idiosyncratic coskewness and equity returns. Available at SSRN .

Chen, J., Hong, H., Stein, J.C., 2001. Forecasting crashes: Trading volume, past returns and conditional skewness in stock prices. Journal of Financial Economics 61, 345–391.

Conrad, J., Dittmar, R.F., Ghysels, E., 2012. Ex ante skewness and expected stock returns. Journal of Finance 68, 85–124.

Daniel, K., Titman, S., 1997. Evidence on the characteristics of cross sectional variation in stock returns. Journal of Finance 52, 1–33.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E.F., French, K.R., 2006. The value premium and the capm. Journal of Finance 61, 2163–2185.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1 – 22.

Goyal, A., Santa-Clara, P., 2003. Idiosyncratic risk matters! The Journal of Finance 58, 975–1007.

Han, B., Kumar, A., 2013. Speculative retail trading and asset prices. Journal of Financial and Quantitative Analysis 48, 377–404.

Han, Y., Lesmond, D., 2011. Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. Review of Financial Studies 24, 1590–1629.

Harvey, C.R., Siddique, A., 2000. Conditional skewness in asset pricing tests. Journal of Finance 55, 1263–1295.

Hou, K., Loh, R.K., 2016. Have we solved the idiosyncratic volatility puzzle? Journal of Financial Economics 121, 167–194.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. The Review of Financial Studies 28, 650–705.

Huang, W., Liu, Q., Rhee, S.G., Zhang, L., 2009. Return reversals, idiosyncratic risk, and expected returns. Review of Financial Studies 23, 147–168.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Jiang, G.J., Yao, T., 2013. Stock price jumps and cross-sectional return predictability. Journal of Financial and Quantitative Analysis 48, 1519–1544.

Kapadia, N., Zekhnini, M., 2019. Do idiosyncratic jumps matter? Journal of Financial Economics 131, 666 – 692.

Kelly, B., Jiang, H., 2014. Tail risk and asset prices. Review of Financial Studies 27, 2841–2871.

Kumar, A., 2009. Who gambles in the stock market? The Journal of Finance 64, 1889–1933.

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

Merton, R.C., 1976. Option pricing when underlying stock returns are discontinuous. Journal of Financial Economics 3, 125–144.

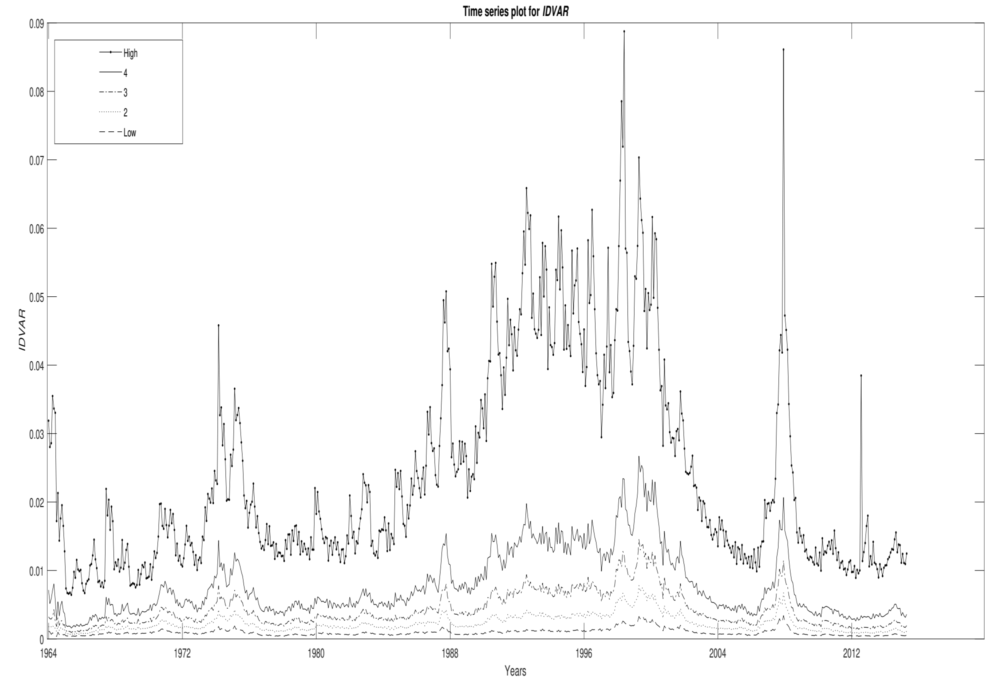
Patton, A., Sheppard, K., 2015. Good volatility, bad volatility: Signed jumps and the persistence of volatility. The Review of Economics and Statistics 97, 683–697.

Paye, B.S., 2012. 'Dèjá vol': Predictive regressions for aggregate stock market volatility using macroeconomic variables. Journal of Financial Economics 106, 527 – 546.

Schwert, G.W., 1989. Why does stock market volatility change over time? Journal of Finance 44, 1115–1153.

Yan, S., 2011. Jump risk, stock returns, and slope of implied volatility smile. Journal of Financial Economics 99, 216 – 233.

Figure 1 : **Time series plots of decomposed idiosyncratic risk measures**



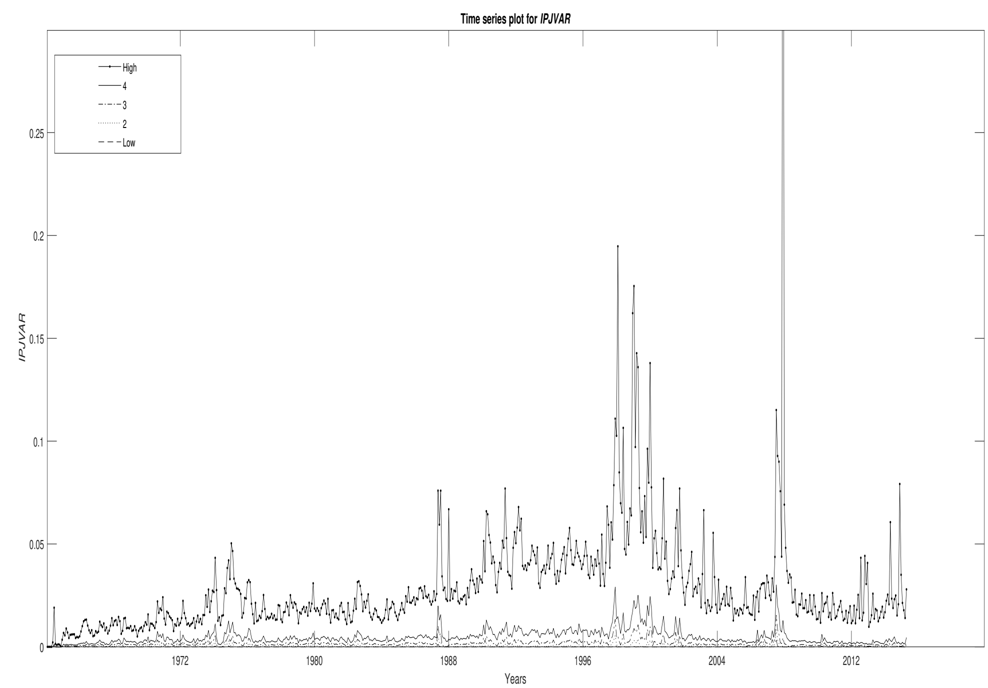
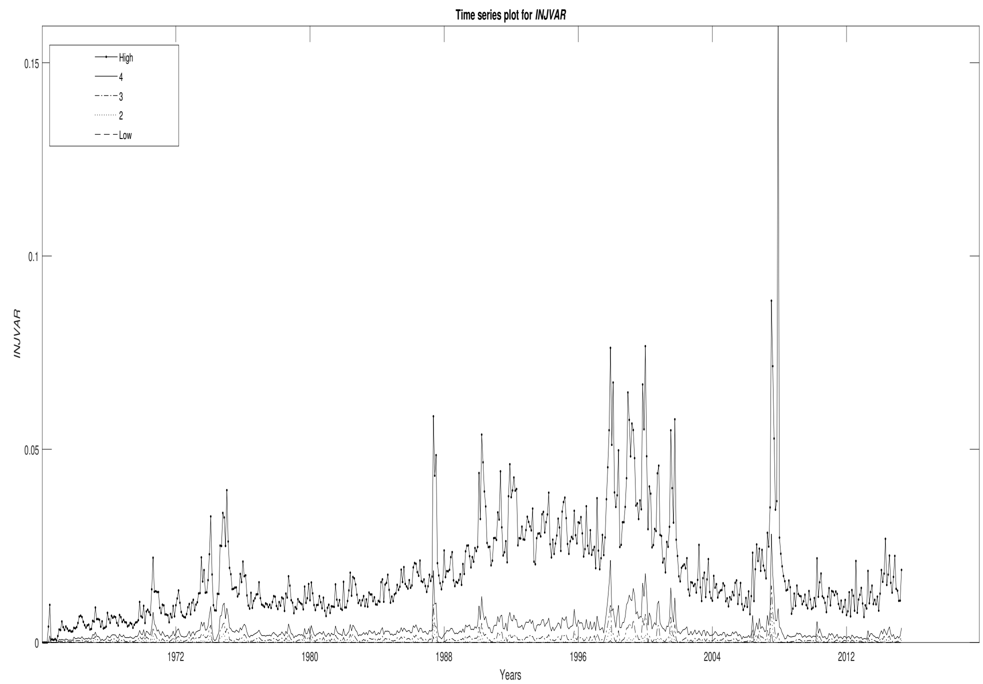
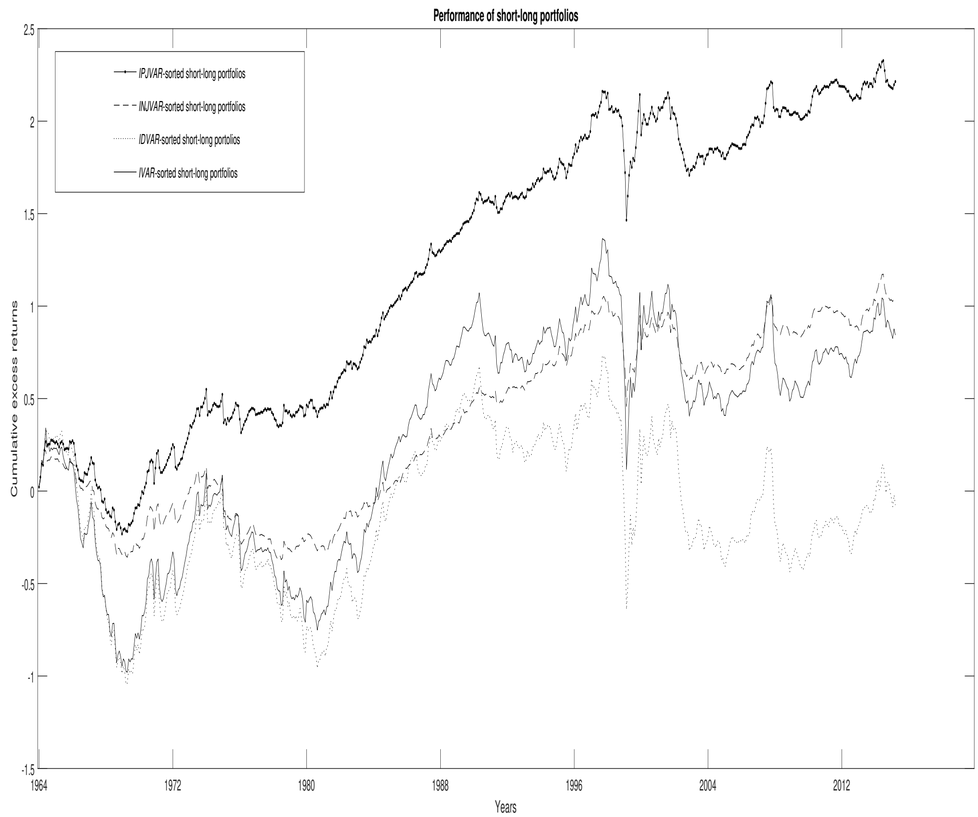


