# Jump Intensities, Jump Sizes, and the Relative Stock Price Level

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# Jump Intensities, Jump Sizes, and the Relative Stock Price Level

**Abstract**

Large stock price movements are modeled as jumps in the stochastic processes of stock prices. In the current literature, the jump intensity is typically specified in models as a function of the current diffusive volatility and past jump intensities, while the jump size is assumed to be independent of the jump intensity. We use a nonparametric jump detection test to identify jumps in several stock indexes and examine the determinants of the jump intensity and the jump size. We find little evidence that the jump intensity depends on the current diffusive volatility. Instead, the jump intensity and the jump size depend on the current stock price level relative to its historical average, beside past jump intensities. The results in this paper provide new perspectives for modeling jumps in the theory of options pricing and in the applications of risk management.

# 1. Introduction

Large stock price changes, especially large price declines, are important events for market participants. While large price changes are rare, they have significant impact on the welfare of investors. Predicting the timing and the size of large price movements has important implications to investment and risk management. There is a growing literature on the modeling of large price changes and much has been learned. Because large price changes are rare, their properties are more difficult to analyze. As a result, there is no consensus on how large price changes should be modeled. We address the issue in this paper.

Since the properties of large price changes are very different from the usual ones, large price movements are modeled separately from the usual price changes. In the continuous-time options pricing literature, large price changes are models as a jump process. It is in the options pricing literature that researchers came to realize the necessity of adding jumps to the stochastic processes of the underlying stock prices. Without jumps, the models of stock prices with diffusive stochastic volatility only have a difficult time to generate theoretical options prices that can be matched with observed market prices. In standard jump-diffusion models used by, for example, Bates (2000), Pan (2002), and Eraker (2004), the jump intensity is modeled as an affine function of the diffusive variance of stock returns and the jump size follows a distribution independent of other state variables. Andersen, Benzoni and Lund (2002) empirically investigate this type of models using equity index returns.

Another strand of the literature borrows from the success of the discrete-time GARCH literature in modeling the total volatility of asset returns. Like the total volatility, large price movements in stock indexes tend to occur in clusters. Aït-Sahalia, Cacho-Diaz and Laeven (2011) propose a continuous-time model of asset returns where jumps are self-excited. In their model, the jump intensity follows a Hawkes process in which past and contemporaneous jumps increase the current jump intensity. Yu (2004) estimates a jump-diffusion model in which the jump intensity is stochastic and follows an autoregressive process. Christoffersen, Jacobs and Ornthanalai (2011) propose a discrete-time model with a GARCH type of dynamics for the jump intensity.[1] In that model, the conditional jump intensity is a function of the jump intensity and the jump size in the previous period. Chan and Maheu (2002) and Maheu and McCurdy (2004) propose a discrete time model of asset returns with an autoregressive jump intensity. In summary, the above papers propose models where the current jump intensity is linked to the past jump activities.

In this paper, we use a nonparametric approach to detecting jumps and examine the relationship between the detected jumps and pre-determined variables such as the diffusive volatility, and past jump intensities. We also propose a new state variable, the stock price level relative to its historical average, to forecast jumps. Our basic findings can be summarized as follows. First, we find little evidence that the jump intensity is related to the diffusive volatility, as specified in the standard jump-diffusion models. Both the past jump intensity and the relative stock price level are useful in determining the jump intensity, and the relative stock price level is useful in determining the jump size. The jump size is not independent of the jump intensity. More specifically, we classify the jumps into positive jumps and negative jumps, and find that the relative stock price level is particularly useful for predicting negative jumps. We also classify jumps according to whether they follow other jumps or they are out of the blue. While both the past jump intensity and the relative price level are useful in predicting jumps, their roles are different for different types of jumps. The past jump intensity can predict follow-on jumps, but, by design, it is not useful in predicting out-of-the-blue jumps. Negative out-of-the-blue jumps can be predicted by the relative price level, while positive out-of-the-blue jumps are simply difficult to predict.

Our methodology has certain advantages over the ones in the existing literature. First, we do not rely on specific parametric models. Jumps filtered from parametric models

[1]The jump in discrete-time models refers to the price movements that are more left-skewed and/or more fat-tailed than the conditionally normal variates.

are sensitive to the models used, and parametric models are subject to the criticism of model mis-specification so that jumps identified from those models are not reliable. More importantly, we do not require assumptions on the jumps size distribution and its relationship with the jump intensity, whereas in the existing literature, the jump size is typically assumed to follow the normal distribution as in Andersen, Benzoni and Lund (2002), Bates (2000), Chan and Maheu (2002), Christoffersen, Jacobs and Ornthanalai (2011), Eraker (2004), Maheu and McCurdy (2004) and Pan (2002), or double exponential distribution as in Aït-Sahalia, Cacho-Diaz and Laeven (2011) and Kou (2002), with fixed parameters, and independent of the jump intensity.

Second, using the relative stock price level as an additional state variable contributes to the literature significantly. The past jump intensities have been found useful in predicting follow-on jumps, but they are not very useful in predicting the out-of-the-blue jumps, which are arguably more important for market participants to predict. The relative stock price level is particularly useful in this situation. It, therefore, complements the past jump intensities in predicting jumps. This finding is related to Chen, Hong and Stein (2001) who examine the predictive power of trading volume and past returns on the conditional skewness of return distributions. In their time-series analysis, they find some evidence that past returns negatively predict skewness for the aggregate market. In a cross-sectional study, Yu (2011) finds that stocks with higher past returns tend to crash more during the US equity market flash crash on May 6, 2010. Although the past return is quantitatively similar to the relative stock price level, our work is different from theirs in the sense that we examine the predictive power of the relative stock price level on quantities directly related to jumps, rather than skewness in general. While the predictive power of the relative stock price level for negative jumps can be easily interpreted in the parlance of bubbles and crashes, we focus on documenting the relationship in this paper and leave its interpretation to future work.

The rest of the paper is organized as follows. Section 2 discusses the nonparametric jump detection methods, provides descriptions of detected jumps in stock indexes, and defines the predictive variables. Section 3 presents the basic results regarding the predictive power of the diffusive volatility, past jump intensities, and the relative stock price level. Section 4 shows the complementary features of the past jump intensities and the relative stock price level in predicting the follow-on jumps and out-of-the-blue jumps. Section 5 reexamines the inability of the diffusive volatility in predicting jumps and reconciles the finding with those in the literature. Section 6 concludes the paper.

# 2. Jump Detection Tests and Predictive Variables

## 2.1. Jump Detection

We focus on the Poisson type of jumps, which are infrequent and in large magnitude, rather than the infinite activity jumps that are used to model high frequency data. We use daily data of the S&P 500 index (SPX) from 1950 to 2011 and the NASDAQ composite index (NDX) from 1971 to 2011 to conduct the empirical analysis. The data are downloaded from Yahoo! Finance.

There are several nonparametric jump detection tests in the literature. Barndorff-Nielsen and Shephard (2004, 2006) propose a bipower variation measure to separate the diffusive variance from the jump variance. Jiang and Oomen (2008) propose a jump detection test based on variance swap prices. Lee and Mykland (2008) develop a rolling jump detection test based on large increments relative to the instantaneous volatility. The test proposed by Aït-Sahalia and Jacod (2009) is based on power variations sampled at different frequencies. Except for the Lee and Mykland (2008) test, other tests are applied to a block of return observations, so the number (except zero) and exact timing of the jumps in the block are not known. The Lee and Mykland (2008) test is applied to individual return observations so that the exact timing and sign of jumps can be identified. Because of this property, we apply the Lee and Mykland (2008) test for the jump detection. The test statistic is based on

$$L_t = \frac{|r_t|}{\sqrt{D_{t-1}}}, \tag{1}$$

where $r_t = S_t - S_{t-1}$ is the daily log return at day $t$, $S_t$ is the logarithm of the index level at day $t$, and $D_{t-1}$ is the estimated diffusive variance for day $t$ by the bipower variation based on past returns up to day $t-1$. The null hypothesis of no jump at day $t$ is rejected if $L_t$ is greater than the critical value of the test. We adopt the rejection region of the maximum of $n$ test statistics as in Lee and Mykland (2008), and the test is applied to each day on a rolling basis. $n$ is chosen to be 22, the number of return observations in a month in this study. The significance level of the test is 0.01. Let $J_t = 1$ if there is a jump at day $t$, and $J_t = 0$ otherwise. We also define a negative jump and a positive jump as $J_t^- = J_t 1_{\{r_t<0\}}$ and $J_t^+ = J_t 1_{\{r_t>0\}}$, respectively, where $1_{\{.\}}$ is an indicator function.

