Volatility Jump Risk in the Cross-Section of Stock Returns

Yu Li

University of Houston

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Abstract

Jumps in aggregate volatility has been established as an important factor affecting the volatility dynamic, the market index price, and the index option price. However, whether it affects the price of other assets is still an open question. This paper provides supportive evidence in the individual equity market. We use a VIX option portfolio to measure the volatility jump risk and test whether it is priced in the cross-section of stock returns. We find a significant negative risk premium associated with the volatility jump risk and it is robust after controlling for a bunch of systematic risk factors.

1 Introduction

While many studies have showed that jumps in aggregate volatility is an important factor affecting the equilibrium asset price (Drechsler and Yaron (2011)), the volatility dynamic (Corsi, Pirino, and Reno (2010), Jacod, Todorov et al. (2010), Todorov and Tauchen (2011)), and the index option pricing (Eraker, Johannes, and Polson (2003), Eraker (2004), Broadie, Chernov, and Johannes (2007)), its impact on the cross-section of stock returns is less explored. This paper tries to fill the gap by constructing an empirical measure about the volatility jump and test how the volatility jump affects the cross-section of stock returns.

The cross-section of stock returns is important for at least two reasons. First, it reveals the risk preference of market participants. Given the ample evidence of volatility jump on the aggregate market level, it would be interesting to test its implication on the cross-section of stock returns. Second, several recent studies have tested the role of price jumps on the cross-section of stock returns. (see, for example, Babaoglu (2015), Bollerslev, Li, and Todorov (2016), and Bollerslev, Li, and Zhao (2016)). Especially, Cremers, Halling, and Weinbaum (2015) compare the impact of the aggregate price jump risk and the aggregate volatility risk on the cross-section of stock returns. We would like to see whether the aggregate volatility jump risk would affect their conclusion.

However, estimating the volatility jump risk is not easy. Previous papers usually employ a fully specified model to filter out the volatility jumps. Thus the estimation results depend on the model specification. In contrast, this paper uses a non-parametric method to estimate the volatility jump risk. Our measure relies on few model assumptions and reflects the market expectation about the future volatility jump risk.

Specifically, we use the return of a Delta-neutral, Vega-neutral, and Gamma-positive VIX option portfolio to track the daily volatility jump risk. We treat VIX as a proxy for the future expected market volatility. Although this proxy has a disadvantage because of the embedded risk premium, it benefits us in the sense that we can observe market prices of various traded derivatives on VIX. Moreover, VIX options are especially informative about the higher moments so we use them to construct the volatility jump measure.

The volatility jump portfolio is a Delta-neutral, Vega-neutral, and Gamma-positive VIX option strategy. We rely on the key insight proposed by Coval and Shumway (2001) and Cremers, Halling, and Weinbaum (2015), which is different option Greeks reflect different risks. In our case, Delta of VIX option measures the sensitivity of option price to the VIX levels, thus it reflects the volatility risk. Vega measures the sensitivity of option price to the volatility of VIX, thus it reflects the volatility of volatility risk. Gamma is the second order derivative of VIX option price to the VIX level thus it captures the effect of large VIX movements, i.e. the volatility jump risk. Because our portfolio is Delta-neutral and Vega-neutral, so its return is immune to small changes of the volatility and the volatility of volatility. The positive Gamma creates the exposure to large volatility movements. Thus the price of this VIX option portfolio is mainly driven by the market expectation about future large movements of the volatility. If the market expects more significant volatility jumps in the future, the price would be high and otherwise it would be low.

We use this strategy to construct a daily volatility jump risk measure and test whether it affects the cross-section of stock returns. We conduct both the sort exercise and the Fama-MacBeth regression. Both methods show that the volatility jump risk is negatively priced in the cross-section of stock returns. The return difference between the portfolio that has lowest sensitivity to the volatility jump and the portfolio that has highest sensitivity is about -7.9% per year. Fama-MacBeth regression estimates the risk premium is about -6.5% per year. Furthermore, our results are robust after controlling for the volatility risk, the volatility risk, the price jump risk, the idiosyncratic volatility, the idiosyncratic skewness, the realized volatility, the co-skewness, the co-kurtosis, the upside beta, as well as the downside beta. Our results are also robust for different sample periods as well as different stock portfolios. Thus we provide supportive evidence that the volatility jump risk is indeed priced in the cross-section of stock returns.

Our paper is related with several strands of literature. First, our paper is related with the large literature which examines what are the systematic risk driving the cross-section of stock returns. (see, for example, Fama and French (1993), Carhart (1997), Pástor and Stambaugh (2003), Ang, Chen, and Xing (2006), Ang et al. (2006), Chang, Christoffersen, and Jacobs (2013), and Cremers, Halling, and Weinbaum (2015)) We contribute by examining whether the volatility jump risk is another systematic risk factor. Our paper also relates with the recent literature which focuses on the higher moments of the volatility (Lin and Chang (2009), Huang and Shaliastovich (2014), Agarwal, Arisoy, and Naik (2015), Song (2012), Mencía and Sentana (2013), Lin (2013), Bakshi, Madan, and Panayotov (2015), Amengual and Xiu (2016), Park (2016), Song and Xiu (2016)). We contribute by examining the implication of volatility jump risk in the cross-section of stock return. Finally, our paper is related with the paper which uses non-parametric method to estimate the jumps in the volatility (Andersen, Bollerslev, and Diebold (2007), Jacod, Todorov et al. (2010), Corsi, Pirino, and Reno (2010), Todorov and Tauchen (2011), Todorov, Tauchen, and Grynkiv (2014), and Bandi and Reno (2016)). We contribute by proposing a volatility jump measure using the VIX options.

This paper proceeds as follows. Section 2 describes the data and section 3 reports the empirical methodology. Section 4 discusses the main results. Section 5 presents the robust tests and section 6 concludes.