Figure 1 : **Time series plots of decomposed idiosyncratic risk measures, continued**



This figure displays the time series of averaged decomposed idiosyncratic risk measures ($IDVAR$, $IPJVAR$, and $INJVAR$) for quintile portfolios, which are created every month by sorting stocks according to each decomposed idiosyncratic risk measure. The decomposed idiosyncratic risk measures are calculated using daily return residuals from the Fama-French three-factor model, and the monthly averages of the three risk measures are plotted for each of the quintile portfolios during the sample period from 1964 to 2016. The top, middle, and bottom panels show the results for the $IDVAR$-sorted portfolios, the $IPJVAR$-sorted portfolios, and the $INJVAR$-sorted portfolios, respectively.

Figure 2 : **Relative performance of decomposed idiosyncratic risk-sorted portfolios**



To demonstrate the economic implications of the empirical findings, this figure illustrates the performance of short-long portfolios in terms of cumulative excess returns. Considering the significant negative risk premium identified mainly for idiosyncratic positive jump variance, the $IPJVAR$-sorted short-long portfolio is created by sorting stocks according to the level of $IPJVAR$ every month and taking short positions on stocks in the highest quintile portfolios and long positions on stocks in the lowest quintile portfolios. For comparison, I also consider similar short-long portfolios for other idiosyncratic risk measures of $IVAR$, $IDVAR$, and $INJVAR$. Because the number of stocks changes over time, the number of stocks in these extreme quintile portfolios changes over time as well. I follow their performance during the sample period from 1964 to 2016. The portfolios are rebalanced every month. The line with point markers represents the cumulative returns for the $IPJVAR$-sorted portfolios, and the dashed, dotted, and solid lines represent the cumulative returns for the $INJVAR$-sorted, $IDVAR$-sorted, and $IVAR$-sorted portfolios, respectively.

Table 1: **Descriptive statistics for monthly sample** †

Variable	Mean	Stdev	1st pctl	5th pctl	10th pctl	25th pctl	50th pctl	75th pctl	90th pctl	95th pctl	99th pctl
Monthly return	0.0117	0.1545	-0.3448	-0.2004	-0.1429	-0.0645	0.0000	0.0743	0.1670	0.2500	0.5000
Size	1795.5	11657	2.745	6.237	10.321	27.801	108.599	549.380	2324.850	5656.011	30351
B/M	0.763	1.2380	0.0267	0.0991	0.1634	0.3135	0.5553	0.9163	1.4270	1.8966	3.7024
Momentum	0.1507	1.6656	-0.7216	-0.5391	-0.4261	-0.2156	0.0126	0.2712	0.6496	1.0403	2.8214
β_{MKT}	0.9100	2.0759	-4.9998	-1.8949	-0.9237	0.0546	0.8420	1.7132	2.9171	3.9481	6.9679
β_{SMB}	0.7172	2.8547	-7.0913	-3.1508	-1.8712	-0.4874	0.5544	1.8348	3.5697	5.0572	9.2941
β_{HML}	0.1895	3.5395	-9.9731	-4.8974	-3.1489	-1.1704	0.1769	1.5737	3.5220	5.2418	10.3411
$IVOL$	0.0266	0.0211	0.0045	0.0072	0.0090	0.0133	0.0209	0.0333	0.0504	0.0645	0.1023
$IVAR$	0.0229	0.2173	0.0004	0.0010	0.0016	0.0035	0.0088	0.0221	0.0507	0.0827	0.2072
$IDVAR$	0.0092	0.0244	0.0002	0.0005	0.0009	0.0018	0.0041	0.0098	0.0214	0.0338	0.0764
$IPJVAR$	0.0084	0.1682	0.0000	0.0000	0.0000	0.0000	0.0015	0.0061	0.0178	0.0323	0.0977
$INJVAR$	0.0053	0.0403	0.0000	0.0000	0.0000	0.0000	0.0009	0.0042	0.0125	0.0228	0.0656
Skewness	0.2392	1.0045	-2.7756	-1.2802	-0.8037	-0.2617	0.2089	0.7353	1.3721	1.8754	3.0778
Coskewness	0.0051	0.6193	-0.4095	-0.1211	-0.0620	-0.0167	0.0008	0.0215	0.0755	0.1457	0.4736
Lag return	0.0153	0.1632	-0.3333	-0.1970	-0.1395	-0.0629	0.0000	0.0750	0.1715	0.2566	0.5250
Max return	0.0701	0.0704	0.0032	0.0154	0.0203	0.0317	0.0523	0.0867	0.1371	0.1818	0.3154
Zero return	0.2011	0.2037	0.0000	0.0000	0.0000	0.0476	0.1429	0.3000	0.4762	0.6316	0.9048
Amihud measure	4.1181	51.3095	0.0000	0.0003	0.0010	0.0093	0.1086	1.0172	5.9702	15.2115	69.6628

† This table presents the cross-sectional distributions of various variables representing stock characteristics. Sample statistics from July 1963 to December 2016 are reported. I remove penny stocks for the main analyses and require at least 10 daily stock returns per month. Monthly return is the CRSP monthly return. Size and B/M (book-to-market ratios) are measured as in Fama and French (2006). Momentum is the holding period return from month $m-12$ to $m-2$. β_{MKT}, β_{SMB}, and β_{HML} are factor loadings for the market, size, and value factors. Idiosyncratic volatility ($IVOL$) is the standard deviation of daily return residuals from a regression of daily stock returns in month $m-1$ on the Fama and French (1993) factors. Idiosyncratic variance ($IVAR$) is the sum of the squared daily return residuals in month $m-1$. Idiosyncratic positive and negative jump variance ($IPJVAR$ and $INJVAR$) are the sum of the squared daily return residuals identified as idiosyncratic jumps in month $m-1$. Idiosyncratic diffusive variance ($IDVAR$) is the sum of the squared daily return residuals that are not identified as idiosyncratic jumps in month $m-1$. The identified jump data are described in Table 2. Skewness is the month $m-1$ skewness of raw daily returns. Coskewness is the month $m-1$ coskewness measure of Chabi-Yo and Yang (2010). Lag return is the month $m-1$ return. Max return is the maximum daily return in month $m-1$. Zero return is the fraction of trading days in month $m-1$ with a zero return.