The summary statistics of $J_t$, $J_t^-$ and $J_t^+$ are shown in Panel A of Table 1. For SPX, the average jump intensity is 0.584%, and negative jumps are twice as frequent as positive jumps. For NDX, the average jump intensity is 0.65%, slightly higher than that of SPX. Negative jumps account for nearly 87% of all the jumps. The standard deviations are also reported. Since the means are all close to zero, the standard deviations are approximately equal to the squared-root of the means.

Table 1 here

For the days with $J_t = 1$, we define the jump size $Z_t = r_t$, otherwise $Z_t$ is undefined. We denote the size of a negative jump and a positive jump by $Z_t^-$ and $Z_t^+$, respectively. For both of SPX and NDX, the mean jump size is negative. The negative jumps are in larger magnitude, more variable, more skewed, and have fatter tails than do the positive jumps.

Beside distinguishing between positive and negative jumps, we also distinguish between jumps that occur suddenly without any jumps in the recent past and jumps that occur following other jumps. We classify jumps into two groups: out-of-the-blue jumps and follow-on jumps, denoted as $J_t^O$ and $J_t^F$, respectively. A jump is defined as an out-of-the-blue jump if there are no jumps in the previous 60 trading days. Otherwise, the jump is defined as a follow-on jump. The choice of 60 days is admittedly a bit arbitrary. The robustness of the result will be briefly discussed in due course.

Panels B and C of Table 1 provide descriptive statistics of the two types of jumps. For SPX, the mean intensity of $J_t^O$ is 0.366%, higher than that of $J_t^F$ of 0.257%. For NDX, the mean intensity of $J_t^O$ is 0.369%, also higher than that of $J_t^F$ of 0.281%. We further classify $J_t^O$ and $J_t^F$ by the sign of the jumps. Denote the negative out-of-the-blue jump, the positive out-of-the-blue jump, the negative follow-on jump, and the positive follow-on jump by $J_t^{O-}$, $J_t^{O+}$, $J_t^{F-}$ and $J_t^{F+}$, respectively. Negative jumps are more frequent regardless the type of the jumps. The sizes of the two types of jumps are also shown in Table 1. The results suggest that the follow-on jumps are more negative on average, move variable, more negatively skewed and have fatter tails than the out-of-the-blue jumps do.

The top panel of Figure 1 shows the time series plot of $r_t J_t$ for SPX. Jumps appear in clusters. Many jumps occur in the periods from 1950s to early 1960s, from late 1980s to early 2000s, and in recent years. Other periods are relatively quiet. Jump sizes also vary significantly over time.

Figure 1 here

The top panel of Figure 2 shows the time series plot of jump size of NDX. From late 1970s to early 1990s, the jump intensity is high, and sizes of jumps are relatively small, except for a few cases.

Figure 2 here

## 2.2. Predictive Variables

We use the following variables to predict jumps in this study: the diffusive variance of asset returns, the past jump intensity, and relative stock price level. The choice of the diffusive variance and the past jump intensity is motivated by the existing literature. In the options pricing literature, as we discussed earlier, the conditional jump intensity is modeled as an affine function of the diffusive variance. In the second strand of the literature, the conditional jump intensity is positively related to the past jump intensity. A new variable proposed in this paper to capture the variation of the jump intensity is the relative stock price level. We discuss these predictive variables in turn.

The bottom panel of Figure 1 shows the time series plot of the diffusive volatility, $\sqrt{D_t}$, of SPX. The diffusive volatility is high around the 1987 crash. However, high diffusive volatility is not always associated with a large number of jumps. In mid 1970s, from late 1990s to early 2000s, and during the 2008-2009 crisis, when the diffusive volatility is the high, only few jumps are observed. The bottom panel of Figure 2 shows the time series plot of the diffusive volatility, $\sqrt{D_t}$, of NDX. During the period of the 1970s to the early 1990s, the diffusive volatility stays at low levels most of the time except around the 1987 crash. In the later period, jumps are infrequent but tend to be in large magnitudes, and the diffusive volatility is relatively high.

We define the moving average of jump intensity $\bar{J}_t$ as

$$\bar{J}_t = \alpha_J \bar{J}_{t-1} + (1 - \alpha_J) J_t. \tag{2}$$

The smoothing parameter $\alpha_J$ is chosen so that $\bar{J}_t$ is the best linear predictor of the occurrence of a jump on the next day. Specifically, $\alpha_J$, together with $a_0$ and $a_1$ are chosen by minimizing $\sum_{t=1}^{T-1} [J_{t+1} - a_0 - a_1 \bar{J}_t(\alpha_J)]^2$. The estimated values of $\alpha_J$ are 0.9984 and 0.9966 for SPX and NDX, respectively. We also define the moving average of intensities of negative jumps and of positive jumps, respectively, as

$$\bar{J}_t^- = \alpha_J \bar{J}_{t-1}^- + (1-\alpha_J) J_t^- \tag{3}$$

$$\bar{J}_t^+ = \alpha_J \bar{J}_{t-1}^+ + (1-\alpha_J) J_t^+. \tag{4}$$

By doing so, we can investigate the predictive power of past intensities of negative jumps and of positive jumps separately.

Figure 3 shows the time series plots of $\bar{J}_t$, $\bar{J}_t^-$, and $\bar{J}_t^+$ for SPX. There are large variations in jump intensities over the sample period. $\bar{J}_t$ has two peaks, one in late 1950s and another in mid 1990s, and it is near zero in late 1970s and mid 2000s. The patterns of $\bar{J}_t^-$ and $\bar{J}_t^+$ are similar to that of $\bar{J}_t$. The level of $\bar{J}_t^-$ is often higher than that of $\bar{J}_t^+$ because negative jumps are more often than positive jumps are.

Figure 3 here

The time series plots of $\bar{J}_t$, $\bar{J}_t^-$, and $\bar{J}_t^+$ for NDX are shown in Figure 4. Since majority of jumps are negative, $\bar{J}_t^-$ is much higher than $\bar{J}_t^+$ is, and $\bar{J}_t^-$ exhibits a similar pattern as $\bar{J}_t$ does. Similar to SPX, the values of $\bar{J}_t$ and $\bar{J}_t^-$ for NDX increase rapidly in late 1970s and late 1980s, and they drop slowly since then. The values of $\bar{J}_t$ and $\bar{J}_t^-$ for NDX are close to zero in late 1990s, whereas for SPX, the values are still moderately high until mid 2000s.

Figure 4 here

We define the relative stock price level as follows. We first define the moving average of the stock price level, $X_t$, by

$$X_t = \alpha_X X_{t-1} + (1-\alpha_X) S_t. \tag{5}$$

The relative stock price level, $Y_t$, is defined as

$$Y_t = S_t - X_t, \tag{6}$$

where the smoothing parameter, $\alpha_X$, is estimated together with $a_0$ and $a_1$ by minimizing $\sum_{t=1}^{T-1}[J_{t+1} - a_0 - a_1 Y_t(\alpha_X)]^2$. The estimated values of $\alpha_X$ are 0.9985 and 0.9981 for SPX and NDX, respectively.

The time series plots of $S_t$, $X_t$ and $Y_t$ for SPX are shown in Figure 5. Since $S_t$ is increasing in general in the sample period, $Y_t$ tends to be positive. $Y_t$ becomes negative when there are sudden and sharp drops in $S_t$. There is a general decreasing trend in $Y_t$ from 1950s to mid 1970s, a increasing trend from then to late 1990s, and $Y_t$ deceases again until late 2000s. It suggests that jumps are likely to occur when the value of $Y_t$ is high.

Figure 5 here

The time series plots of $S_t$, $X_t$ and $Y_t$ for NDX are shown in Figure 6. The time series pattern of $Y_t$ for NDX is similar to that for SPX for the same sample period. The noticeable difference between the two indexes is that $Y_t$ for NDX is only moderately high before the 1987 crash and it is the highest before the burst of the internet bubble in 2000, whereas $Y_t$ for SPX is about equally high for these two periods.

Figure 6 here

# 3. Predicting Jumps

## 3.1. Jump Intensities

In this subsection, we examine the predictive power of $Y_t$, $\bar{J}_t$, $\bar{J}_t^-$, $\bar{J}_t^+$ and $D_t$ on the conditional jump intensity by running the following logit regression,

$$P(J_{t+1} = 1|U_t) = \frac{1}{1 + e^{-(\beta_0 + U_t\beta)}} \quad (7)$$

$$P(J_{t+1} = 0|U_t) = 1 - \frac{1}{1 + e^{-(\beta_0 + U_t\beta)}}, \quad (8)$$

where $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}_t^-/\sigma(\bar{J}^-), \bar{J}_t^+/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$.