2 Data Description

Our main data, VIX futures options, is from OptionMetrics. For each day, we collect all the VIX options maturing in the next calendar month and the month after that. We drop the observation if it meets any one of the following criteria, (1) the bid price, ask price, implied volatility, or any Greeks is missing, (2) the trade volume or open interest is zero, (3) the bid price is greater than the offer price. In addition, we drop the data in the early sample period because VIX options are not very liquid in the first several months.[1] Our final sample ranges from April 2nd, 2007 to August 31st, 2015, yielding to 2037 days in total.

As for other data, VIX futures are from the official website of CBOE. We collect the daily close prices of VIX futures of all maturities and match them with the corresponding options based on the option expiration date. We exclude the observation if the close price of VIX futures is either zero or missing. Individual equity data is from CRSP. We clean it by dropping all missing values and deleting all non-financial firms and non-common shares. Daily and monthly Fama-French factors are from Prof. French's website.

3 Empirical Methodology

In this section, we will first introduce the volatility jump risk measure and then the empirical methodology.

3.1 Construct the Volatility Jump Risk Measure

Our volatility jump risk measure is the return of a Delta-neutral, Vega-neutral, and Gamma-positive VIX option portfolio, which is constructed as follows. On each day, we first rank all VIX calls and puts based on their moneyness, which is defined as the strike to the underlying price ratio. Then we choose the closet ATM call and put pair to formulate a ATM straddle. The weights of call and put are calculated as follow.

$$\begin{aligned} \theta_{Call,t} + \theta_{Put,t} &= 1 \\ \theta_{Call,t}\Delta_{Call,t} + \theta_{Put,t}\Delta_{Put,t} &= 0 \end{aligned} \tag{1}$$

where $\Delta_{Call,t}$ is the market Delta of the call option at time t and $\Delta_{put,t}$ is the market Delta of the put option at time t. We conduct the above procedure for VIX options maturing in 1

[1] This is consistent with the existing literature such as Jackwerth and Vilkov (2015), Park (2015), and Song and Xiu (2016).

month and 2 months respectively, yielding to a 1 month straddle and a 2 month straddle every day. The straddle returns are calculated as follows.

$$ret^i_{Straddle,t} = \theta^i_{Call,t} ret^i_{Call,t} + \theta^i_{Put,t} ret^i_{Put,t} \quad i = 1,2 \tag{2}$$

where $ret^i_{Call,t}$ is the return of the Call option maturing in month i and $ret^i_{Put,t}$ is the return of the put option maturing in month i. Next we short 1 contract of 2 month straddle and long δ_t contract of 1 month straddle. δ_t is solved by the following equation to make the portfolio Vega-neutral.

$$\delta_t \nu^1_t - \nu^2_t = 0 \tag{3}$$

ν^1_t denotes the Vega of the 1 month straddle at time t and ν^2_t denotes the Vega of the 2 month straddle at time t. Because short term options have larger Gamma than long term options, the Gamma of this position is positive. On each day, we construct the position and hold it for one day. On the next day, we sell the outstanding position formed on previous day and reconstruct a new position using the same methodology. Thus, we can get a daily measure of the volatility jump risk using the daily return of this portfolio, which can be calculated as follows.

$$ret_{\text{Vol Jump},t} = \delta_t ret^1_{Straddle,t} - ret^2_{Straddle,t} \tag{4}$$

$ret_{\text{Vol Jump},t}$ would be high if market expects a high probability of the volatility jump and would be low otherwise.

3.2 Test whether the Volatility Jump Risk is Priced

To prove the volatility jump risk is a priced systematic risk factor, we need to show a contemporaneous relationship between the volatility jump beta and the portfolio returns. We follow the empirical procedure in Ang et al. (2006) and Cremers, Halling, and Weinbaum (2015) to detect the empirical relationship. The procedure is as follows.

For each individual stock i, on the end of each month, we regress its daily excess returns on the daily excess returns of the market portfolio and the daily returns of the volatility jump portfolio over the past 12 months.

$$R_t^i = \alpha^i + \beta_{\text{MKT}}^i \text{MKT}_t + \beta_{\text{Vol Jump}}^i \text{Vol Jump}_t + \epsilon^i \tag{5}$$

where R_t^i is the excess return of stock i on time t, MKT_t is the excess return of the market portfolio on time t, and Vol Jump_t is the return of the volatility jump portfolio at time t. We don't control the SMB and HML factor in equation 5 to be consistent with Ang et al. (2006), but our main results are robust for adding those two factors.

Then we sort the stocks into 5 portfolios based on the estimated $\beta_{\text{Vol Jump}}^i$ and calculate the value-weighted and equal-weighted holding-period returns of each portfolio over the same period, i.e. the past 12 months. Then we move to the next month and repeat the exercise. As a result, we get a time-series of monthly returns for every portfolio. We calculate Fama-French 3 factor α for each portfolio as follows.

$$R_t^j = \alpha^j + \beta_{\text{MKT}}^j \text{MKT}_t + \beta_{\text{SMB}}^j \text{SMB}_t + \beta_{\text{HML}}^j \text{HML}_t + \epsilon_t, \quad j = 1, 2, ..., 5 \tag{6}$$

where R_t^j is the holding-period return calculated in month t, MKT_t is the holding-period return of the market portfolio in month t, SMB_t is the holding-period return of the SMB portfolio in month t, and HML_t is the holding-period return of the HML portfolio in month t.

We also run the Fama-Macbeth regression to estimate the risk premium. At each month, we regress the excess return of each individual stock on the estimated β_{MKT}^i and $\beta_{\text{Vol Jump}}^i$ over the past 12 months as follows.

$$R_t^i = \gamma_0 + \gamma_{\text{Vol Jump},t} \hat{\beta}_{\text{Vol Jump},t}^i + \gamma_{\text{MKT},t} \hat{\beta}_{\text{MKT},t}^i + \epsilon^i \tag{7}$$

$\gamma_{\text{Vol Jump},t}$ are averaged across time to get the final estimate. So does the t-stats. All the standard errors are adjusted using Newey and West (1987) method with 12 lags.

4 Empirical Results

This section discusses our main results. We first check whether the volatility jump risk measure that extracted from VIX options is consistent with the realized jump in VIX, then we test whether the volatility jump risk is priced in the cross-section of stork returns by using both the sorting exercise and cross-sectional regression exercise.