Table 2: **Descriptive statistics for idiosyncratic jump intensity and sizes**†

Variable	Mean	Stdev	1st pctl	5th pctl	10th pctl	25th pctl	50th pctl	75th pctl	90th pctl	95th pctl	99th pctl
Panel A: Idiosyncratic jump intensity distribution											
Nobs per firm	2951.4	2750.5	252	376	499	900	2015	4166	6714	8864	12586
Positive jump intensity	0.0553	0.0092	0.0238	0.0368	0.0434	0.0519	0.0575	0.0609	0.0638	0.0660	0.0716
Negative jump intensity	0.0501	0.009	0.0198	0.0328	0.0390	0.0464	0.0514	0.0553	0.0590	0.0620	0.0688
Panel B: Positive idiosyncratic jump size distribution											
Positive jump size mean	0.0787	0.0531	0.0213	0.0282	0.0338	0.0465	0.0676	0.0977	0.1344	0.1620	0.2406
Positive jump size stdev	0.0464	0.0431	0.0032	0.0127	0.0161	0.0242	0.0375	0.0560	0.0815	0.1063	0.1929
Positive jump size median	0.0668	0.0479	0.0178	0.0238	0.0285	0.0391	0.0571	0.0829	0.1145	0.1400	0.2019
Panel C: Negative idiosyncratic jump size distribution											
Negative jump size mean	-0.0698	0.0385	-0.2008	-0.1401	-0.1176	-0.0875	-0.0611	-0.0425	-0.0312	-0.0265	-0.0199
Negative jump size stdev	0.0330	0.0223	0.0026	0.0099	0.0125	0.0183	0.0288	0.0422	0.0576	0.0700	0.1104
Negative jump size median	-0.0618	0.0357	-0.1846	-0.1277	-0.1057	-0.0770	-0.0535	-0.0369	-0.0273	-0.0232	-0.0174

† This table presents the cross-sectional distributions of positive and negative idiosyncratic jumps in terms of their intensities (frequencies) and sizes. Sample statistics in this table are based on daily data. I define both idiosyncratic jump and diffusive risk with respect to the Fama-French three-factor model. Specifically, I obtain daily residuals from the regression model with the three factors of market, size, and value factors. To distinguish idiosyncratic jump components from diffusive components in idiosyncratic risk, I apply idiosyncratic jump tests to the daily return residuals and categorize them into three groups (positive idiosyncratic jumps, negative idiosyncratic jumps, and diffusive residuals). I separately report the cross-sectional distributions for positive and negative jumps identified in this table. Nobs per firm is the total number of daily residuals available for each firm. The sample covers the years from 1963 to 2016. I limit the sample to firms that have survived at least one year because jump tests require a sufficient number of observations to estimate jump-robust volatility during a certain period before each testing time. Positive (negative) jump intensities in Panel A are computed as the number of positive (negative) jumps relative to the total number of observations available for each firm. I include positive and negative jump size distribution in Panels B and C, respectively. Basic distributional statistics, such as the mean, standard deviation, and various percentiles, are reported. These jumps are used to compute the decomposed measures of idiosyncratic risk such as *IDVAR*, *IPJVAR*, and *INJVAR* whose summary statistics are reported in Table 1.

Table 3: **Pricing decomposed idiosyncratic variances**†

Variable	(1)	(2)	(3)	(4)	(5)
$IVOL$	-10.643**				
	(-2.461)				
$IVAR$		-6.698***			
		(-2.926)			
$IDVAR$			-5.050	2.638	2.277
			(-0.604)	(0.330)	(0.286)
$IPJVAR$				-16.384***	-21.126***
				(-5.748)	(-3.613)
$INJVAR$					5.769
					(1.083)
β_{MKT}	-0.028	-0.038	-0.042	-0.039	-0.043
	(-0.552)	(-0.741)	(-0.819)	(-0.765)	(-0.833)
β_{SMB}	-0.036*	-0.036	-0.038*	-0.036*	-0.035
	(-1.720)	(-1.607)	(-1.813)	(-1.687)	(-1.611)
β_{HML}	0.036	0.047*	0.041*	0.042	0.043*
	(1.539)	(1.804)	(1.657)	(1.647)	(1.708)
Size	-0.030***	-0.029***	-0.025**	-0.027**	-0.026**
	(-3.115)	(-2.636)	(-2.407)	(-2.577)	(-2.546)
B/M	0.396***	0.400***	0.406***	0.400***	0.402***
	(7.846)	(7.867)	(8.004)	(7.867)	(7.888)
Momentum	0.406***	0.417***	0.419***	0.405***	0.411***
	(4.140)	(4.079)	(4.422)	(4.249)	(4.287)
Lagged return	0.050	0.069	0.095	-0.011	0.031
	(0.202)	(0.262)	(0.368)	(-0.044)	(0.124)
Constant	0.666***	0.547**	0.495**	0.510**	0.502**
	(3.480)	(2.438)	(2.311)	(2.394)	(2.357)
Observations	1700013	1697355	1697355	1697355	1697355
R-squared	0.043	0.040	0.043	0.046	0.048

† This table provides the results of the asset pricing tests of whether idiosyncratic jump risks are cross-sectionally priced in U.S. equity markets. I run the traditional Fama-MacBeth regression:

$$r_{i,m} = c_m + \gamma_d IDVAR_{i,m-1} + \gamma_{pj} IPJVAR_{i,m-1} + \gamma_{nj} INJVAR_{i,m-1} + \lambda'_\beta \beta_{i,m} + \lambda'_z z_{i,m} + e_{i,m},$$

where $r_{i,m}$ is stock i's excess return in month m, $IDVAR_{i,m-1}$, $IPJVAR_{i,m-1}$ and $INJVAR_{i,m-1}$ are decomposed idiosyncratic risk measures computed using daily return residuals during the previous month $m-1$, and $z_{i,m}$ is a vector of control variables for firm i and month m. The main variables of interest are *IDVAR*, *IPJVAR*, and *INJVAR*. Columns (1) and (2) present the estimation results of the regressions without separating the idiosyncratic risk measures. $IVOL$ ($IVAR$) denotes the idiosyncratic risk measured using the standard deviation of the return residuals (sum of squared return residuals). Columns (3)-(5) show the results using the decomposed risk measures. All of the results are after controlling for factor loadings and the usual firm characteristics, such as size, book-to-market ratios (B/M), momentum, and lagged variables. Numbers in parentheses are test statistics for the coefficient estimates. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: **Implication for decomposed variance sorted portfolios** †

	IPJVAR-sort	*INJVAR*-sort	*IDVAR*-sort	*IVAR*-sort
	Panel A: Using equal-weighted quintile portfolios			
Mean (%)	0.35***	0.16*	-0.011787	0.13
	(2.663)	(1.387)	(-0.050)	(0.599)
CAPM alpha (%)	0.34***	0.14	0.003	0.138
	(2.563)	(1.210)	(0.012)	(0.624)
FF 3-factor alpha (%)	0.31**	0.13	-0.087	0.07
	(2.329)	(1.092)	(-0.364)	(0.313)
FF 5-factor alpha (%)	0.33**	0.14	-0.059	0.094
	(2.380)	(1.106)	(-0.237)	(0.404)
FF 6-factor alpha (%)	0.35**	0.16	-0.036	0.129
	(2.546)	(1.302)	(-0.143)	(0.550)
q-factor alpha (%)	0.34**	0.162	-0.058	0.13
	(2.289)	(1.214)	(-0.217)	(0.526)
Annualized mean return (%)	4.2	1.92	-0.22	1.56
Annualized standard deviation (%)	11.36	10.32	20.71	19.29
Annualized Sharpe ratio	0.37	0.19	-0.01	0.08
	Panel B: Using value-weighted quintile portfolios			
Mean (%)	0.37***	0.26**	0.15	0.32*
	(2.603)	(2.002)	(0.601)	(1.406)
CAPM alpha (%)	0.355**	0.232*	0.15	0.314
	(2.458)	(1.775)	(0.593)	(1.357)
FF 3-factor alpha (%)	0.319**	0.208	0.051	0.238
	(2.183)	(1.569)	(0.200)	(1.018)
FF 5-factor alpha (%)	0.345**	0.229*	0.096	0.282
	(2.290)	(1.680)	(0.365)	(1.166)
FF 6-factor alpha (%)	0.371**	0.257*	0.117	0.314
	(2.421)	(1.857)	(0.437)	(1.278)
q-factor alpha (%)	0.37**	0.00275*	0.114	0.341
	(2.269)	(1.861)	(0.401)	(1.311)
Annualized mean return (%)	4.44	3.12	1.8	3.84
Annualized standard deviation (%)	12.54	11.36	21.93	20.13
Annualized Sharpe ratio	0.35	0.27	0.08	0.19