The results for the predictive power on the jump intensity are shown in Table 2. The coefficient estimates for $\beta$ are reported in the first row, and the corresponding t-statistics are reported in the parentheses. The average marginal effects, $\overline{P_{U_i}} = \sum_{t=1}^{T-1} \partial P(J_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the square brackets. The results suggest that for SPX, in simple regressions, both $Y_t$ and $\bar{J}_t$ are positively and significantly related to the future jump intensity, whereas $D_t$ is negatively and significantly related to the future jump intensity. In multiple regressions, $Y_t$ and $D_t$ are still significant, but $\bar{J}_t$ becomes insignificant. For the economic significance, the results indicate that when $Y_t$ is used alone in the regression, a one-standard-deviation increase in $Y_t$ leads to an increase of 0.219% on average in the probability of a jump on the next day. The number can be compared with the mean jump intensity of 0.584%. In multiple regressions, the number is reduced to 0.17-0.18%. The predictive power of $\bar{J}_t$ is lower than that of $Y_t$. In the simple regression, the marginal effect is 0.173%, and in multiple regressions, the number drops below 0.1%.

Table 2 here

The results on $D_t$ is in contrast to the options pricing literature where the relation between jump intensity and diffusive volatility is found to be positive. The negative relation found here is due to the mechanical reason that $D_t$ is also used in detecting jumps. Since the diffusive variance shows up in the denominator in (1), positive errors in the estimation of the diffusive variance can lead to the failure to identify true jumps, and negative errors can lead to finding false jumps, which results in a spurious negative relation between diffusive variance and jumps. The large magnitude of the marginal effect of $D_t$ is also due to the large standard deviation of $D_t$, which is the result of its highly skewed distribution. We will investigate this issue in detail in Section 5.

For NDX, the predictive power of past jump intensities is particularly strong evidenced by the high values of coefficients and t-statistics. The results suggest that jumps are more clustered for NDX than for SPX. A one-standard-deviation increase in $\bar{J}_t$ leads to an increase of 0.316% on average in the probability of a jump on the next day, which is about half of the mean jump intensity (0.65%). $\bar{J}_t^-$ and $\bar{J}_t^+$ also tend to be positively and significantly related to the future jump intensity. $Y_t$ is significantly and positively in the simple regression, however, it becomes insignificant in multiple regressions. Nevertheless, a one-standard-deviation increase in $Y_t$ leads to an increase of more than 0.1% in the probability of a jump on the next day. $D_t$ is negative and significant for the same reason as explained above.

To examine the predictive power of those variables on the future intensity of negative jumps and positive separately, we run the following logit regression,

$$P(J_{t+1}^* = 1|U_t) = \frac{1}{1+e^{-(\beta_0+U_t\beta)}} \tag{9}$$

$$P(J_{t+1}^* = 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+U_t\beta)}}, \tag{10}$$

where $J_{t+1}^* = J_{t+1}^-$, the negative jump, or $J_{t+1}^* = J_{t+1}^+$, the positive jumps. The results for the negative jump are shown in Panel A of Table 3. For SPX, $Y_t$ has a strong predictive power on the intensity of negative jumps, and $\bar{J}_t$ becomes insignificant. For NDX, since majority of jumps are negative, the results for the predictive power on the intensity of negative jumps are similar to those for the total jump intensity except that $Y_t$ becomes stronger. $\bar{J}_t$ still has a higher predictive power. The results for the positive jump are shown in Panel B of Table 3. For SPX, only $\bar{J}_t$ is positively and significantly related to the intensity of positive jumps. For NDX, none of the variables have strong predictive power on the intensity of positive jumps because of the low frequency of positive jumps.

Table 3 here

From Table 3, we observe that $Y_t$ is positively related to the intensity of negative jumps and it also tends to be negatively related to the intensity of positive jumps. The results suggest that $Y_t$ can predict not only the jump intensity, but also the sign of jumps.

To capture this effect, we consider the following ordered logit regression,

$$P(J^s_{t+1} = -1|U_t) = \frac{1}{1 + e^{-(\beta_0^- + U_t\beta)}} \tag{11}$$

$$P(J^s_{t+1} = 0|U_t) = \frac{1}{1 + e^{-(\beta_0^+ + U_t\beta)}} - \frac{1}{1 + e^{-(\beta_0^- + U_t\beta)}} \tag{12}$$

$$P(J^s_{t+1} = 1|U_t) = 1 - \frac{1}{1 + e^{-(\beta_0^+ + U_t\beta)}}, \tag{13}$$

where $J^s_t$ is a signed jump, defined as, $J^s_t = -1$ if there is a negative jump at day $t$, $J^s_t = 1$ if there is a positive jump at day $t$, and zero otherwise.

The results are shown in Table 4. For SPX, as expected, $Y_t$ is positive and significant. $\bar{J}_t$ is negative and insignificant in the simple regression, but becomes significant in multiple regressions. $D_t$ also becomes insignificant. To measure the economic significance, we define two marginal effects, one for a negative jump and one for a positive jump. Specifically, we define the marginal effect of a negative jump, and of a positive jump, respectively by $\overline{P^-_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^s_{t+1} = -1|U_t)/\partial U_{it}/(T-1)$, and $\overline{P^+_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^s_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, both multiplied by 1000. The results suggest that $Y_t$ and $\bar{J}_t$ are economically significant. Take the regression with $Y_t$ and $\bar{J}_t$ as independent variables as the example. A one-standard-deviation increase in $Y_t$ ($\bar{J}_t$) leads to an increase (a decrease) of 0.145% (0.108%) in the probability of a negative jump and a decrease (an increase) of 0.075% (0.056%) in the probability of a positive jump on the next day. Note that for SPX, the mean intensity of negative and positive jumps are merely 0.385% and 0.199%, respectively. For NDX, $Y_t$ is positive and significant, and the effect is stronger than that in Table 2, suggesting that $Y_t$ better predicts signed jumps than unsigned jumps. $\bar{J}_t$ is still positive and significant, and has the highest predictive power. However, the effect is opposite to that for SPX.

Table 4 here

## 3.2. Jump Size

In this subsection, we examine the predictive power of the predictive variables on the jump size. The scatter plots of the jump size on day $t+1$, $Z_{t+1}$, against the relative level $Y_t$ and against the past jump intensity $\bar{J}_t$ are shown in Figure 7.

Figure 7 here

The figure shows that there is a general decreasing relation between the jump size and $Y_t$. The effect is particularly strong for NDX. The scatter plots of $Z_{t+1}$ against $\bar{J}_t$ show no clear relation between the past jump intensity and the jump size.

To quantify the relations, we run the following OLS regression

$$Z_{t+1} = \gamma_0 + U_t\gamma + \varepsilon_{t+1}, \qquad (14)$$

where $\gamma = (\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5)'$. Table 5 reports the coefficient estimates for $\gamma$ multiplied by 1000 in the first row, and the corresponding t-statistics adjusted for heteroscedasticity in the parentheses. For SPX, $Y_t$ is significantly and negatively related to $Z_{t+1}$, suggesting when the relative level is high, jumps tend to be negative in large magnitude or positive in small magnitude. The effect of $D_t$ is also negative and significant. This is partially due to the definition of the jump detection test and that majority of jumps are negative. $\bar{J}_t$ is insignificant in the simple regression, but gains some explanatory power in multiple regressions. The economic significance of these variables can be examined by comparing the estimates of $\gamma$ with the standard deviation of the jump size of 3.783%, as reported in Table 1. For the regression with $Y_t$, $\bar{J}_t$ and $D_t$ as independent variables, a one-standard-deviation change in $Y_t$, $\bar{J}_t$ and $D_t$ leads to a change in $Z_{t+1}$ corresponding to about 0.42, 0.27 and 2.15 standard deviations, respectively. For NDX, $Y_t$ and $D_t$ are significantly and negatively related to $Z_{t+1}$, but $\bar{J}_t$ becomes insignificant. For the regression with $Y_t$, $\bar{J}_t$ and $D_t$ as independent variables, a one-standard-deviation change in $Y_t$, $\bar{J}_t$ and $D_t$ leads to a change in $Z_{t+1}$ corresponding to about 0.75, 0.09 and 2.21 standard deviations, respectively.