4.1 Volatility Jump Measures

To test whether the portfolio return tracks the large movement of volatility, we compare it with the realized jumps of the volatility. We expect to see the portfolio return spikes whenever a physical volatility jump occurs. Figure 1 plots the daily return of the volatility jump portfolio (the solid line) and the days when jumps of VIX occurred (the vertical dashed line). The realized jumps of VIX are identified by the Lee and Mykland (2008) non-parametric method. The method procedure is given in the 6. In general, we find the return peaks when VIX jumps occur, suggesting the volatility jump portfolio the volatility jump risk.

Table 1 reports the statistical property of the volatility jump measure. Panel A reports the summary statistics and Panel B reports the correlation coefficients of volatility jump with other systematic factors.

The third column in Panel A shows the average return of the volatility jump portfolio is negative, about -0.02% per year or -5.04% per year, suggesting a negative risk premium for the volatility jump return. The negative return is consistent with the fact that the VIX options are used as a hedge tool against the market downside drops, so investors are willing to pay for holding the volatility jump portfolio. The fourth to sixth columns reports the standard deviation, the daily minimum return and the maximum return. Large magnitudes of those numbers suggest the volatility jump measure is time-varying and quite volatile. The last two columns presents the skewness and kurtosis. Both number suggest that the volatility jump measure is non-normal and follows a highly leptokurtic distribution.

Panel B shows the correlation coefficient between the volatility jump measure and other related systematic risk factors. We find the coefficients are moderate except for the volatility of volatility and the aggregate jump of S&P 500. This suggests that the volatility jump is closely correlated with the volatility of volatility and the price jump.

4.2 Portfolio Sorting Results

Table 2 reports average returns of the equal-weighted portfolios sorted by the $\beta_{VolJump}$. It reports the raw return as well as the return in the CAPM model, in the Fama-French 3-factor model, as well as in the Cahart 4-factor model. Given the negative risk premium of volatility jump which is shown in Table 1, we should observe a decreasing relationship between the $\beta_{VolJump}$ and the portfolio returns, i.e. the higher the $\beta_{VolJump}$, the lower the portfolio return. More importantly, the difference between the return of the portfolio that has the highest $\beta_{VolJump}$ with the portfolio that has the lowest $\beta_{VolJump}$ should be negative and significant. And this difference should not be explained by other existing risk factors.

This is exactly what we find in Table 2. First we find that on average, there is a decreasing pattern between the portfolio return and the Table 2. The portfolio with a higher sensitivity to the volatility jump risk earns a lower return, consistent with the hedging story. Moreover, we find the difference between the portfolio 5 and 1 is about -7.9% per year and significant on the 1% percent level. Furthermore, the negative alpha persists across in the CAPM model, the FF3 model, as well as the Carhart 4 model. Overall, we find our results provide strong evidence showing that the volatility jump risk is negatively priced in the cross-section of stock returns. The return of value-weighted portfolio are in the Table A.1.

4.3 Controlling for Other Related Risks

In this section, we test our previous results while controlling for the volatility risk, the volatility of volatility risk (vol of vol) and the price jump risk. The volatility risk is measured as the change of daily VIX, following Ang et al. (2006). The volatility of volatility risk measure is the return of a Delta-neutral, Gamma-neutral, but Vega-positive VIX option portfolio. The price jump risk measure is the return of a Delta-neutral, Vega-neutral, but Gamma-positive S&P 500 option portfolio. Both portfolios are constructed following Cremers, Halling, and Weinbaum (2015).

Our first exercise is to control the related risks when we calculate the $\beta_{VolJump}$. Specifically, we re-run equation 5 with one related risk measure each time. Then we test the relationship between the $\beta_{VolJump}$ and the portfolio return. Table 3 reports the equal-weighted portfolio results. For each control variable, it reports the raw portfolio return as well the one in the Carhart 4 factor model. We find that for all three control variables, the decreasing pattern remains. In addition, the return difference between two extreme portfolio is still negative and significant. Thus Table 3 shows that the volatility jump risk is a different systematic risk factor than the volatility risk, the volatility of volatility risk, and the price jump risk. The value-weighted results are similar and reported in Table A.2.

4.4 Double Sorts with Other Related Risks

Our next exercise is the double sort exercise. Particularly, we double sort the portfolio with respect to $\beta_{VolJump}$ and $\beta_{\Delta VIX}$ and $\beta_{VolJump}$ and $\beta_{PriceJump}$. Table 4 and 5 report the equal-weighted results and Table A.3 and A.4 reports the value-weighted results.

Table 4 shows that the volatility jump risk and the volatility risk are different. For each $\beta_{\Delta VIX}$ quintile, the decreasing pattern remains for the $\beta_{VolJump}$ and the return difference is negative and significant. Thus this shows that the volatility risk cannot explain the volatility jump risk. The volatility jump risk doesn't fully explain the volatility risk neither.

We find the volatility risk is also priced for each volatility jump risk quintile. This shows that the volatility risk contains another component, which is consistent with the fact that the volatility of volatility risk is also priced.

Table 5 shows that the volatility jump risk and the price jump risk are somewhat correlated. For example, the Carhart 4 alpha of $\beta_{VolJump}$ portfolio are only significant in the first two quintiles of $\beta_{PriceJump}$. This could be due to the fact that there is a strong co-jump structure of the S&P 500 and the VIX.

4.5 Fama-Macbeth Regression

In this section, we estimate the risk premium associated with the volatility jump using the Fama-Macbeth regression. Table 6 reports the results in the CAPM model as well as the Carhart 4 factor model. We find that the coefficient of volatility jump is significantly negative. The magnitude is about -0.5% per month, or -6% per year. The coefficient cannot be explained by other market variables. Table 7 shows that the coefficient controlling for a bunch of stock characteristics. We find the stock characteristics affect the magnitude of estimated coefficients, they cannot explain the significance level. So the volatility jump risk is both different from the market factors and the firm characteristics.

5 Robust Test

This section investigates whether different regression specification alter our conclusion. We re-examine our results using different estimation periods, in different samples, and with different portfolios.