† This table compares the relative performance of four different short-long portfolio strategies using extreme quintile portfolios sorted on decomposed idiosyncratic risk measures (*IPJVAR*, *INJVAR*, and *IDVAR*) and the total idiosyncratic risk measure (*IVAR*). I create the *IPJVAR*-sorted short-long portfolio by sorting stocks according to the level of *IPJVAR* every month and taking short (long) positions on stocks in the highest (lowest) quintile portfolios. Because the number of stocks changes over time in my unbalanced panel data, the number of stocks included in these extreme quintile portfolios changes as well. I also consider similar short-long portfolios for other idiosyncratic risk measures such as *INJVAR*, *IDVAR*, and *IVAR*. These portfolios are rebalanced every month during the sample period from 1964 to 2016. The time series of subsequent month returns for each portfolio are obtained for comparison. As performance measures, I present their monthly mean returns, CAPM alphas, Fama French 3-factor alphas, FF 5-factor alphas, FF 6-factor + momentum alphas, and q-factor alphas. Annualized returns, standard deviations, as well as their Sharpe ratios are also reported. Panel A uses equal-weighted portfolios, while Panel B uses value-weighted portfolios. I use size (log market capitalization) for the value weighting scheme. Numbers in parentheses are test statistics for the parameter estimates. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: **Effects of nonnormal market conditions**†

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IDVAR	2.277	3.099	3.106	-0.346	1.204	14.370*	-6.656
	(0.286)	(0.392)	(0.391)	(-0.043)	(0.158)	(1.960)	(-1.005)
IPJVAR	-21.126***	-19.095***	-19.956***	-21.302***	-22.371***	-4.163	-13.650***
	(-3.613)	(-3.285)	(-4.243)	(-3.404)	(-3.707)	(-0.678)	(-5.807)
INJVAR	5.769	2.877	4.822	-0.993	7.634	4.565	-1.292
	(1.083)	(0.539)	(1.016)	(-0.180)	(1.456)	(0.905)	(-0.385)
Lagged return	0.031						
	(0.124)						
Skewness		-0.053**					
		(-2.488)					
Coskewness			-0.529**				
			(-2.491)				
Amihud measure				0.043***			
				(2.721)			
Zero returns					0.806**		
					(2.252)		
Max return						-6.775***	
						(-5.245)	
Expected idiosyncratic skewness							0.198
							(1.632)
Constant	0.502**	0.521**	0.510**	0.481**	0.400*	0.723***	0.405*
	(2.357)	(2.425)	(2.375)	(2.296)	(1.885)	(3.673)	(1.946)
Observations	1697355	1692871	1698064	1587042	1698064	1698064	1352624
R-squared	0.048	0.045	0.046	0.051	0.049	0.047	0.042

† This table reports the results of tests examining whether the main results are robust to other nonnormal market conditions that tend to be related to jumps. To examine the individual impact of each jump-related variable on the results, I include each variable one-by-one in addition to other control variables such as factor loadings, size, book-to-market ratios (B/M), and momentum considered in Table 3. Specifically, I run the Fama-MacBeth regression:

$$r_{i,m} = c_m + \gamma_d IDVAR_{i,m-1} + \gamma_{pj} IPJVAR_{i,m-1} + \gamma_{nj} INJVAR_{i,m-1} + \lambda'_\beta \beta_{i,m} + \lambda'_z z_{i,m} + e_{i,m},$$

where $r_{i,m}$ is stock i's excess return in month m, and $IDVAR_{i,m-1}$, $IPJVAR_{i,m-1}$ and $INJVAR_{i,m-1}$ are decomposed idiosyncratic risk measures computed using daily return residuals during the previous month $m-1$. I consider various jump-related variables, such as skewness, coskewness, maximum daily return, the Amihud illiquidity measure, fraction of trading days with a zero return, and expected idiosyncratic skewness of Boyer et al. (2010). I use the expected idiosyncratic skewness data available online at Brian Boyer's website. The main variables of interest are *IDVAR*, *IPJVAR*, and *INJVAR*, which are computed based on the jumps reported in Table 2. For comparison, I first report in column (1) the results obtained in Table 3. Then, in columns (2)-(6), I report regression results in the presence of each jump-related variable. Numbers in parentheses are test statistics for the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: **Maximum return effects with and without positive jumps**†

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Max return	-6.741***					
	(-5.139)					
Max return without jumps		0.026		-5.374**	-1.014	-0.443
		(0.025)		(-2.493)	(-0.797)	(-0.474)
Max return with jumps			-4.322***	-6.329***		
			(-5.698)	(-4.958)		
IPJVAR					-19.820***	-15.290***
					(-4.591)	(-3.318)
IDVAR						-1.897
						(-0.243)
INJVAR						-7.914
						(-1.588)
Lagged return	0.178	0.325	0.202	0.159	0.23	0.242
	(0.698)	(1.202)	(0.767)	(0.624)	(0.88)	(0.978)
Skewness	0.016	-0.129***	-0.028	0.007	-0.075***	-0.074***
	(0.585)	(-4.566)	(-1.227)	(0.265)	(-3.258)	(-3.416)
Coskewness	-0.415**	-0.539***	-0.462**	-0.428**	-0.574***	-0.448**
	(-1.990)	(-2.753)	(-2.238)	(-2.078)	(-2.752)	(-2.178)
Amihud measure	0.040***	0.033**	0.037**	0.039***	0.038***	0.037***
	(2.774)	(2.324)	(2.533)	(2.79)	(2.648)	(2.877)
Zero returns	0.815**	0.652*	0.738*	0.808**	0.707*	0.655*
	(2.196)	(1.695)	(1.875)	(2.213)	(1.856)	(1.865)
Constant	0.623***	0.358*	0.482**	0.586***	0.404*	0.415**
	(3.165)	(1.68)	(2.308)	(3.021)	(1.93)	(2.072)
Observations	1588761	1588761	1586441	1586441	1586441	1586441
R-squared	0.055	0.051	0.052	0.057	0.055	0.062

† This table shows that the maximum daily return's ability to predict subsequent returns is mainly driven by positive idiosyncratic jumps. I separate maximum return data into those realized without and with positive idiosyncratic jumps as follows:

$$\text{Max return}_{i,m} = \text{Max return}_{i,m} \times IPJ_{i,m} + \text{Max return}_{i,m} \times (1 - IPJ_{i,m}),$$

where $\text{Max return}_{i,m} \times (1 - IPJ_{i,m})$ is the maximum return for stock i in month m realized without jumps and $\text{Max return}_{i,m} \times IPJ_{i,m}$ is that with positive idiosyncratic jumps. The presence of positive idiosyncratic jumps for stock i in month m is captured by $IPJ_{i,m} = I[\int_{t \in M_m} dJ_{i,t}^{(+)} > 0]$. I report the estimation results for the Fama-MacBeth regression where its dependent variable $r_{i,m}$ is stock i's excess return in month m and separated maximum daily return are used to show the role of positive idiosyncratic jumps. *IDVAR*, *IPJVAR* and *INJVAR* are included to present the results when maximum daily returns do not include positive idiosyncratic jumps. For further robustness checks, I also consider various control variables including lagged return, skewness, coskewness, the Amihud illiquidity measure, and the fraction of trading days with a zero return. For comparison, I first report in column (1) the maximum return effect without separation. In columns (2) and (3), I report results which separate the maximum return effects without and with jumps. The results in columns (4)-(6) shows the inconsistent effects of maximum returns in the absence of positive idiosyncratic jumps. Numbers in parentheses are test statistics for the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: **Skewness prediction with decomposed variances**†

Variable	Skewness Raw (1)	Skewness Raw (2)	Skewness with jumps (3)	Skewness with jumps (4)
IPJ	0.010***	0.017***	0.027***	0.030***
	(3.339)	(5.92)	(9.421)	(9.195)
IPJVAR	2.197***	1.913***	1.787***	1.676***
	(4.534)	(4.705)	(5.816)	(5.516)
INJVAR	-0.856***	-0.122	-0.309	-0.025
	(-2.872)	(-0.337)	(-1.283)	(-0.078)
IDVAR	4.414***	4.316***	1.335***	1.279***
	(11.884)	(11.684)	(4.511)	(4.374)
Lagged return	-0.355***	-0.355***	-0.262***	-0.262***
	(-18.725)	(-18.667)	(-18.386)	(-18.390)
Turnover	0.029***	0.029***	0.007**	0.007**
	(4.794)	(4.717)	(2.086)	(2.08)
Size	-0.023***	-0.023***	-0.032***	-0.032***
	(-10.385)	(-10.309)	(-20.047)	(-19.978)
Amihud	-0.002***	-0.002***	-0.001***	-0.001***
	(-5.284)	(-5.276)	(-4.034)	(-4.039)
Price	-0.001***	-0.001***	-0.0004***	-0.0004***
	(-6.048)	(-6.054)	(-6.392)	(-6.403)
B/M	0.006***	0.006***	0.002*	0.002*
	(2.945)	(2.945)	(1.957)	(1.947)
INJ		-0.015***		-0.006***
		(-5.005)		(-2.661)
Constant	0.321***	0.324***	0.404***	0.406***
	(19.364)	(19.536)	(32.274)	(32.475)
Observations	1643276	1643276	1643276	1643276
R-squared	0.025	0.025	0.024	0.025