Table 5 here

The results suggest that a high value of $Y_t$ robustly predicts a negative jump with a large size, and the predictive power is economically and statistically significant. Since $Y_t$ is also the determinant of the conditional jump intensity as shown in the previous subsection, the results cast doubts on the assumption that the conditional jump intensity and jump size are independent.

# 4. Predicting Out-of-the-blue Jumps and Follow-up Jumps

The above analysis shows that both the relative asset price level and past jump intensities are positively associated with the conditional jump intensity. Do they play different roles in capturing the variation of jump intensity? Past jump intensities perform very well in the situation where jumps show a strong clustering effect such as for NDX. However, if there are no jumps in the recent past, the values of the past jump intensities are low, and as a result, past jump intensities may fail to predict the next jump. The relative asset price level may perform well in this situation.

To test this conjecture, we run the following logit regression to examine the predictive power of the predictive variables on the intensity of out-of-the-blue jumps,

$$P(J^O_{t+1} = 1|U_t) = \frac{1}{1+e^{-(\beta_0+U_t\beta)}} \quad (15)$$

$$P(J^O_{t+1} = 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+U_t\beta)}}. \quad (16)$$

The results are reported in Table 6. $Y_t$ is significantly and positively associated with the intensity of the out-of-the-blue jumps for SPX. In the simple regression, a one-standard-deviation increase in $Y_t$ leads to an increase of 0.119% in the probability of an out-of-the-blue jump on the next day, which is about 33% of the mean intensity of the out-of-the-blue jumps. For NDX, $Y_t$ is positive, but insignificant. Nevertheless, a one-standard-deviation increase in $Y_t$ leads to an increase of 0.097% in the probability of an out-of-the-blue jump on the next day, which is about 26% of the mean intensity of the out-of-the-blue jumps. For both of the indexes, $\bar{J}_t$ does not show any predictive power on the intensity of the out-of-the-blue jumps. This is in contrast to the results in Table 2 where $\bar{J}_t$ is a stronger predictor of the jump intensity, especially for NDX.

Table 6 here

Next, we run the logit regression to examine the predictive power on the intensity of negative and positive out-of-the-blue jumps separately, and the results are reported in Table 7. For predicting negative out-of-the-blue jumps, $Y_t$ is positive and significant for both SPX and NDX. The effect is economically significant as well. For the regressions with $Y_t$, $\bar{J}_t$ and $D_t$ as independent variables, the marginal effect of $Y_t$ is 0.182% and 0.193% for SPX and NDX, respectively, which corresponds to about 71% and 62% of the mean intensity of negative out-of-the-blue jumps for SPX and NDX, respectively. Table 7 also shows that none of the variables predicts positive out-of-the-blue jumps.

Table 7 here

To examine the predictive power on the intensity of follow-on jumps, we run the logit regression as follows,

$$P(J^F_{t+1} = 1|U_t) = \frac{1}{1+e^{-(\beta_0+U_t\beta)}} \tag{17}$$

$$P(J^F_{t+1} = 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+U_t\beta)}}. \tag{18}$$

The results are reported in Table 8. The effect of past jump intensities becomes much stronger. For both the indexes, $\bar{J}_t$ and $\bar{J}^-_t$ are positive and significant. For the simple regressions, the marginal effect of $\bar{J}_t$ is 0.172% and 0.263% for SPX and NDX, respectively, which corresponds to about 79% and 94% of the mean intensity of follow-on jumps for SPX and NDX, respectively. The effect of $Y_t$ becomes weak. $Y_t$ is significant only for SPX and in the simple regression.

Table 8 here

The results for predicting negative and positive follow-on jumps are reported in Table 9. For SPX, $\bar{J}_t^-$ is positively and significantly associated with the intensity of negative follow-on jumps, and $Y_t$ and $\bar{J}_t$ are positive and significant only in simple regressions. For NDX, $\bar{J}_t$ and $\bar{J}_t^-$ are positive and significantly associated with the intensity of negative follow-on jumps. All the past jump intensities are positively and significantly related to the intensity of positive follow-on jumps for SPX, however, no variables are significant for NDX.

Table 9 here

As we argued earlier, $Y_t$ can not only predict the jump intensity, but also the sign of a jump. The effect should hold for out-of-the-blue jumps as well. To test this, we run the ordered logit regression

$$\begin{aligned} P(J_{t+1}^{Os} = -1|U_t) &= \frac{1}{1+e^{-(\beta_0^- + U_t\beta)}} \\ P(J_{t+1}^{Os} = 0|U_t) &= \frac{1}{1+e^{-(\beta_0^+ + U_t\beta)}} - \frac{1}{1+e^{-(\beta_0^- + U_t\beta)}} \\ P(J_{t+1}^{Os} = 1|U_t) &= 1 - \frac{1}{1+e^{-(\beta_0^+ + U_t\beta)}}, \end{aligned}$$

where $J_t^{Os} = -1$ if there is a negative out-of-the-blue jump at day $t$, $J_t^{Os} = 1$ if there is a positive out-of-the-blue jump at day $t$, and zero otherwise. The results are shown in Table 10. For both SPX and NDX, $Y_t$ is positive and significant. The economic significance of $Y_t$ can be seen from the marginal effects. For example, in the regression with $Y_t$ and $\bar{J}_t$ as independent variables, for SPX, a one-standard-deviation increase in $Y_t$ leads to an increase of 0.108% in the probability of a negative out-of-the-blue jump (about 42% of the mean intensity), and a decrease of 0.046% in the probability of a positive out-of-the-blue jump (about 42% of the mean intensity). For NDX, the marginal effects are 0.121% for a negative out-of-the-blue jump (about 39% of the mean intensity), and -0.023% for a positive out-of-the-blue jump (about 40% of the mean intensity).

Table 10 here

For completeness, the results for the ordered logit regression for signed follow-on jumps are also reported in Table 10. Only $\bar{J}_t$ and $\bar{J}_t^-$ for NDX are significant, and most of the effect is from predicting negative follow-on jumps.

The results in Tables 6-10 suggest that $Y_t$ and past jump intensities play complementary roles in capturing the variation of conditional jump intensities. $Y_t$ strongly predicts initial jumps, whereas past jump intensities strongly predict succeeding jumps.

Finally, we examine the predictive power of the predictive variables on the sizes of the out-of-the-blue jumps and of the follow-on jumps. The scatter plots in Figure 8 and Figure 9 show that the sizes of out-of-the-blue jumps are negatively related to $Y_t$, but the sizes of follow-on jumps are not. The sizes of the out-of-the-blue jumps or the follow-on jumps do not appear to be related to $\bar{J}_t$.

Figure 8 here

Figure 9 here

The regression results are reported in Table 11. For SPX, $Y_t$ is negative and significant, although it is only marginally significant in the simple regression. $D_t$ is also negative and significant, and $\bar{J}_t$ is positive and significant only in multiple regressions. For the regression with $Y_t$, $\bar{J}_t$ and $D_t$ as independent variables, a one-standard-deviation change in $Y_t$, $\bar{J}_t$ and $D_t$ leads to a change in the size of the out-of-the-blue jump corresponding to 0.5, 0.34, and 1.68 standard deviations. For NDX, $Y_t$ is negative and significant, and $D_t$ is negative but only significant in multiple regressions. For the regression with three independent variables, a one-standard-deviation change in $Y_t$, $\bar{J}_t$ and $D_t$ leads to a change in the size of the out-of-the-blue jump corresponding to 0.99, 0.13, and 1.23 standard deviations. The results in Table 11 also show that $Y_t$ tends to be negatively related to the size of follow-on jumps, but the effect is much weaker than that for the size of out-of-the-blue jumps.

Table 11 here

To check the robustness of the results, we consider different cutoffs for defining the out-of-the-blue and follow-on jumps. The results are qualitatively the same for a range of cutoffs from 50 days to 100 days. Beyond this range, the number of the out-of-the-blue or the follow-on jumps is too few, and as a result, the statistical power of the test is low.

# 5. Diffusive Variance and the Bias of Jump Detection Test

The negative relationship between diffusive variance and jump intensity found in the previous sections may be spurious because, as argued earlier, the errors in the diffusive variance estimation affect the detection of jumps. In this section, we use simulation to examine the impact of the estimation error.