5.1 Different Estimation Periods

First we alter the estimation periods for getting the $\beta_{VolJump}$. We change the estimation period to 3 months, 6 months, as well as 24 months. Table 8 shows both the equal-weighted and value-weighted results. We find the results hold for all three specifications.

5.2 Different Sample Periods

We also find that our results hold for different sample periods. Table 8 reports the equal-weighted and value-weighted portfolio returns in 2007 to 2011 and 2012 to 2015. The same pattern shows in both periods. Particularly, the return difference is larger and more significant in the first sample period. This is consistent with the fact that the effect of volatility jump risk is stronger when the market is more volatile.

5.3 Different Portfolios

Finally, we test whether the volatility jump risk can explain the other portfolio returns. We repeat our exercise with the Fama-French 25 portfolios sorted on size and book-to-market as well as the 49 industry portfolio. Table 10 shows the average return as well as the Carhart 4 alpha. We find for both portfolios, the alphas are significant and robust for the other market risk factors.

6 Concluding Remarks

In summary, this paper studies the impact of market volatility jump risk on the cross-section of stock returns. We measure the volatility jump risk using the VIX options and find it's priced in the individual equity market. We show that the volatility jump risk carries a negative risk premium. The risk premium is robust for different empirical specifications, different sample periods, and different stock portfolios. Our results imply that the volatility jump risk is another important risk factor and it's independent of the volatility risk, the volatility of volatility risk, and the price jump risk.

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Figure 1
Daily Returns of the Volatility Jump Portfolio

This figure plots the daily returns of the volatility jump portfolio. The volatility jump portfolio is a Delta-neutral, Vega-neutral, and Gamma positive VIX option portfolio, which is consisted with a ATM VIX straddle maturing in 1 month and a ATM VIX straddle maturing in 2 months. The return of the volatility jump portfolio positively relates with the jump magnitude of VIX. Vertical dashed lines represents the largest 100 jumps in VIX, which are estimated using the 5 minutes high frequency data of VIX by Lee and Mykland (2008) method.

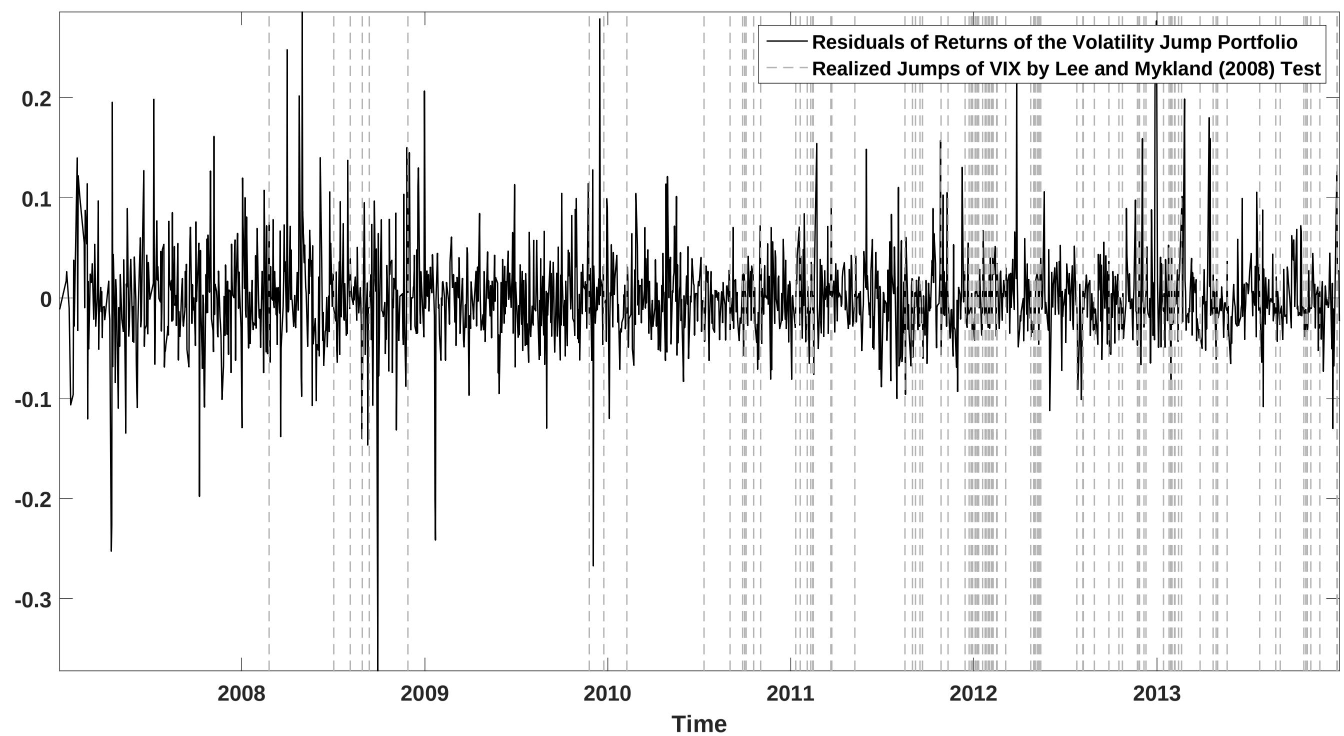

Table 1
Summary Statistics of Daily Returns of the Volatility Jump Portfolio

This table reports the summary statistics of daily returns of the volatility jump portfolio (Vol Jump). Panel A reports the number of observations, the daily average return, the daily median return, the standard deviation, the minimum, the maximum, the skewness, the kurtosis, and the autocorrelation coefficient. Panel B reports the Pearson correlation coefficients of Vol Jump with the level of VIX, the change of VIX (ΔVIX), the return of a VIX portfolio tracking the change of volatility of volatility (Vol of Vol), the return of a SPX portfolio tracking the change of jumps in S&P 500 (Price Jump), the market excess return (MKT), the SMB factor (SMB), the HML factor (HML), and the momentum factor (UMD). The sample period is from April, 2007 to August 2015.