† This table shows the results of skewness prediction with realized variances associated with positive idiosyncratic jumps. I use a cross-sectional regression model as follows:

$$Skewness_{i,m} = \theta_0 + \theta_1 IPJ_{i,m-1} + \theta_{pj} IPJVAR_{i,m-1} + \delta_x' X_{i,m-1} + e_{i,m},$$

where the main variable $IPJVAR_{i,m-1}$ is included. To test the jump arrivals matter for skewness prediction, I also include $IPJ_{i,m}(INJ_{i,m})$, a positive (negative) idiosyncratic jump indicator for stock i in month m, which is one if there is at least one positive (neative) jump in month m (i.e., $IPJ_{i,m} = I[\int_{t \in M_m} dJ_{i,t}^{(+)} > 0]$ and $INJ_{i,m} = I[\int_{t \in M_m} dJ_{i,t}^{(-)} > 0]$, respectively). $X_{i,m-1}$ is a vector of potential skewness predictors known in the previous month $m-1$. Variables included are *INJVAR*, *IDVAR*, lagged return, turnover, size, the Amihud measure, and book-to-market ratio (B/M), all of which are based on observations from month $m-1$. To demonstrate positive jump effects within skewness measure, I consider an additional dependent variable, that is skewness only when there are positive idiosyncratic jumps (i.e., $Skewness_{i,m} \times I[\int_{t \in M_m} dJ_{i,t}^{(+)} > 0]$ in columns (3) and (4)). Numbers in parentheses are test statistics for the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: **Robustness to microstructure effects and outliers**†

Variable	Full (1)	Below median zero returns (2)	Above median zero returns (3)	Below median Amihud measure (4)	Above median Amihud measure (5)	Lagged variances (6)	Winsorized variables (7)	Logged variances (8)
IDVAR	2.276684	-8.96382	25.26652	-21.8168	9.28836	7.116528	3.53918	0.0760866
	(0.29)	(-0.86)	(0.86)	(-1.44)	(1.15)	(0.85)	(0.41)	(1.15)
IPJVAR	-21.126 ***	-19.15098 **	-42.22425 **	-26.81029 *	-22.92069 ***	-12.8452 ***	-27.17421***	-0.2143567***
	(-3.61)	(-2.34)	(-2)	(-1.91)	(-4.18)	(-3.98)	(-4.62)	(-5.84)
INJVAR	5.768627	-25.64835 ***	65.94395 **	-18.26555	0.3022846	4.950152	8.731049	0.0341613
	(1.08)	(-2.76)	(2.15)	(-1.4)	(0.05)	(0.8)	(1.53)	(1.10)
β_{MKT}	-0.0429652	-0.0480856	0.0343963	-0.0276253	-0.0124779	-0.0403482	-0.059051	-0.0388154
	(-0.83)	(-0.85)	(0.25)	(-0.41)	(-0.25)	(-0.79)	(-1.27)	(-0.84)
β_{SMB}	-0.034614	-0.0223645	-0.1063854	0.0062292	-0.0337084	-0.0379262*	-0.024086 **	-0.0466565
	(-1.61)	(-0.96)	(-1.16)	(0.24)	(-1.42)	(-1.78)	(-1.24)	(-2.29)
β_{HML}	0.0433558 *	0.059148 **	-0.0084229	0.0520407	0.0212013	0.0367781	0.0202644*	0.0427135
	(1.71)	(2.06)	(-0.1)	(1.6)	(0.81)	(1.51)	(0.94)	(1.94)
Size	-0.0262495 **	-0.0174398	1.00966	-0.0191156 **	-2.394465 ***	-0.04397*	-0.0267217	-0.1083562 *
	(-2.55)	(-2.43)	(1.2)	(-2.49)	(-5.47)	(-1.98)	(-2.18)	(-2.12)
B/M	0.4018119 ***	0.422156 ***	0.4489007 ***	0.4347279 ***	0.4665249 ***	0.4043365***	0.7958393***	0.3840981***
	(7.89)	(6.49)	(4.09)	(6.21)	(8.75)	(7.99)	(10.94)	(6.88)
Momentum	0.4109917 ***	0.5222038 ***	0.2207972	0.484349 ***	0.4427675 ***	0.410628***	0.5778445***	0.3588049 ***
	(4.29)	(5.58)	(0.74)	(4.73)	(4.46)	(4.38)	(4.58)	(3.24)
Lagged return	0.0312271	0.641044 **	-0.0399787	0.0545734	0.5805708	0.3220076	-0.0633394	0.371866
	(0.12)	(2.18)	(-0.05)	(0.17)	(1.65)	(1.14)	(-0.23)	(1.14)
Constant	0.5015153 **	0.4946814 **	0.3276305	0.4321246 **	0.7270835 ***	0.4768053 **	0.1844322	-0.1930764
	(2.36)	(2.46)	(1.17)	(2.29)	(2.85)	(2.27)	(0.87)	(-0.29)
Observations	1697355	857625	839730	907259	790096	1688362	1697355	862580
R-squared	0.0476	0.069	0.1155	0.0773	0.0516	0.0472	0.0514	0.0634

† This table provides the results of the robustness test to check whether the main findings are affected by microstructure effects and outliers. For each test, I run the Fama-MacBeth regression:

$$r_{i,m} = c_m + \gamma_d IDVAR_{i,m-1} + \gamma_{pj} IPJVAR_{i,m-1} + \gamma_{nj} INJVAR_{i,m-1} + \lambda'_\beta \beta_{i,m} + \lambda'_z z_{i,m} + e_{i,m},$$

where $r_{i,m}$ is stock i's excess return in month m, $IDVAR_{i,m-1}$, $IPJVAR_{i,m-1}$ and $INJVAR_{i,m-1}$ are decomposed idiosyncratic variance measures computed using daily return residuals during the previous month $m-1$, and $z_{i,m}$ is a vector of control variables for firm i and month m. Column (1) presents the main results using the entire sample. Columns (2) and (3) report the results using subsamples based on the median of the fraction of trading days with a zero return. Columns (4) and (5) report the results using subsamples based on the median level of the Amihud measure. To skip a month to take out the effect of a bid-ask bounce, column (6) reports the results using variances measured in month $m-2$ instead of month $m-1$. Columns (7) and (8) report the results using winsorized independent variables and log-transformed variances to check outlier effects. Numbers in parentheses are test statistics for the coefficient estimates. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9: **Robustness to sample period selection**[†]

Variable	Full (1)	Expansion (2)	Recession (3)	First (4)	Second (5)	6070s (6)	8090s (7)	0010s (8)
IDVAR	-1.761	0.086	-5.185	1.758	-5.427	17.479	-10.044	-11.903
	(-0.224)	(0.010)	(-0.244)	(0.136)	(-0.622)	(0.948)	(-1.163)	(-0.935)
IPJVAR	-17.459***	-16.267***	-25.630***	-27.977***	-6.501***	-30.993**	-16.230***	-4.547**
	(-3.611)	(-2.950)	(-3.559)	(-3.040)	(-4.109)	(-2.195)	(-4.674)	(-1.978)
INJVAR	-6.078	-7.434	-1.194	-11.145	-0.799	-13.997	0.409	-5.771
	(-1.159)	(-1.286)	(-0.111)	(-1.171)	(-0.203)	(-0.969)	(0.092)	(-1.024)
Lagged return	0.235	0.309	-0.390	0.253	0.216	0.428	0.288	-0.039
	(0.948)	(1.196)	(-0.458)	(0.719)	(0.618)	(0.854)	(0.852)	(-0.086)
Skewness	-0.072***	-0.055**	-0.174***	-0.105***	-0.039	-0.139***	-0.033	-0.051
	(-3.349)	(-2.262)	(-4.400)	(-3.923)	(-1.149)	(-4.044)	(-0.836)	(-1.465)
Coskew	-0.447**	-0.285	-1.390**	-0.753**	-0.129	-1.058**	-0.292	0.009
	(-2.178)	(-1.334)	(-2.414)	(-2.288)	(-0.547)	(-2.275)	(-1.202)	(0.029)
Amihud measure	0.037***	0.041***	0.012	0.062**	0.012***	0.086**	0.014***	0.014**
	(2.851)	(2.761)	(0.759)	(2.475)	(2.981)	(2.231)	(3.100)	(2.415)
Zero returns	0.649*	0.683*	0.949	0.774*	0.518	1.350**	-0.251	1.030
	(1.845)	(1.907)	(0.727)	(1.919)	(0.888)	(2.578)	(-0.632)	(1.176)
Constant	0.411**	0.474***	0.534	0.090	0.746***	0.014	0.380	0.875***
	(2.043)	(2.688)	(0.631)	(0.304)	(2.859)	(0.038)	(1.116)	(2.604)
Observations	1586441	1393413	169735	656344	930097	296275	852714	437452
R-squared	0.061	0.058	0.081	0.075	0.047	0.096	0.039	0.051

[†] This table provides the results of the robustness tests using subsamples. Column (1) reports the main results from the cross-sectional asset pricing tests using the entire sample. Then, I split the sample into two or three subsamples according to business cycles and sample periods. Columns (2) and (3) report the results for subsamples based on business cycles (expansion vs. recession). Columns (4)-(8) show the results for samples from the subsample periods (first vs. second half of the sample period or different years during the entire sample period). For all estimations, I simultaneously include all control variables including jump-related variables. To save space, I do not report the coefficients for the first set of control variables, including systematic factor loadings, size, book-to-market ratios (B/M), and momentum, but we report the other coefficients. Numbers in parentheses are test statistics for the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10: **Robustness to asset pricing model selection**†