The data are simulated from the model

$$dS_u = \left(\mu - \frac{1}{2}D_u^*\right)du + \sqrt{D_u^*}dw_{1,u} + Z_u dN_u \quad (19)$$

$$d\ln D_u^* = (\theta - \kappa \ln D_u^*)du + \eta dw_{2,u}, \quad (20)$$

where $S_u$ is the log asset price, $D_u^*$ is the diffusive variance, $w_{1,u}$ and $w_{2,u}$ are standard Brownian motions with correlation $\rho$, $N_u$ is a counting process, and $Z_u$ is the jump size. For the diffusive components of the model, the parameters estimated in Andersen et al. (2002) on the S&P index are used: $\mu = 0.0304$, $\theta = -0.012$, $\kappa = 0.0145$, $\eta = 0.1153$, and $\rho = -0.6127$, where the parameters are expressed in daily unit and returns are in percentage. For the jump component, we bootstrap the jump sizes from those detected from the actual data. Specifically, we resample with replacement from the normalized jump sizes of the actual data, $r_t/\sqrt{D_{t-1}}$, and the jump sizes in the simulated data are the resampled normalized jump sizes multiplied by the diffusive volatility, $\sqrt{D_u^*}$. The jump intensity is specified as $\lambda_0^* + \lambda^* D_u^*$. We consider three sets of parameter values for different degrees of the dependence of the jump intensity on the diffusive variance. For the first set of parameters, $(\lambda_0^* = 0.01, \lambda^* = 0)$, the jump intensity is unrelated to the diffusive variance. For the second set of parameters, $(\lambda_0^* = 0.005, \lambda^* = 0.015)$, the jump intensity is specified as a linear function of the diffusive variance, and the degree of the dependence is considered as moderate. For the last set of parameters, $(\lambda_0^* = 0, \lambda^* = 0.03)$, the jump intensity has the strongest relationship with the diffusive variance. We simulate 15601 days of data, which correspond to the sample size of the actual S&P 500 index data. To reduce the discretization error from simulating the continuous-time model, 10 steps are simulated for each day. We simulate 100 samples.

We detect the jumps from the simulated data the same way as we did for the actual data, and estimate the following logit regression

$$P(J_{t+1} = 1|U_t) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 U_t)}} \tag{21}$$

$$P(J_{t+1} = 0|U_t) = 1 - \frac{1}{1 + e^{-(\beta_0 + \beta_1 U_t)}}, \tag{22}$$

where $U_t = D_t/\sigma(D)$. Table 12 reports the 5th percentile, 50th percentile, and 95th percentile of the average jump intensity, $\tilde{J} = \sum_{t=1}^{T} J_t/T$, power and size in percentage, the coefficient estimate for $\beta_1$, the t-statistic for $\beta_1$, the average marginal effect, $\overline{P_U} = \sum_{t=1}^{T-1} \partial P(J_{t+1} = 1|U_t)/\partial U_t/(T-1)$, and $\lambda_1 = \overline{P_U}/\sigma(D)$. For the first set of parameters, the 95th percentile of the estimated $\beta_1$ is negative, which suggests a negative bias in the estimated relationship between the diffusive variance and the jump intensity. For the second set of parameters, more than half of the estimated $\beta_1$ become more positive. For the third set of parameters, the median t-statistic indicates that the positive relationship is statistically significant. The results from the simulated data suggest that the nonparametric jump detection method we adopt here leads to a negative bias in the estimated relationship between jump intensity and diffusive variance, the bias is moderate, however. The method is able to detect the positive relationship between jump intensity and diffusive variance when the relationship is relatively strong.

Table 12 here

## 6. Concluding Remarks

In this paper, we examine the determinants of the conditional jump intensities and jump sizes of the S&P 500 index and the NASDAQ composite index. Two variables for the jump intensity suggested in the existing literature are the diffusive variance and the past jump intensity. A new variable we propose in this paper is the price level of the index relative to its past average.

Diffusive volatility is found to be negatively associated with future jumps. This result is partially due to the errors in the diffusive volatility estimation in the nonparametric jump detection test. However, simulation results show that, if the conditional jump intensity is indeed strongly, positively related to the diffusive variance, the estimation error does not subsume the positive relationship. Therefore, it appears that, at least, the conditional jump intensity is not driven by the diffusive variance. This result cast doubts on the positive relation between diffusive variance and conditional jump intensity specified in options pricing models.

The relative asset price level is useful in predicting jumps and jump sizes. A higher value of the asset price relative to its historical average is associated with higher conditional jump intensities, especially, the intensity of negative jumps, and a larger magnitude of negative jump size. The past jump intensity is also associated with conditional jump intensity. The relative asset price level and the past jump intensity play different roles in predicting future jumps. The relative asset price level predicts the so-called out-of-the-blue negative jumps, whereas the past jump intensity predicts follow-on jumps. The positive out-of-the-blue jumps are relatively rare and more difficult to predict.

The results in the paper have important implications to options pricing and risk management. Empirical studies show that the existing options pricing models are still inadequate in explaining the volatility smile, which refers to the phenomena that the implied volatility from the Black-Scholes formula is a smile-shaped function of the strike price. The insufficiency of the existing options pricing models lies in their failure to capture the dynamics of the negatively skewed and fat tailed return distribution. This paper shows that the relative asset price level captures the dynamic features of the conditional jump intensities and jump size distributions most successfully. This suggests that it is a promising direction to improve the performance of options pricing models by incorporating the relative asset price level as an additional state variable.

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**Table 1**
**Summary Statistics of Jump Intensities and Jump Sizes**
This table reports the mean and standard deviation (std) of jump intensities and the mean , standard deviation, skewness (skew) and kurtosis (kurt) of jump sizes. Numbers reported for mean and std are multiplied by 1000. $J_t = 1$ if there is a jump at day $t$, and zero otherwise. The superscript -/+ indicates the sign of a jump, and O/F indicates whether it is an out-of-the-blue jump or a follow-on jump. The jump size $Z_t$ is equal to the return at day $t$ if there is a jump on the day, otherwise it is undefined. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

| | SPX | | | NDX | | |
|---|---|---|---|---|---|---|
| A. All jumps. | | | | | | |
| | $J_t$ | $J_t^-$ | $J_t^+$ | $J_t$ | $J_t^-$ | $J_t^+$ |
| mean | 5.84 | 3.85 | 1.99 | 6.50 | 5.63 | 0.87 |
| std | 76.19 | 61.93 | 44.56 | 80.38 | 74.82 | 29.54 |
| | $Z_t$ | $Z_t^-$ | $Z_t^+$ | $Z_t$ | $Z_t^-$ | $Z_t^+$ |
| mean | -14.18 | -33.70 | 23.60 | -22.61 | -30.67 | 29.30 |
| std | 37.83 | 31.39 | 10.89 | 28.88 | 20.47 | 19.81 |
| skew | -1.93 | -4.21 | 0.71 | 0.10 | -2.20 | 1.47 |
| kurt | 12.65 | 26.09 | 2.50 | 5.96 | 8.84 | 4.19 |
| B. Out-of-the-blue jumps. | | | | | | |
| | $J_t^O$ | $J_t^{O-}$ | $J_t^{O+}$ | $J_t^O$ | $J_t^{O-}$ | $J_t^{O+}$ |
| mean | 3.66 | 2.57 | 1.09 | 3.69 | 3.11 | 0.58 |
| std | 60.37 | 50.60 | 33.01 | 60.62 | 55.64 | 24.12 |
| | $Z_t^O$ | $Z_t^{O-}$ | $Z_t^{O+}$ | $Z_t^O$ | $Z_t^{O-}$ | $Z_t^{O+}$ |
| mean | -13.12 | -29.14 | 24.59 | -20.85 | -30.26 | 29.34 |
| std | 29.64 | 18.18 | 10.78 | 28.76 | 17.85 | 23.60 |
| skew | 0.07 | -1.09 | 0.70 | 0.77 | -1.66 | 1.39 |
| kurt | 2.45 | 3.04 | 2.47 | 5.49 | 5.76 | 3.49 |
| C. Follow-up jumps. | | | | | | |
| | $J_t^F$ | $J_t^{F-}$ | $J_t^{F+}$ | $J_t^F$ | $J_t^{F-}$ | $J_t^{F+}$ |
| mean | 2.18 | 1.28 | 0.90 | 2.81 | 2.52 | 0.29 |
| std | 46.66 | 35.80 | 29.96 | 52.98 | 50.17 | 17.06 |
| | $Z_t^F$ | $Z_t^{F-}$ | $Z_t^{F+}$ | $Z_t^F$ | $Z_t^{F-}$ | $Z_t^{F+}$ |
| mean | -15.95 | -42.81 | 22.41 | -24.92 | -31.16 | 29.23 |
| std | 49.07 | 47.44 | 11.30 | 29.37 | 23.66 | 13.29 |
| skew | -2.40 | -3.22 | 0.77 | -0.72 | -2.36 | 0.69 |
| kurt | 11.50 | 13.20 | 2.56 | 6.13 | 9.07 | 1.50 |