Panel A: Summary Statistics

	N	Mean	Median	Std Deviation	Min	Max	Skewness	Kurtosis	AR(1)
Vol Jump	2077	-0.02%	-0.56%	4.04%	-19.77%	45.07%	2.18	14.32	-0.04

Panel B: Pairwise Correlation Coefficients

	Vol Jump	VIX	ΔVIX	Vol of Vol	Price Jump	MKT	SMB	HML	UMD
Vol Jump	1.00								
VIX	0.04	1.00							
ΔVIX	0.29	0.10	1.00						
Vol of Vol	−0.68	−0.01	−0.13	1.00					
Price Jump	0.48	0.09	0.40	−0.28	1.00				
MKT	−0.19	−0.13	−0.84	0.10	−0.25	1.00			
SMB	0.01	−0.02	−0.07	0.04	−0.01	0.17	1.00		
HML	−0.04	−0.08	−0.29	0.03	−0.09	0.43	−0.02	1.00	
UMD	−0.05	−0.01	0.23	0.04	−0.01	−0.41	−0.01	−0.59	1.00

Table 2
Equal-weighted Returns of Sorted Portfolios

This table reports the average return, CAPM alpha, Fama-French 3 factor alpha, and Carhart4 factor alpha of the equal-weighted portfolio sorted on $\beta_{VolJump}$. On each month, we regress the excess returns of each individual stock over the next 12 months on the returns of the volatility jump portfolio, controlling for the market excess returns. Then we sort the stocks in to 5 portfolio based on the $\beta_{VolJump}$ loading and calculate the equal-weighted average return in the 12 months. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

EW Portfolio	Average Return	CAPM Alpha	FF 3 Alpha	Carhart4 Alpha
1 Low $\beta_{\text{Vol Jump}}$	21.85	11.65	6.04	9.11
	(3.38)	(1.73)	(3.12)	(7.65)
2	16.89	8.96	5.44	6.95
	(3.27)	(2.39)	(4.70)	(13.87)
3	15.66	8.18	4.58	6.21
	(3.13)	(2.09)	(3.59)	(11.17)
4	16.49	8.49	3.91	6.05
	(3.09)	(1.63)	(2.93)	(7.76)
5 High $\beta_{\text{Vol Jump}}$	13.95	4.21	-1.70	1.28
	(2.05)	(0.56)	(-0.79)	(1.53)
5-1	-7.90***	-7.44***	-7.74***	-7.83***
	(-4.94)	(-5.98)	(-11.25)	(-13.81)

Table 3
Equal-weighted Returns of Sorted Portfolios Controlling for Other Risk Factors

This table reports the average return and Carhart4 factor alpha of the equal-weighted portfolio sorted on $\beta_{VolJump}$, while controlling for other risk factors. The empirical procedure is the same as in Table 2, but we control other risk factors in the time series estimation. Specifically, we control the change of VIX (ΔVIX), the return of a VIX option portfolio tracking the volatility of volatility risk (Vol of Vol), and the return of a SPX option portfolio tracking the aggregate price jump risk (Price Jump). Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

	X = ΔVIX		X = Vol of Vol		X = Price Jump	
EW Portfolio	Average Return	Carhart4 Alpha	Average Return	Carhart4 Alpha	Average Return	Carhart4 Alpha
1 Low $\beta_{\text{Vol Jump}}$	20.13	7.75	19.23	6.52	19.93	6.64
	(3.19)	(5.86)	(2.86)	(9.44)	(2.99)	(8.42)
2	17.49	7.52	17.52	8.14	16.50	6.47
	(3.42)	(13.46)	(3.53)	(16.13)	(3.15)	(13.43)
3	15.74	6.19	16.75	7.43	16.83	7.25
	(3.13)	(11.19)	(3.46)	(13.48)	(3.51)	(13.39)
4	16.17	5.74	16.08	5.52	15.77	5.26
	(3.00)	(11.61)	(3.03)	(6.48)	(2.95)	(7.42)
5 High $\beta_{\text{Vol Jump}}$	15.06	2.33	14.81	1.60	15.69	3.67
	(2.16)	(2.84)	(2.23)	(1.44)	(2.37)	(2.58)
5 -1	-5.07***	-5.42***	-4.42***	-4.92***	-4.24**	-2.96***
	(-2.90)	(-5.83)	(-3.75)	(-5.02)	(-2.52)	(-2.85)

Table 4
Equal-weighted Returns of Double Sorted Portfolios on $\beta_{VolJump}$ and $\beta_{\Delta VIX}$

This table reports the Carhart4 factor alpha of the equal-weighted portfolio double sorted on $\beta_{VolJump}$ and $\beta_{\Delta VIX}$. On each month, we regress the excess returns of each individual stock over the next 12 months on the returns of the volatility jump portfolio and the change of VIX, controlling for the market excess returns. Then we double sort the stocks in to 5 portfolio based on the $\beta_{VolJump}$ loading and on the $\beta_{\Delta VIX}$ loading. We calculate the equal-weighted average return in the 12 months for each of the 25 portfolios and the Carhart4 factor alpha. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

Carhart4 Alpha	1 Low $\beta_{\Delta\text{VIX}}$	2	3	4	5 High $\beta_{\Delta\text{VIX}}$	5-1
1 Low $\beta_{\text{Vol Jump}}$	10.62	10.57	8.72	7.05	2.58	-8.04***
	(8.12)	(10.25)	(9.46)	(5.84)	(1.10)	(-3.56)
2	10.10	9.97	7.37	6.87	4.90	-5.20***
	(8.40)	(12.50)	(8.61)	(8.51)	(3.74)	(-5.42)
3	9.01	9.10	7.56	5.74	1.87	-7.14***
	(8.67)	(10.72)	(8.79)	(10.54)	(3.30)	(-7.85)
4	8.49	7.39	6.78	5.37	0.30	-8.19***
	(10.61)	(8.13)	(9.39)	(9.63)	(0.38)	(-7.35)
5 High $\beta_{\text{Vol Jump}}$	2.93	5.94	2.75	0.62	-1.64	-4.57**
	(1.64)	(4.45)	(2.97)	(0.70)	(-1.21)	(-2.34)
5 - 1	-7.70***	-4.63***	-5.97***	-6.43***	-4.22**	
	(-6.15)	(-2.91)	(-4.96)	(-5.04)	(-2.59)	