Factor model selection	No factor	CAPM	q-Factor	FF3+Momentum	FF-5	FF-4+coskew	FF-5+coskew
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$IDVAR$	0.345	-2.303	-3.465	2.536	-2.892	2.584	-4.906
	(-0.037)	(-0.260)	(-0.456)	(0.241)	(-0.309)	(0.22)	(-0.424)
$IPJVAR$	-20.196***	-15.272***	-22.052***	-21.009***	-13.140***	-24.455***	-22.050**
	(-8.002)	(-2.919)	(-9.566)	(-3.603)	(-3.310)	(-3.095)	(-2.421)
$INJVAR$	11.796***	-8.346	13.957***	-2.581	-3.179	-0.633	3.336
	(2.635)	(-1.328)	(3.525)	(-0.342)	(-0.434)	(-0.070)	(0.224)
Lagged return	0.081	0.17	0.226	0.187	0.228	0.144	0.198
	(0.292)	(0.642)	(0.882)	(0.721)	(0.878)	(0.546)	(0.768)
Skewness	-0.052**	-0.056**	0.070***	-0.060***	-0.043*	-0.062**	-0.066***
	(-2.298)	(-2.429)	(3.314)	(-2.615)	(-1.758)	(-2.497)	(-2.712)
Coskewness	-0.081	-0.461*	0.065	-0.458	-0.637**	-0.571*	-0.620**
	(-0.334)	(-1.846)	(0.331)	(-1.493)	(-2.452)	(-1.830)	(-2.437)
Amihud measure	0.036***	0.040***	0.037***	0.035***	0.040***	0.035***	0.032**
	(2.829)	(3.103)	(2.7743)	(2.591)	(3.089)	(2.654)	(2.248)
Zero returns	0.631	0.620*	0.615	0.56	0.569	0.532	0.651*
	(1.636)	(1.762)	(1.605)	(1.586)	(1.573)	(1.477)	(1.869)
β_{MKT}		-0.018	-0.023	-0.016	-0.023	-0.018	
		(-0.347)	(-0.434)	(-0.306)	(-0.435)	(-0.342)	
$\beta_{SMB}(\beta_{ME})$			-0.020	-0.023	-0.027	-0.024	-0.021
			(-1.039)	(-1.135)	(-1.314)	(-1.175)	(-0.986)
$\beta_{HML}(\beta_{IA})$			0.041**	0.047*	0.039	0.048*	0.043*
			(2.254)	(1.786)	(1.55)	(1.807)	(1.675)
$\beta_{MOM}(\beta_{ROE})$			0.037*	-0.016		-0.017	
			(1.674)	(-0.370)		(-0.395)	
β_{RMW}					0.057***		0.052***
					(2.848)		(2.629)
β_{CMA}					0.03		0.037*
					(1.436)		(1.825)
$\beta_{co-skew}$						0.125	0.16
						(1.218)	(1.344)
Constant	0.304	0.383*	0.352	0.404**	0.420**	0.408**	0.405**
	(1.44)	(1.937)	(1.732)	(2.027)	(2.127)	(2.049)	(2.041)
Observations	1532934	1532934	1517825	1532934	1532934	1532934	1532934
R-squared	0.059	0.062	0.062	0.069	0.071	0.071	0.072

† This table provides the results of the robustness tests using asset pricing models other than Fama-French three-factor models used in the main analysis. Column (1) reports the results using total volatility, which is based on the no-factor model. Columns (2)-(5) present the results using decomposed idiosyncratic variance measures with respect to the CAPM, the q-Factor model of Hou et al. (2015), the Fama-French three-factor model with a momentum factor, and the Fama and French (2015) five-factor model. Columns (6) and (7) present the results using decomposed idiosyncratic variance measures with respect to the models with market coskewness, which is estimated following Harvey and Siddique (2000). To save space, I do not report the coefficients for the control variables of firm characteristics, such as firm size, book-to-market ratios (B/M), and momentum. Numbers in parentheses are test statistics for the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 11: **Summary statistics for market and common jumps†**

Panel A: Summary statistics for market index jumps											
	Total number of jumps			Per day			Per month			Per year	
Positive index jump	646			0.0479			0.9580			11.4938	
Negative index jump	805			0.0597			1.1936			14.3228	
	Mean	Std	1st pctl	5th pctl	10th pctl	25th pctl	50th pctl	75th pctl	90th pctl	95th pctl	99th pctl
Positive index jump size	0.0172	0.0106	0.0055	0.0069	0.0083	0.0108	0.0146	0.0202	0.0272	0.0375	0.0620
Negative index jump size	-0.0181	0.0112	-0.0682	-0.0372	-0.0293	-0.0206	-0.0151	-0.0117	-0.0090	-0.0079	-0.0062
Panel B: Summary statistics for common jumps											
Variables per day	Mean	Stdev	1st pctl	5th pctl	10th pctl	25th pctl	50th pctl	75th pctl	90th pctl	95th pctl	99th pctl
Number of stocks	3308.5	1371.1	91	712	1392	2241	3628	4012	5261	5731	6119
Number of positive cojumps	193.2081	104.9283	0	38	66	116	188	256	322	370	491
Percentage of positive cojumps	0.0575	0.0208	0.0007	0.0279	0.0349	0.0453	0.0564	0.0681	0.0810	0.0918	0.1179
Number of negative cojumps	173.8224	96.6796	0	33	57	104	169	229	289	334	453
Percentage of negative cojumps	0.0518	0.0202	0	0.0239	0.0308	0.0400	0.0502	0.0613	0.0740	0.0852	0.1145

† This table presents summary statistics for market and common idiosyncratic jumps, which are used to further decompose the negative risk premium associated with positive idiosyncratic jump risk. For consistency I detect market jumps by applying jump detection tests on daily market returns that are calculated based on the return data for all individual stocks in the sample. In Panel A, I list the total number of market jumps along with the average jump intensities (frequencies) per day, per month, and per year. Distributional statistics, such as the means, standard deviations, and percentiles for both positive and negative market jump sizes, are also reported. Only nonzero jump sizes are considered for the distribution of market jump sizes. In Panel B, I show the relevant statistics for calculating common idiosyncratic jumps, which are defined as as idiosyncratic jumps that arise simultaneously with other stock-specific jumps on a day. Because the panel data are unbalanced, the number of stocks each day changes over time. Because of these changes, the threshold to determine the commonality of idiosyncratic jump arrivals in my analysis is not based on the number of idiosyncratic jumps in a day but on the percentage of those jumps (i.e., the ratio of the number of stocks that experience idiosyncratic jumps relative to the total number of stocks available in a given day). Distributional statistics, such as the means, standard deviations, and percentiles, are reported in Panel B for the number of stocks per day, number of positive or negative common idiosyncratic jumps per day, and percentage of positive and negative common idiosyncratic jumps per day.

Table 12: **Robustness to market and common jumps**†

Common Jump Definition	No split	Market	COM >20%	COM >15%	COM >10%
Variables	(1)	(2)	(3)	(4)	(5)
$IDVAR$	-1.761	-1.677	-1.758	-1.800	-1.759
	(-0.224)	(-0.214)	(-0.224)	(-0.229)	(-0.223)
$IPJVAR$	-17.459***				
	(-3.611)				
$IPJVAR^C(IPJVAR^M)$		-12.672	-0.343	-1.461	-3.259
		(-0.951)	(-1.119)	(-1.181)	(-0.886)
$IPJVAR^U(IPJVAR^{NM})$		-18.673***	-17.438***	-17.289***	-17.505***
		(-3.881)	(-3.607)	(-3.579)	(-3.618)
$INJVAR$	-6.078	-5.268	-6.080	-6.154	-5.843
	(-1.159)	(-1.010)	(-1.159)	(-1.174)	(-1.117)
Lagged Return	0.235	0.216	0.235	0.236	0.233
	(0.948)	(0.869)	(0.949)	(0.953)	(0.942)
Skewness	-0.072***	-0.071***	-0.073***	-0.073***	-0.074***
	(-3.349)	(-3.286)	(-3.356)	(-3.371)	(-3.461)
Coskewness	-0.447**	-0.563**	-0.431**	-0.430**	-0.402*
	(-2.178)	(-2.512)	(-2.084)	(-2.108)	(-1.920)
Amihud measure	0.037***	0.037***	0.037***	0.037***	0.037***
	(2.851)	(2.862)	(2.851)	(2.850)	(2.839)
Zero returns	0.649*	0.636*	0.646*	0.649*	0.653*
	(1.845)	(1.811)	(1.838)	(1.846)	(1.856)
Constant	0.411**	0.414**	0.412**	0.411**	0.410**
	(2.043)	(2.058)	(2.047)	(2.043)	(2.038)
Observations	1586441	1586441	1586441	1586441	1586441
R-squared	0.061	0.062	0.061	0.061	0.061