**Table 2**
**Jump Intensity**

This table reports the results for the following logit regression

$$P(J_{t+1} = 1|U_t) = \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$
$$P(J_{t+1} = 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$

where $J_t = 1$ if there is a jump at day $t$, and zero otherwise, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}_t^-/\sigma(\bar{J}^-), \bar{J}_t^+/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}_t^-$ is the past intensity of negative jumps, $\bar{J}_t^+$ is the past intensity of positive jumps, $D_t$ is the diffusive variance, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$. The coefficient estimates for $\beta$ are reported in the first row, and the corresponding t-statistics are reported in the parentheses. The average marginal effects, $\overline{P_{U_i}} = \sum_{t=1}^{T-1} \partial P(J_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the square brackets. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}_t^-$ | $\bar{J}_t^+$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}_t^-$ | $\bar{J}_t^+$ | $D_t$ |
| 0.38 | | | | | 0.27 | | | | |
| ( 3.41) | | | | | ( 2.13) | | | | |
| [ 2.19] | | | | | [ 1.73] | | | | |
| | 0.30 | | | | | 0.49 | | | |
| | ( 2.85) | | | | | ( 4.60) | | | |
| | [ 1.73] | | | | | [ 3.16] | | | |
| | | 0.12 | 0.22 | | | | 0.37 | 0.22 | |
| | | ( 1.02) | ( 2.12) | | | | ( 3.15) | ( 2.33) | |
| | | [ 0.70] | [ 1.30] | | | | [ 2.36] | [ 1.44] | |
| | | | | -1.83 | | | | | -2.78 |
| | | | | ( -4.59) | | | | | ( -4.52) |
| | | | | [ -10.84] | | | | | [ -18.18] |
| 0.30 | 0.16 | | | | 0.19 | 0.46 | | | |
| ( 2.35) | ( 1.30) | | | | ( 1.28) | ( 4.25) | | | |
| [ 1.74] | [ 0.92] | | | | [ 1.22] | [ 2.99] | | | |
| 0.30 | | 0.05 | 0.13 | | 0.22 | | 0.32 | 0.24 | |
| ( 2.31) | | ( 0.44) | ( 1.11) | | ( 1.45) | | ( 2.66) | ( 2.49) | |
| [ 1.72] | | [ 0.32] | [ 0.75] | | [ 1.39] | | [ 2.08] | [ 1.52] | |
| 0.29 | 0.12 | | | -1.82 | 0.19 | 0.35 | | | -2.53 |
| ( 2.08) | ( 1.02) | | | ( -4.29) | ( 1.01) | ( 2.99) | | | ( -3.63) |
| [ 1.73] | [ 0.72] | | | [ -10.74] | [ 1.23] | [ 2.27] | | | [ -16.38] |
| 0.30 | | 0.14 | 0.01 | -1.86 | 0.21 | | 0.23 | 0.20 | -2.51 |
| ( 2.13) | | ( 1.14) | ( 0.06) | ( -4.33) | ( 1.11) | | ( 1.76) | ( 2.10) | ( -3.58) |
| [ 1.77] | | [ 0.81] | [ 0.04] | [ -11.00] | [ 1.38] | | [ 1.46] | [ 1.27] | [ -16.23] |

**Table 3**
**Intensity of Negative and Positive Jumps**
This table reports the results for the following logit regressions

$$
\begin{aligned}
P(J^*_{t+1} &= 1|U_t) = \frac{1}{1+e^{-(\beta_0+U_t\beta)}} \\
P(J^*_{t+1} &= 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+U_t\beta)}}
\end{aligned}
$$

where $J^*_{t+1} = J^-_{t+1}$, the negative jump, in Panel A and $J^*_{t+1} = J^+_{t+1}$, the positive jump, in Panel B, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}^-_t/\sigma(\bar{J}^-), \bar{J}^+_t/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}^-_t$ is the past intensity of negative jumps, $\bar{J}^+_t$ is the past intensity of positive jumps, $D_t$ is the diffusive variance, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$. The coefficient estimates for $\beta$ are reported in the first row, and the corresponding t-statistics are reported in the parentheses. The average marginal effects, $\overline{P_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^*_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the square brackets. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

A. $J^-_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.48 | | | | | 0.35 | | | | |
| ( 3.49) | | | | | ( 2.63) | | | | |
| [ 1.84] | | | | | [ 1.98] | | | | |
| | 0.17 | | | | | 0.52 | | | |
| | ( 1.30) | | | | | ( 4.51) | | | |
| | [ 0.64] | | | | | [ 2.88] | | | |
| | | 0.01 | 0.18 | | | | 0.40 | 0.21 | |
| | | ( 0.07) | ( 1.34) | | | | ( 3.23) | ( 2.06) | |
| | | [ 0.04] | [ 0.69] | | | | [ 2.23] | [ 1.19] | |
| | | | | -1.38 | | | | | -2.76 |
| | | | | ( -2.77) | | | | | ( -4.20) |
| | | | | [ -5.30] | | | | | [ -15.67] |
| 0.52 | -0.08 | | | | 0.31 | 0.48 | | | |
| ( 3.37) | ( -0.53) | | | | ( 1.92) | ( 4.10) | | | |
| [ 1.98] | [ -0.31] | | | | [ 1.71] | [ 2.69] | | | |
| 0.52 | | -0.12 | 0.02 | | 0.33 | | 0.34 | 0.23 | |
| ( 3.33) | | ( -0.74) | ( 0.12) | | ( 2.06) | | ( 2.65) | ( 2.29) | |
| [ 1.98] | | [ -0.45] | [ 0.07] | | [ 1.85] | | [ 1.92] | [ 1.30] | |
| 0.57 | -0.12 | | | -1.44 | 0.40 | 0.35 | | | -2.52 |
| ( 3.38) | ( -0.81) | | | ( -2.67) | ( 1.95) | ( 2.81) | | | ( -3.39) |
| [ 2.20] | [ -0.47] | | | [ -5.54] | [ 2.23] | [ 1.98] | | | [ -14.13] |
| 0.57 | | -0.05 | -0.10 | -1.46 | 0.42 | | 0.23 | 0.19 | -2.49 |
| ( 3.39) | | ( -0.29) | ( -0.64) | ( -2.66) | ( 2.05) | | ( 1.72) | ( 1.89) | ( -3.35) |
| [ 2.20] | | [ -0.17] | [ -0.38] | [ -5.63] | [ 2.36] | | [ 1.31] | [ 1.05] | [ -13.97] |

**Table 3** (Cont'd)

B. $J^+_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.18 | | | | | -0.26 | | | | |
| ( 0.99) | | | | | ( -0.81) | | | | |
| [ 0.37] | | | | | [ -0.23] | | | | |
| | 0.56 | | | | | 0.32 | | | |
| | ( 3.02) | | | | | ( 1.08) | | | |
| | [ 1.11] | | | | | [ 0.28] | | | |
| | | 0.35 | 0.31 | | | | 0.13 | 0.30 | |
| | | ( 1.73) | ( 1.82) | | | | ( 0.38) | ( 1.15) | |
| | | [ 0.69] | [ 0.62] | | | | [ 0.11] | [ 0.26] | |
| | | | | -2.55 | | | | | -2.69 |
| | | | | ( -3.93) | | | | | ( -1.70) |
| | | | | [ -5.42] | | | | | [ -2.39] |
| -0.15 | 0.63 | | | | -0.46 | 0.45 | | | |
| ( -0.66) | ( 2.95) | | | | ( -1.24) | ( 1.45) | | | |
| [ -0.29] | [ 1.25] | | | | [ -0.40] | [ 0.40] | | | |
| -0.15 | | 0.38 | 0.36 | | -0.41 | | 0.28 | 0.28 | |
| ( -0.66) | | ( 1.85) | ( 1.96) | | ( -1.10) | | ( 0.79) | ( 1.04) | |
| [ -0.29] | | [ 0.75] | [ 0.72] | | [ -0.36] | | [ 0.24] | [ 0.24] | |
| -0.41 | 0.63 | | | -2.44 | -0.97 | 0.45 | | | -3.17 |
| ( -1.65) | ( 3.18) | | | ( -3.79) | ( -2.08) | ( 1.40) | | | ( -2.06) |
| [ -0.87] | [ 1.33] | | | [ -5.16] | [ -0.88] | [ 0.41] | | | [ -2.87] |
| -0.40 | | 0.48 | 0.26 | -2.48 | -0.96 | | 0.25 | 0.31 | -3.18 |
| ( -1.60) | | ( 2.57) | ( 1.47) | ( -3.85) | ( -2.02) | | ( 0.70) | ( 1.19) | ( -2.08) |
| [ -0.84] | | [ 1.03] | [ 0.56] | [ -5.26] | [ -0.87] | | [ 0.23] | [ 0.28] | [ -2.89] |