Table 5
Equal-weighted Returns of Double Sorted Portfolios on $\beta_{VolJump}$ and $\beta_{PriceJump}$

This table reports the Carhart4 factor alpha of the equal-weighted portfolio double sorted on $\beta_{VolJump}$ and $\beta_{PriceJump}$. On each month, we regress excess returns of each individual stock over the next 12 months on returns of the volatility jump portfolio and returns of the price jump portfolio, controlling for the market excess returns. Then we double sort the stocks in to 5 portfolio based on the $\beta_{VolJump}$ loading and on the $\beta_{PriceJump}$ loading. We calculate the equal-weighted average return in the 12 months for each of the 25 portfolios and the Carhart4 factor alpha. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

Carhart4 Alpha	1 Low $\beta_{\text{Price Jump}}$	2	3	4	5 High $\beta_{\text{Price Jump}}$	5-1
1 Low $\beta_{\text{Vol Jump}}$	12.23	11.05	6.20	4.04	0.59	-11.64***
	(7.65)	(10.73)	(9.74)	(4.00)	(0.28)	(-4.55)
2	10.27	8.73	7.64	6.95	2.06	-8.22***
	(8.19)	(12.39)	(19.09)	(11.17)	(2.63)	(-6.43)
3	10.26	9.23	7.85	7.18	2.41	-7.85***
	(6.34)	(10.65)	(11.86)	(21.16)	(4.20)	(-4.67)
4	7.26	8.01	7.30	4.71	1.15	-6.11***
	(4.02)	(8.08)	(10.02)	(8.14)	(1.37)	(-3.12)
5 High $\beta_{\text{Vol Jump}}$	2.31	5.03	4.88	2.65	-2.93	-5.24
	(1.18)	(2.86)	(3.24)	(2.60)	(-1.11)	(-1.57)
5 - 1	-9.92***	-6.02***	-1.32	-1.38	-3.52	
	(-4.43)	(-4.02)	(-1.00)	(-0.94)	(-1.51)	

Table 6
Fama-MacBeth Regression Controlling for ΔVIX, Vol of Vol, and the Price Jump

This table reports the Fama-Macbeth regression results. On each month, we regress excess returns of each individual stock over the next 12 months on returns of the volatility jump portfolio, while controlling for different factors. Then we conduct Fama-Macbeth regression on each month. Standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

	CAPM Model				Carhart4 Factor Model			
Vol Jump	-0.55^{***}	-0.48^{***}	-0.33^{**}	-0.47^{***}	-0.50^{***}	-0.49^{***}	-0.34^{**}	-0.39^{**}
	(-5.57)	(-4.25)	(-2.15)	(-2.88)	(-4.83)	(-4.19)	(-2.30)	(-2.58)
MKT	0.01	0.01	0.01	0.02	0.01	0.01	0.01	0.02
	(1.11)	(1.12)	(0.97)	(1.37)	(1.41)	(1.30)	(1.41)	(1.58)
ΔVIX		-2.14^{**}				-2.40^{**}		
		(-1.76)				(-2.28)		
Vol of Vol			0.00				0.00	
			(1.15)				(1.15)	
Price Jump				-0.15^{***}				-0.11^{***}
				(-3.39)				(-2.88)
SMB					0.00	0.01	0.00	0.00
					(0.98)	(1.08)	(1.07)	(0.98)
HML					0.00	(0.00)	(0.01)	(0.00)
					(-0.03)	(-0.20)	(-0.72)	(-0.54)
UMD					0.03^{*}	0.03^{*}	0.03^{*}	0.03^{*}
					(1.93)	(1.95)	(1.82)	(1.94)
Constant	0.05^{*}	0.05^{*}	0.05^{**}	0.05^{*}	0.05^{*}	0.05^{*}	0.05^{*}	0.05^{*}
	(1.92)	(1.92)	(2.01)	(1.75)	(1.85)	(1.93)	(1.91)	(1.74)

Table 7
Fama MacBeth Regression with Other Control Variables

This table reports the Fama-Macbeth regression results with other control variables. We control the idiosyncratic volatility, idiosyncratic skewness, realized volatility, coskewness, cokurtosis, upside beta, and downside beta. Standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

	CAPM Model	Carhart4 Factor Model
	$\beta_{\text{Vol Jump}}$	$\beta_{\text{Vol Jump}}$
Idio. Vol	-0.18***	-0.11**
	(-3.75)	(-2.16)
Idio. Skew	-0.16***	-0.10**
	(-4.57)	(-2.17)
Realized Vol	-0.18***	-0.11**
	(-3.76)	(-2.17)
CoSkew	-0.23***	-0.17***
	(-4.53)	(-3.16)
CoKurt	-0.20***	-0.14**
	-4.24	-2.43
Upside Beta	-0.21***	-0.14**
	(-4.59)	(-2.75)
Downside Beta	-0.26***	-0.21***
	(-7.82)	(-4.31)

Table 8
Robust Results with Different Estimation Length

This table reports the Carhart4 factor alpha of both equal-weighted and value-weighted portfolio with different estimation length. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

	3 Months		6 Months		24 Months	
	EW Carhart4 Alpha	VW Carhart4 Alpha	EW Carhart4 Alpha	VW Carhart4 Alpha	EW Carhart4 Alpha	VW Carhart4 Alpha
1 Low $\beta_{\text{Vol Jump}}$	5.60	0.21	6.15	2.26	6.55	13.06
	(1.64)	(0.06)	(2.42)	(0.99)	(4.79)	(13.16)
2	3.79	3.49	7.13	5.97	10.30	8.23
	(1.97)	(2.06)	(5.51)	(6.66)	(20.38)	(33.23)
3	4.67	5.67	5.45	4.89	8.10	8.07
	(3.36)	(3.70)	(4.42)	(3.68)	(20.36)	(52.38)
4	1.57	2.40	2.75	2.18	5.69	2.97
	(1.01)	(1.22)	(1.79)	(1.65)	(14.62)	(10.02)
5 High $\beta_{\text{Vol Jump}}$	0.07	-1.15	1.25	-3.02	-1.08	-3.28
	(0.02)	(-0.38)	(0.64)	(-1.68)	(-1.12)	(-3.87)
5 - 1	-5.54**	-1.35	-4.90***	-5.27*	-7.63***	-16.34***
	(-2.59)	(-0.26)	(-3.349)	(-1.85)	(-11.89)	(-42.11)