† This table provides the results of testing whether idiosyncratic jumps arriving with market jumps or common idiosyncratic jumps are important in explaining the cross-section of stock returns. I measure the commonality of idiosyncratic jumps by $COM = \frac{\sum_{i=1}^{K_d} I(T_{i,d}>\tau)}{K_d}$ where K_d is the total number of stocks available on day d, $T_{i,d}$ is the idiosyncratic jump test statistic for stock i on day d, and τ is the threshold for jump detection test. Using COM, I further decompose $IPJVAR$ into two components: one attributable to common jump arrivals ($IPJVAR^C$) and the other attributable to uncommon jump arrivals ($IPJVAR^U$). Then, I run the Fama-MacBeth regression:

$$r_{i,m} = c_m + \gamma_d IDVAR_{i,m-1} + \gamma_{cpj} IPJVAR^C_{i,m-1} + \gamma_{upj} IPJVAR^U_{i,m-1} + \gamma_{nj} INJVAR_{i,m-1}$$

$$+\lambda'_\beta \beta_{i,m} + \lambda'_z z_{i,m} + e_{i,m},$$

where $r_{i,m}$ is stock i's excess return in month m, and $IDVAR_{i,m-1}$, $IPJVAR^C_{i,m-1}$, $IPJVAR^U_{i,m-1}$ and $INJVAR_{i,m-1}$ are idiosyncratic variance measures computed using daily return residuals over the previous month $m-1$. Based on market jump arrivals, I perform similar analyses and list the results in column (2). For this exercise, I run the regression using decomposed $IPJVAR$s into two components ($IPJVAR^M$ and $IPJVAR^{NM}$) attributable to market and nonmarket jump arrivals. Numbers in parentheses are test statistics for the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix A. Finite sample performance of jump variance estimators

In this appendix, I discuss a Monte Carlo simulation study that examine the finite sample performance of the jump variance estimators. Lee and Mykland (2008) show that jump tests identify jump arrivals well in finite samples, mostly based on intraday data. Since this study aims to cover more cross-sectional data over much longer time horizons by using daily stock market data, I check whether daily samples can also be applied to provide useful results on the impact of large daily realized jumps.

There are two specific goals. The first is to show how accurately the jump tests can detect jump arrivals using daily data. Showing this accuracy is important because the performance of jump variance estimators depends on the power of jump detection upon daily arrivals and affects the key results. After showing the jump test performance in detecting daily jumps under various model specifications, I report estimation errors that can potentially result from using the jump variance estimators. The overall simulation results demonstrate that the jump variance estimators based on daily data perform well, as expected, in estimating variances associated with jump components in the model under general market conditions.

Considering that elevated volatility levels can also generate large returns and may lead to misclassification, I design this study with four different scenarios for volatilities. The first scenario is the simplest possible benchmark case where volatility is set to be constant over time. In the second, I consider the case with stochastic volatility that follows a typical mean reverting process. The third and fourth cases consider elevated volatility to the first and second cases by incorporating 30% jumps in (both constant and stochastic) volatility at the time of price jumps. I study the last two cases to address the misclassification issue.

Table A.1: Finite sample performance of jump variance estimators†

Price jump sizes	$0.1\sigma_{i,t-}$	$0.25\sigma_{i,t-}$	$0.5\sigma_{i,t-}$	$1\sigma_{i,t-}$	$3\sigma_{i,t-}$	$5\sigma_{i,t-}$	$7\sigma_{i,t-}$
Panel A: Power of jump test at daily level							
Constant volatility	0.3280	0.7638	0.9734	0.9848	0.9897	0.9908	0.9915
Stochastic volatility	0.3292	0.7666	0.9737	0.9841	0.9905	0.9886	0.9912
Constant volatility with jumps	0.3488	0.7398	0.9680	0.9859	0.9887	0.9903	0.9904
Stochastic volatility with jumps	0.3538	0.7474	0.9674	0.9841	0.9893	0.9886	0.9914
Panel B: MSEs of jump variance estimator							
Constant volatility	0.00035	0.00042	0.00067	0.00068	0.00070	0.00071	0.00071
Stochastic volatility	0.00049	0.00053	0.00087	0.00092	0.00091	0.00091	0.00090
Constant volatility with jumps	0.00050	0.00051	0.00087	0.00092	0.00092	0.00092	0.00090
Stochastic volatility with jumps	0.0007	0.0007	0.0011	0.0012	0.0012	0.0012	0.0012

† This table presents the finite sample performance of jump variance estimators based on daily data. Panel A shows the power of jump tests based on daily data, while Panel B shows the mean squared errors made from applying the jump variance estimators to the 10,000 simulated series. Price jump sizes are set at various levels depending on the volatility levels at testing times. Volatility jump sizes are set at 30%. See Appendix A for additional details of the selected models and parameter values.

I generate daily return data over give years using the Euler-Maruyama scheme, which is widely used to simulate data from the following models:

$$d\log S_{i,t} = \mu_{i,t}dt + \sigma_{i,t}dW_{i,t} + Y_{i,t}dJ_{i,t}, \tag{8}$$

where the stochastic volatility model is specified as the following square root processes:

$$d\sigma^2_{i,t} = \kappa(\theta - \sigma^2_{i,t})dt + \omega\sigma_{i,t}dB_{i,t} + Y^{\sigma}_{i,t}dJ_{i,t}. \tag{9}$$

The terms $dW_{i,t}$ and $dB_{i,t}$ are standard Brownian motion processes. $dJ_{i,t}$ denotes the jump arrival indicator for price and volatility at time t. Price jump sizes of $Y_{i,t}$ are selected relative to the volatility level $\sigma_{i,t-}$ immediately before jump time t. When Iassume that the volatility is stochastic, jump sizes are also time-varying and are set at $5\sigma_{i,t-}$, $3\sigma_{i,t-}$, $1\sigma_{i,t-}$, $0.5\sigma_{i,t-}$, and $0.25\sigma_{i,t-}$. Volatility jump sizes of $Y^{\sigma}_{i,t}$ are set at 30% of the volatility level prior to jump time t. I ignore the drift term in this simulation by setting $\mu_{i,t} = 0$ for simplicity, assuming that the magnitudes of drift terms compared to those of diffusion and jump terms are negligible. I use the following parameters for the volatility process: $\kappa = 0.0162$, $\theta = 0.8465$, and

$\omega = 0.47$. I discard the first five hundred observations to avoid starting value effects every time I generate a time series of daily data. I simulate 10,000 paths of the log price process and compute daily returns, which are used for jump tests with the 1% significance levels. Then, I apply jump variance estimators in each simulation.

I report simulation results in Table A. As shown in Panel A, the jump test performs well in detecting large jumps (whose sizes are greater than contemporaneous volatility levels) at daily levels. Even when there are 30% jumps in stochastic volatility, the probability of detecting daily jumps is greater than 98% when I aim to identify jumps with relatively large magnitudes. Panel B shows the mean squared error of jump variance estimators based on daily jump data. Note that the estimation error levels do not grow as jump sizes grow but rather stabilize once large jumps are detected.

Appendix B. Stock and jump data description

I collect U.S. individual stock return data from the CRSP common stock (share codes of 10 or 11) universe from July 1963 to December 2016. Sample firms are required to have nonmissing size and nonnegative book-to-market equity. I remove penny stocks from the main analyses. To reduce the small sample bias, I require at least 10 daily stock returns per month. The results are robust to alternative choices in this requirement. Because I detect jump arrivals using the "nonparametric" jump test, the detection results are robust to the specification of the residual return generating process. However, those results may be sensitive to the window sizes used for jump tests, as is typical of nonparametric approaches. This window should include a sufficient number of observations to properly estimate the jump-robust idiosyncratic volatility. Hence, I require sample firms to have survived for at least one year. For the main presentation of the results, I set the window size for jump tests to be 6 months. In the end, the estimates of $IVAR$, $INJVAR$, and $IPJVAR$ start in January 1964, and month $m-1$ estimates of $IVAR$, $INJVAR$, and $IPJVAR$ are matched to month m returns from February 1964 to December 2016.