## Table 4
## Intensity of Signed Jumps

This table reports the results for the following logit regression

$$
\begin{aligned}
P(J^s_{t+1} = -1|U_t) &= \frac{1}{1+e^{-(\beta_0^- + U_t\beta)}} \\
P(J^s_{t+1} = 0|U_t) &= \frac{1}{1+e^{-(\beta_0^+ + U_t\beta)}} - \frac{1}{1+e^{-(\beta_0^- + U_t\beta)}} \\
P(J^s_{t+1} = 1|U_t) &= 1 - \frac{1}{1+e^{-(\beta_0^+ + U_t\beta)}},
\end{aligned}
$$

where $J^s_t = -1$ if there is a negative jump at day $t$, $J^s_t = 1$ if there is a positive jump at day $t$, and zero otherwise, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}^-_t/\sigma(\bar{J}^-), \bar{J}^+_t/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}^-_t$ is the past intensity of negative jumps, $\bar{J}^+_t$ is the past intensity of positive jumps, $D_t$ is the diffusive variance, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$. The coefficient estimates for $\beta$ are reported in the first row, and the corresponding t-statistics are reported in the parentheses. The average marginal effects for a negative jump, $\overline{P^-_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^s_{t+1} = -1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the square brackets. The average marginal effects for a positive jump, $\overline{P^+_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^s_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the curly braces. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.24 | | | | | 0.34 | | | | |
| ( 2.23) | | | | | ( 2.74) | | | | |
| [ 0.90] | | | | | [ 1.89] | | | | |
| {-0.47} | | | | | {-0.30} | | | | |
| | -0.08 | | | | | 0.43 | | | |
| | ( -0.74) | | | | | ( 3.88) | | | |
| | [ -0.30] | | | | | [ 2.41] | | | |
| | { 0.16} | | | | | {-0.38} | | | |
| | | -0.10 | 0.01 | | | | 0.35 | 0.17 | |
| | | ( -0.84) | ( 0.07) | | | | ( 2.88) | ( 1.57) | |
| | | [ -0.38] | [ 0.03] | | | | [ 1.93] | [ 0.93] | |
| | | { 0.20} | {-0.02} | | | | {-0.30} | {-0.15} | |
| | | | | -0.04 | | | | | -0.29 |
| | | | | ( -0.34) | | | | | ( -2.56) |
| | | | | [ -0.14] | | | | | [ -1.62] |
| | | | | { 0.07} | | | | | { 0.25} |
| 0.38 | -0.28 | | | | 0.28 | 0.39 | | | |
| ( 3.12) | ( -2.23) | | | | ( 2.02) | ( 3.38) | | | |
| [ 1.45] | [ -1.08] | | | | [ 1.55] | [ 2.17] | | | |
| {-0.75} | { 0.56} | | | | {-0.24} | {-0.34} | | | |
| 0.38 | | -0.18 | -0.15 | | 0.30 | | 0.28 | 0.19 | |
| ( 3.08) | | ( -1.49) | ( -1.12) | | ( 2.14) | | ( 2.18) | ( 1.84) | |
| [ 1.44] | | [ -0.70] | [ -0.56] | | [ 1.67] | | [ 1.55] | [ 1.07] | |
| {-0.75} | | { 0.36} | { 0.29} | | {-0.26} | | {-0.24} | {-0.17} | |
| 0.39 | -0.29 | | | 0.05 | 0.27 | 0.36 | | | -0.23 |
| ( 3.14) | ( -2.27) | | | ( 0.49) | ( 1.87) | ( 3.11) | | | ( -1.69) |
| [ 1.51] | [ -1.11] | | | [ 0.19] | [ 1.49] | [ 2.04] | | | [ -1.31] |
| {-0.78} | { 0.57} | | | {-0.10} | {-0.23} | {-0.32} | | | { 0.20} |
| 0.39 | | -0.20 | -0.14 | 0.05 | 0.29 | | 0.25 | 0.19 | -0.24 |
| ( 3.12) | | ( -1.56) | ( -1.08) | ( 0.52) | ( 2.00) | | ( 1.97) | ( 1.82) | ( -1.71) |
| [ 1.50] | | [ -0.75] | [ -0.54] | [ 0.21] | [ 1.61] | | [ 1.42] | [ 1.05] | [ -1.32] |
| {-0.78} | | { 0.39} | { 0.28} | {-0.11} | {-0.25} | | {-0.22} | {-0.16} | { 0.21} |

**Table 5**
**Jump Size**
This table reports the results for the following OLS regression

$$Z_{t+1} = \gamma_0 + U_t\gamma + \varepsilon_{t+1},$$

where $Z_{t+1}$ is jump size on a jump day and undefined otherwise, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}_t^-/\sigma(\bar{J}^-), \bar{J}_t^+/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}_t^-$ is the past intensity of negative jumps, $\bar{J}_t^+$ is the past intensity of positive jumps, $D_t$ is the diffusive variance, and $\gamma = (\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5)'$. The coefficient estimates for $\gamma$ multiplied by 1000 are reported in the first row, and the corresponding t-statistics adjusted for heteroscedasticity are reported in the parentheses. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}_t^-$ | $\bar{J}_t^+$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}_t^-$ | $\bar{J}_t^+$ | $D_t$ |
| -10.12 | | | | | -20.54 | | | | |
| ( -2.01) | | | | | ( -3.15) | | | | |
| | 3.58 | | | | | -2.96 | | | |
| | ( 0.95) | | | | | ( -0.64) | | | |
| | | -0.08 | 4.30 | | | | -2.58 | -0.81 | |
| | | ( -0.02) | ( 1.05) | | | | ( -0.65) | ( -0.28) | |
| | | | | -81.03 | | | | | -56.74 |
| | | | | ( -3.67) | | | | | ( -2.40) |
| -15.58 | 10.61 | | | | -20.42 | -0.32 | | | |
| ( -3.05) | ( 2.92) | | | | ( -3.08) | ( -0.08) | | | |
| -17.42 | | 2.06 | 11.41 | | -20.61 | | 0.31 | -0.93 | |
| ( -3.05) | | ( 0.49) | ( 2.40) | | ( -3.09) | | ( 0.09) | ( -0.31) | |
| -15.98 | 10.10 | | | -81.31 | -21.56 | -2.61 | | | -63.81 |
| ( -3.24) | ( 3.04) | | | ( -3.88) | ( -2.64) | ( -0.77) | | | ( -3.83) |
| -15.85 | | 6.36 | 5.42 | -81.66 | -21.75 | | -1.71 | -1.52 | -63.82 |
| ( -3.19) | | ( 2.16) | ( 1.63) | ( -3.84) | ( -2.65) | | ( -0.61) | ( -0.65) | ( -3.86) |