Table 9
Robust Results with Sub-samples

This table reports the estimated Carhart4 factor alpha in subsamples. The first sample is from April 2007 to December 2011. The second is from January 2012 to December 2015. For each period, we report the Carhart4 factor alpha of both the equal-weighted portfolio and the value-weighted portfolio. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

	2007 - 2011			2012 - 2015		
EW Portfolio	Average Return	CAPM Alpha	FF3 Alpha	Average Return	CAPM Alpha	FF3 Alpha
1	8.61	8.38	4.44	9.35	3.96	2.31
Low $\beta_{\text{Vol Jump}}$	(1.01)	(1.91)	(1.56)	(1.90)	(1.32)	(1.36)
2	6.55	6.27	3.46	8.05	3.63	2.66
	(1.02)	(2.31)	(2.06)	(2.20)	(2.01)	(2.83)
3	5.88	5.59	2.74	7.48	3.34	2.37
	(0.97)	(2.08)	(1.91)	(2.24)	(1.97)	(3.19)
4	5.14	4.87	1.37	6.77	2.32	1.26
	(0.77)	(1.57)	(0.88)	(1.86)	(1.22)	(1.64)
5	4.85	4.63	0.35	7.02	1.50	0.16
High $\beta_{\text{Vol Jump}}$	(0.56)	(1.03)	(0.13)	(1.40)	(0.51)	(0.10)
5 - 1	-3.76^{***}	-3.76^{***}	-4.10^{***}	-2.33^{***}	-2.45^{***}	-2.14^{**}
	(−9.40)	(−9.66)	(−8.65)	(−2.85)	(−2.82)	(−2.56)

Table 10
Robust Results with Fama-French 25 Portfolios and Industry 49 Portfolios

This table reports the average return and the Carhart 4 alpha of Fama-French 25 Size and Book-to-Market portfolios and the 49 industry portfolios. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

	25 FF Portfolios			49 Industry Portfolios		
EW Portfolio	Average Return	CAPM Alpha	FF3 Alpha	Average Return	CAPM Alpha	FF3 Alpha
1	6.30	1.96	1.90	6.63	2.62	2.26
Low $\beta_{\text{Vol Jump}}$	(1.85)	(1.98)	(3.08)	(2.07)	(2.76)	(2.28)
2	5.54	1.43	1.16	6.42	2.61	2.11
	(1.69)	(1.14)	(1.87)	(2.09)	(2.87)	(3.54)
3	5.41	1.34	0.97	5.34	1.34	0.97
	(1.71)	(1.19)	(2.22)	(1.66)	(1.26)	(1.43)
4	4.78	0.85	0.48	4.99	0.84	0.58
	(1.53)	(0.67)	(0.99)	(1.51)	(0.86)	(0.94)
5	3.74	−0.40	−0.80	3.29	−1.05	−1.35
High $\beta_{\text{Vol Jump}}$	(1.13)	(−0.36)	(−1.85)	(0.94)	(−0.86)	(−1.88)
5 - 1	-2.56^{***}	-2.37^{***}	-2.71^{***}	-3.35^{***}	-3.67^{***}	-3.61^{***}
	(−3.29)	(−3.16)	(−3.73)	(−3.23)	(−3.23)	(−3.46)

Appendix

A.1 Lee and Mykland (2008) Non-Parametric Method

Following Lee and Mykland (2008), we calculate the statistics $L(i)$ as follows.

$$L(i) = \frac{logVIX(t_i)/VIX(t_{i-1})}{\hat{\sigma}(t_i)} \tag{8}$$

where

$$\hat{\sigma}(t_i) = \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} |logVIX(t_j)/VIX(t_{j-1})||logVIX(t_{j-1})/VIX(t_{j-2})| \tag{9}$$

$VIX(t_i)$ is the closing price of VIX at time t_i and K is the length of the rolling window. Because we use daily observations, we let $K = 16$ as suggested by the original paper. The threshold for $\frac{|L(i)-C_n|}{S_n}$ is β, where

$$C_n = \frac{(2logn)^{0.5}}{c} - \frac{log\pi + log(logn)}{2c(2logn)^{0.5}} \tag{10}$$

and

$$S_n = \frac{1}{c(2logn)^{0.5}} \tag{11}$$

.

n is the number of observations, $\beta = -log(-log(1 - \text{Significance Level}))$.

Table A.1
Value-weighted Returns of Sorted Portfolios

This table reports the average return, CAPM alpha, Fama-French 3 factor alpha, and Carhart4 factor alpha of the value-weighted portfolio sorted on $\beta_{VolJump}$. On each month, we regress the excess returns of each individual stock over the next 12 months on the returns of the volatility jump portfolio, controlling for the market excess returns. Then we sort the stocks in to 5 portfolio based on the $\beta_{VolJump}$ loading and calculate the value-weighted average return in the 12 months. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

VW Portfolio	Average Return	CAPM Alpha	FF 3 Alpha	Carhart4 Alpha
1 Low $\beta_{\text{Vol Jump}}$	16.00	8.28	6.08	6.66
	(2.82)	(5.01)	(5.56)	(6.26)
2	12.92	6.76	6.21	6.48
	(2.55)	(12.41)	(10.87)	(11.00)
3	13.16	7.52	6.32	7.10
	(3.17)	(6.01)	(9.70)	(12.22)
4	11.75	4.54	1.96	3.45
	(2.56)	(1.37)	(1.71)	(2.78)
5 High $\beta_{\text{Vol Jump}}$	9.82	0.26	-5.55	-3.62
	(1.51)	(0.04)	(-2.84)	(-1.80)
5 - 1	-6.18	-8.02*	-11.63***	-10.27***
	(-1.58)	(-1.80)	(-5.49)	(-4.83)