The inference method to separate the impact of decomposed idiosyncratic variances is based on a framework that allows for various risk factors. The cross section of individual stock prices is denoted by $S_{i,t}$ with $i = 1.., n$, where n is the total number of stocks. The instantaneous logarithmic return for the ith individual stock at time t can be described as follows:

$$d \log S_{i,t} = \mu_{i,t} dt + \sum_{k=1}^{K} \beta_{i,t}^{k} \sigma_t^k dW_{k,t} + \tilde{\sigma}_{i,t} dW_{i,t} + Y_{i,t}^{(+)} dJ_{i,t}^{(+)} + Y_{i,t}^{(-)} dJ_{i,t}^{(-)}, \tag{10}$$

where $\mu_{i,t}$ represents the instantaneous drift, and $\sum_{k=1}^{K} \beta_{i,t}^{k} \sigma_t^k dW_{k,t}$ represents the sum of the terms associated with K systematic factors and $\beta_{i,t}^{k}$ which is the k-th factor loading of the i-th stock at time t, and $dW_{k,t}$ is a Brownian motion capturing shocks to the k-th systematic factor, scaled by its volatility σ_t^k.$\tilde{\sigma}_{i,t} dW_{i,t}$ is an idiosyncratic diffusion term, where $\tilde{\sigma}_{i,t}$ is the idiosyncratic diffusive volatility and $dW_{i,t}$ is a Brownian motion capturing idiosyncratic diffusive shocks. For all k's, $W_{k,t}$ and $W_{i,t}$ are orthogonal to each other, but $W_{i,t}$ and $W_{j,t}$ for two different stocks i and j, where $i \neq j$ can be correlated. The last two terms reflect idiosyncratic jumps of the i-th individual stock. $Y_{i,t}^{(+)} (Y_{i,t}^{(-)})$ indicates the positive (negative) idiosyncratic jump size at time t. $dJ_{i,t}^{(+)} (dJ_{i,t}^{(-)})$ indicates the positive (negative) idiosyncratic jump arrival at time t with stochastic jump intensities $\nu_{i,t}^{(+)} (\nu_{i,t}^{(-)})$. $dJ_{i,t}$ and $dJ_{j,t}$ for two different stocks i and j with $i \neq j$ can be correlated.[38]

[38]To be consistent with the idiosyncratic volatility literature, I do not specifically model the market jump components. However, accommodating market jumps or other general factor models with higher market

The daily return residual $\epsilon_{i,d}$ for stock i and day d is expected to include the daily realization of idiosyncratic diffusive component $\tilde{\sigma}_{i,t} dW_{i,t}$, as well as both positive and negative idiosyncratic jump components, $Y_{i,t}^{(+)} dJ_{i,t}^{(+)}$ and $Y_{i,t}^{(-)} dJ_{i,t}^{(-)}$. These daily residuals mainly capturing diffusive, positive and negative jump components are denoted by $\epsilon_{df,i,d}$, $\epsilon_{pj,i,d}$, and $\epsilon_{nj,i,d}$, respectively. Then, the return residual for stock i and day d are expressed as follows:

$$\epsilon_{i,d} = \epsilon_{df,i,d} + \epsilon_{pj,i,d} + \epsilon_{nj,i,d}, \tag{11}$$

where

$$\epsilon_{df,i,d} \approx \int_{t \in D_d} \tilde{\sigma}_{i,t} dW_{i,t}, \epsilon_{pj,i,d} \approx \int_{t \in D_d} Y_{i,t}^{(+)} dJ_{i,t}^{(+)}, \text{ and } \epsilon_{nj,i,d} \approx \int_{t \in D_d} Y_{i,t}^{(-)} dJ_{i,t}^{(-)},$$

with $D_d \in [0, T]$ denoting the time interval for day d: $D_d = \{s | s \text{ belongs to day } d\}$. In practice, the aforementioned decomposition must be approximated using statistical tests as described in Subsection 2.1.

Most jump tests are not suitable for this study because they are not designed to extract signed jumps within a time interval (for this study, this time interval is one month). Therefore, I do not perform robustness checks to test whether the results are sensitive to the choice of jump tests. One exception is the test proposed by Andersen et al. (2007), which is designed with a similar mathematical structure to that of the Lee and Mykland (2008) test. The results are expected to be similar because of the similar structure of the test statistics. Although the detection power of the jump test may increase as I increase the frequency of observations up to intraday levels, the benefit of using daily instead of intraday data in this study is substantial. The application of daily data allows me to cover a much longer

moments is straightforward and does not affect the overall conclusion, as shown in Section 5.

sample period beginning in the 1960s. A much larger number of stocks can be included in the sample, enabling greater cross-sectional variation. Such large cross-sectional variation is critical for this analyses but cannot be captured using high-frequency intraday data because of data limitations. Additionally, the focus of this study is not the impact of very small-sized (intraday) idiosyncratic jumps but that of relatively large-sized jumps compared to the prevailing volatility levels.

The average raw return of the sample stocks is 1.17% per month. The average monthly idiosyncratic volatility estimated using the typical standard deviation calculation is 2.66%. The average idiosyncratic diffusive, positive, and negative jump variances are 0.0092, 0.0084, and 0.0053, respectively. The average betas for market, size, and value factors are 0.91, 0.71, and 0.18, respectively. The average size, B/M ratio (computed based on Fama and French (2006)), momentum (return to a buy and hold strategy from month $m-12$ to $m-2$), and lagged return (the month $m-1$ return) are \$1.795 billion, 0.763, 15.07%, and 1.53%, respectively. The average skewness is 0.239, indicating that individual stock returns are on average positively skewed. The average coskewness is 0.0051, indicating that market returns on average tend to move positively with individual stock return variance. The average maximum daily return is 7.01%. The Amihud measure is 4.118 on average, whereas the zero return variable, which is the fraction of trading days with a zero return in month $m-1$, has an average of 20.11%.

Positive (negative) jump intensities are computed as the number of positive (negative) jumps relative to the total number of observations available for each firm. The cross-sectional averages of positive and negative idiosyncratic jump intensities are 0.055 and 0.050, respectively, indicating that positive idiosyncratic jumps are detected slightly more frequently than negative idiosyncratic jumps. Notably, the type I error rate for the positive (negative) jump test is 2.5% because I set the significance level at 5% for the two-sided idiosyncratic jump tests. Idiosyncratic jump sizes are the return residuals when idiosyncratic jump arrivals occur, assuming the magnitudes of return residuals attributable to the jump component dominate the magnitudes of the return residuals due to the diffusion component. The cross-sectional averages of the positive (negative) jump size mean, standard deviation, and median are 7.87% (-6.98%), 4.64% (3.30%), and 6.68% (-6.18%), respectively.

Appendix C. Additional robustness checks: window size selection

For additional robustness checks, Table C.1 reports the estimation results using the entire sample but with various window sizes for jump tests to assess whether the results are affected by the window size selection. For these sensitivity analyses, I select window sizes of 20, 40, 60, 80, 120, and 240 daily data points. The sizes are approximately equivalent to one, two, three, four, six, and 12 months. Column (5) show the original results. The other columns show the same results, thus the main finding is robust to window size selection.

Table C.1: **Robustness to window size selection for jump tests**[†]

Window size K	20	40	60	80	120	240
Variable	(1)	(2)	(3)	(4)	(5)	(6)
IDVAR	-5.563	-7.122	-4.559	-5.345	-1.761	-0.841
	(-0.896)	(-0.924)	(-0.553)	(-0.637)	(-0.224)	(-0.134)
IPJVAR	-12.760***	-19.726***	-18.183***	-20.261***	-17.459***	-9.033*
	(-4.407)	(-3.934)	(-3.713)	(-3.343)	(-3.611)	(-1.777)
INJVAR	-9.628**	-1.48	-4.485	-0.325	-6.078	-17.732**
	(-2.055)	(-0.300)	(-0.800)	(-0.048)	(-1.159)	(-2.135)
Lagged return	0.258	0.246	0.243	0.256	0.235	0.268
	(1.024)	(0.985)	(0.973)	(1.028)	(0.948)	(1.054)
Skewness	-0.077***	-0.065***	-0.069***	-0.066***	-0.072***	-0.083***
	(-3.408)	(-2.918)	(-3.196)	(-3.023)	(-3.349)	(-3.880)
Coskewness	-0.501**	-0.510**	-0.506**	-0.458**	-0.447**	-0.478**
	(-2.387)	(-2.468)	(-2.466)	(-2.209)	(-2.178)	(-2.290)
Amihud measure	0.039***	0.038***	0.037***	0.038***	0.037***	0.038***
	(2.85)	(2.86)	(2.833)	(2.9)	(2.851)	(2.807)
Zero returns	0.738**	0.722**	0.708**	0.685*	0.649*	0.617*
	(1.978)	(2.004)	(1.979)	(1.936)	(1.845)	(1.723)
Constant	0.419**	0.423**	0.425**	0.422**	0.411**	0.415**
	(2.054)	(2.086)	(2.107)	(2.098)	(2.043)	(2.038)
Observations	1586441	1586441	1586441	1586441	1586441	1586441
R-squared	0.059	0.061	0.061	0.061	0.061	0.06

[†] This table provides the results to show that the overall results are robust to window size selection for idiosyncratic jump tests. I present the results using $K = 20, 40, 60, 80, 120$, and 240 for this sensitivity analysis. With each selection, I run the following Fama-MacBeth regression:

$$r_{i,m} = c_m + \gamma_d IDVAR_{i,m-1} + \gamma_{pj} IPJVAR_{i,m-1} + \gamma_{nj} INJVAR_{i,m-1} + \lambda'_\beta \beta_{i,m} + \lambda'_z z_{i,m} + e_{i,m},$$

where $r_{i,m}$ is stock i's excess return in month m and $IDVAR_{i,m-1}$, $IPJVAR_{i,m-1}$, and $INJVAR_{i,m-1}$ are decomposed idiosyncratic risk measures computed using the daily return residuals during the previous month $m-1$. All of the results are after controlling for factor loadings and the usual firm characteristics, as well as month $m-1$ jump-related variables, such as skewness and liquidity measures considered in Table 5. $z_{i,m}$ is a vector of those control variables. To save space, I do not report the coefficients for the first set of control variables considered in Table 3 but report the other coefficients. Numbers in parentheses are test statistics for the coefficient estimates. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.