Table A.2
Value-weighted Returns of Sorted Portfolios Controlling for Other Risk Factors

This table reports the average return and Carhart4 factor alpha of the value-weighted portfolio sorted on $\beta_{VolJump}$, while controlling for other risk factors. The empirical procedure and the control variables are the same as in Table 3. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

	X = ΔVIX		X = Vol of Vol		X = Price Jump	
VW Portfolio	Average Return	Carhart4 Alpha	Average Return	Carhart4 Alpha	Average Return	Carhart4 Alpha
1 Low $\beta_{\text{Vol Jump}}$	16.15	7.86	16.49	7.81	14.29	4.83
	(3.29)	(6.03)	(3.18)	(8.93)	(2.61)	(8.20)
2	12.62	5.64	12.53	6.52	12.73	5.97
	(2.41)	(7.78)	(2.48)	(9.64)	(2.43)	(8.31)
3	13.07	6.84	12.23	5.50	13.23	7.18
	(2.87)	(8.53)	(3.06)	(8.56)	(3.15)	(10.86)
4	12.43	4.97	12.87	4.41	13.29	5.39
	(2.79)	(6.98)	(2.83)	(3.60)	(3.06)	(4.83)
5 High $\beta_{\text{Vol Jump}}$	10.94	(1.65)	10.05	(3.50)	11.14	-1.24
	(1.69)	(-1.10)	(1.54)	(-1.42)	(1.90)	(-0.56)
5 - 1	-5.21	-9.51***	-6.45*	-11.31***	-3.15	-6.07***
	(-1.32)	(-8.19)	(-1.82)	(-5.82)	(-0.93)	(-3.19)

Table A.3
Value-weighted Returns of Double Sorted Portfolios on $\beta_{VolJump}$ and $\beta_{\Delta VIX}$

This table reports the Carhart4 factor alpha of the value-weighted portfolio double sorted on $\beta_{VolJump}$ and $\beta_{\Delta VIX}$. On each month, we regress the excess returns of each individual stock over the next 12 months on the returns of the volatility jump portfolio and the change of VIX, controlling for the market excess returns. Then we double sort the stocks in to 5 portfolio based on the $\beta_{VolJump}$ loading and on the $\beta_{\Delta VIX}$ loading. We calculate the value-weighted average return in the 12 months for each of the 25 portfolios and the Carhart4 factor alpha. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

Carhart4 Alpha	1 Low $\beta_{\Delta\text{VIX}}$	2	3	4	5 High $\beta_{\Delta\text{VIX}}$	5-1
1 Low $\beta_{\text{Vol Jump}}$	9.02	11.58	6.07	1.58	-0.71	-9.73**
	(3.38)	(9.60)	(4.23)	(0.96)	(-0.17)	(-2.39)
2	11.28	8.40	6.05	3.61	-3.89	-15.17***
	(8.71)	(10.04)	(5.79)	(3.00)	(-3.33)	(-7.98)
3	10.76	9.59	6.68	5.33	-0.66	-11.42***
	(7.18)	(9.11)	(7.80)	(6.35)	(-0.71)	(-4.92)
4	9.26	7.20	4.89	-0.73	-4.54	-13.80***
	(7.26)	(6.41)	(6.28)	(-0.45)	(-3.76)	(-7.08)
5 High $\beta_{\text{Vol Jump}}$	6.17	2.29	-2.01	-0.15	-8.53	-14.70***
	(2.45)	(1.26)	(-0.77)	(-0.10)	(-8.39)	(-5.26)
5 - 1	-2.85	-9.29***	-8.07***	-1.74	-7.82*	
	(-0.72)	(-5.96)	(-2.93)	(-0.98)	(-1.78)	

Table A.4
Value-weighted Returns of Double Sorted Portfolios on $\beta_{VolJump}$ and $\beta_{PriceJump}$

This table reports the Carhart4 factor alpha of the value-weighted portfolio double sorted on $\beta_{VolJump}$ and $\beta_{PriceJump}$. On each month, we regress excess returns of each individual stock over the next 12 months on returns of the volatility jump portfolio and returns of the price jump portfolio, controlling for the market excess returns. Then we double sort the stocks in to 5 portfolio based on the $\beta_{VolJump}$ loading and on the $\beta_{PriceJump}$ loading. We calculate the value-weighted average return in the 12 months for each of the 25 portfolios and the Carhart4 factor alpha. Portfolio 1 has the lowest $\beta_{VolJump}$ loadings and Portfolio 5 has the highest $\beta_{VolJump}$ loadings. Returns are annualized and standard errors are adjusted by Newey and West (1987) method with 12 lags. T-statistics are reported in the parenthesis. The sample period is from April, 2007 to August 2015.

Carhart4 Alpha	1 Low $\beta_{\text{Price Jump}}$	2	3	4	5 High $\beta_{\text{Price Jump}}$	5-1
1 Low $\beta_{\text{Vol Jump}}$	18.78	9.27	1.62	-0.47	-1.08	-19.85***
	(4.04)	(5.92)	(1.16)	(-0.38)	(-0.46)	(-4.61)
2	11.71	6.20	6.09	6.93	2.50	-9.21***
	(7.57)	(6.21)	(7.82)	(9.43)	(3.05)	(-5.53)
3	11.79	8.01	7.67	6.19	-0.36	-12.15***
	(8.58)	(7.96)	(11.13)	(8.68)	(-0.35)	(-6.98)
4	8.48	6.51	5.84	2.76	-1.34	-9.82***
	(3.91)	(5.58)	(7.81)	(1.99)	(-0.53)	(-2.86)
5 High $\beta_{\text{Vol Jump}}$	0.75	3.00	0.76	-3.66	-6.39	-7.13**
	(0.33)	(0.97)	(0.52)	(-1.58)	(-2.56)	(-2.51)
	-18.03***	-6.27*	-0.86	-3.19	-5.31***	
	(-3.44)	(-1.98)	(-0.42)	(-1.57)	(-2.78)	