**Table 6**

**Intensity of Out-of-the-Blue Jumps**

This table reports the results for the following logit regression

$$P(J^O_{t+1} = 1|U_t) = \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$
$$P(J^O_{t+1} = 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$

where $J^O_t = 1$ if there is an out-of-the-blue jump at day $t$, and zero otherwise, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}^-_t/\sigma(\bar{J}^-), \bar{J}^+_t/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}^-_t$ is the past intensity of negative jumps, $\bar{J}^+_t$ is the past intensity of positive jumps, and $D_t$ is the diffusive variance, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$. The coefficient estimates for $\beta$ are reported in the first row, and the corresponding t-statistics are reported in the parentheses. The average marginal effects, $\overline{P_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^O_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the square brackets. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.33 | | | | | 0.26 | | | | |
| ( 2.34) | | | | | ( 1.58) | | | | |
| [ 1.19] | | | | | [ 0.97] | | | | |
| | 0.02 | | | | | 0.12 | | | |
| | ( 0.17) | | | | | ( 0.79) | | | |
| | [ 0.08] | | | | | [ 0.45] | | | |
| | | -0.18 | 0.20 | | | | -0.02 | 0.22 | |
| | | ( -1.17) | ( 1.40) | | | | ( -0.13) | ( 1.56) | |
| | | [ -0.66] | [ 0.72] | | | | [ -0.08] | [ 0.80] | |
| | | | | -1.99 | | | | | -2.48 |
| | | | | ( -4.08) | | | | | ( -3.09) |
| | | | | [ -7.47] | | | | | [ -9.20] |
| 0.42 | -0.19 | | | | 0.25 | 0.07 | | | |
| ( 2.68) | ( -1.22) | | | | ( 1.47) | ( 0.45) | | | |
| [ 1.54] | [ -0.71] | | | | [ 0.92] | [ 0.26] | | | |
| 0.42 | | -0.29 | 0.06 | | 0.31 | | -0.12 | 0.25 | |
| ( 2.58) | | ( -1.76) | ( 0.39) | | ( 1.77) | | ( -0.63) | ( 1.82) | |
| [ 1.52] | | [ -1.05] | [ 0.22] | | [ 1.13] | | [ -0.44] | [ 0.92] | |
| 0.44 | -0.23 | | | -2.14 | 0.35 | -0.10 | | | -2.50 |
| ( 2.55) | ( -1.47) | | | ( -4.04) | ( 1.60) | ( -0.56) | | | ( -3.10) |
| [ 1.66] | [ -0.86] | | | [ -8.07] | [ 1.30] | [ -0.36] | | | [ -9.29] |
| 0.44 | | -0.18 | -0.09 | -2.15 | 0.41 | | -0.28 | 0.20 | -2.51 |
| ( 2.51) | | ( -1.12) | ( -0.56) | ( -3.90) | ( 1.82) | | ( -1.42) | ( 1.54) | ( -3.10) |
| [ 1.65] | | [ -0.67] | [ -0.34] | [ -8.07] | [ 1.51] | | [ -1.03] | [ 0.76] | [ -9.30] |

**Table 7**
**Intensity of Negative and Positive Out-of-the-Blue Jumps**
This table reports the results for the following logit regressions

$$P(J^{O*}_{t+1} = 1|U_t) = \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$
$$P(J^{O*}_{t+1} = 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$

where $J^{O*}_{t+1} = J^{O-}_{t+1}$, negative out-of-the-blue jump, in Panel A and $J^{O*}_{t+1} = J^{O+}_{t+1}$, positive out-of-the-blue jump, in Panel B, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}^-_t/\sigma(\bar{J}^-), \bar{J}^+_t/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}^-_t$ is the past intensity of negative jumps, $\bar{J}^+_t$ is the past intensity of positive jumps, $D_t$ is the diffusive variance, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$. The coefficient estimates for $\beta$ are reported in the first row, and the corresponding t-statistics are reported in the parentheses. The average marginal effects, $\overline{P_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^{O*}_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the square brackets. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

A. $J^{O-}_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.44 | | | | | 0.39 | | | | |
| ( 2.63) | | | | | ( 2.19) | | | | |
| [ 1.13] | | | | | [ 1.22] | | | | |
| | -0.03 | | | | | 0.12 | | | |
| | ( -0.21) | | | | | ( 0.72) | | | |
| | [ -0.09] | | | | | [ 0.38] | | | |
| | | -0.29 | 0.24 | | | | -0.00 | 0.20 | |
| | | ( -1.58) | ( 1.43) | | | | ( -0.02) | ( 1.27) | |
| | | [ -0.75] | [ 0.61] | | | | [ -0.01] | [ 0.61] | |
| | | | | -1.83 | | | | | -2.48 |
| | | | | ( -3.09) | | | | | ( -2.84) |
| | | | | [ -4.80] | | | | | [ -7.74] |
| 0.61 | -0.35 | | | | 0.39 | 0.06 | | | |
| ( 3.27) | ( -1.80) | | | | ( 2.12) | ( 0.32) | | | |
| [ 1.55] | [ -0.90] | | | | [ 1.21] | [ 0.18] | | | |
| 0.62 | | -0.47 | 0.05 | | 0.44 | | -0.13 | 0.25 | |
| ( 3.18) | | ( -2.32) | ( 0.28) | | ( 2.38) | | ( -0.64) | ( 1.63) | |
| [ 1.58] | | [ -1.20] | [ 0.14] | | [ 1.37] | | [ -0.41] | [ 0.76] | |
| 0.69 | -0.40 | | | -2.03 | 0.61 | -0.14 | | | -2.59 |
| ( 3.44) | ( -2.13) | | | ( -3.19) | ( 2.59) | ( -0.74) | | | ( -3.06) |
| [ 1.82] | [ -1.05] | | | [ -5.36] | [ 1.93] | [ -0.43] | | | [ -8.13] |
| 0.69 | | -0.37 | -0.10 | -1.99 | 0.67 | | -0.32 | 0.19 | -2.60 |
| ( 3.37) | | ( -1.88) | ( -0.53) | ( -2.95) | ( 2.79) | | ( -1.47) | ( 1.34) | ( -3.06) |
| [ 1.81] | | [ -0.96] | [ -0.27] | [ -5.23] | [ 2.11] | | [ -1.00] | [ 0.61] | [ -8.14] |

**Table 7** (Cont'd)

B. $J^{O+}_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.06 | | | | | -0.39 | | | | |
| ( 0.26) | | | | | ( -1.03) | | | | |
| [ 0.07] | | | | | [ -0.23] | | | | |
| | 0.15 | | | | | 0.12 | | | |
| | ( 0.64) | | | | | ( 0.32) | | | |
| | [ 0.17] | | | | | [ 0.07] | | | |
| | | 0.07 | 0.10 | | | | -0.12 | 0.33 | |
| | | ( 0.28) | ( 0.41) | | | | ( -0.26) | ( 1.01) | |
| | | [ 0.08] | [ 0.11] | | | | [ -0.07] | [ 0.19] | |
| | | | | -2.26 | | | | | -2.40 |
| | | | | ( -2.68) | | | | | ( -1.25) |
| | | | | [ -2.61] | | | | | [ -1.41] |
| -0.02 | 0.16 | | | | -0.52 | 0.30 | | | |
| ( -0.08) | ( 0.58) | | | | ( -1.20) | ( 0.75) | | | |
| [ -0.03] | [ 0.18] | | | | [ -0.30] | [ 0.18] | | | |
| -0.03 | | 0.08 | 0.11 | | -0.46 | | 0.09 | 0.30 | |
| ( -0.09) | | ( 0.29) | ( 0.41) | | ( -1.04) | | ( 0.20) | ( 0.88) | |
| [ -0.03] | | [ 0.09] | [ 0.12] | | [ -0.27] | | [ 0.05] | [ 0.17] | |
| -0.26 | 0.20 | | | -2.24 | -1.06 | 0.31 | | | -3.08 |
| ( -0.80) | ( 0.76) | | | ( -2.70) | ( -1.95) | ( 0.75) | | | ( -1.77) |
| [ -0.30] | [ 0.23] | | | [ -2.60] | [ -0.65] | [ 0.19] | | | [ -1.87] |
| -0.24 | | 0.21 | 0.01 | -2.28 | -1.05 | | 0.06 | 0.35 | -3.12 |
| ( -0.75) | | ( 0.84) | ( 0.05) | ( -2.73) | ( -1.89) | | ( 0.12) | ( 1.09) | ( -1.82) |
| [ -0.28] | | [ 0.24] | [ 0.02] | [ -2.64] | [ -0.64] | | [ 0.03] | [ 0.22] | [ -1.90] |

**Table 8**
**Intensity of Follow-up Jumps**
This table reports the results for the following logit regression

$$P(J^F_{t+1} = 1|U_t) = \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$
$$P(J^F_{t+1} = 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$

where $J^F_t = 1$ if there is a follow-on jump at day $t$, and zero otherwise, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}^-_t/\sigma(\bar{J}^-), \bar{J}^+_t/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}^-_t$ is the past intensity of negative jumps, $\bar{J}^+_t$ is the past intensity of positive jumps, $D_t$ is the diffusive variance, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$. The coefficient estimates for $\beta$ are reported in the first row, and the corresponding t-statistics are reported in the parentheses. The average marginal effects, $\overline{P_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^F_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the square brackets. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.46 | | | | | 0.27 | | | | |
| ( 2.54) | | | | | ( 1.43) | | | | |
| [ 1.01] | | | | | [ 0.76] | | | | |
| | 0.79 | | | | | 0.94 | | | |
| | ( 4.26) | | | | | ( 5.59) | | | |
| | [ 1.72] | | | | | [ 2.63] | | | |
| | | 0.63 | 0.33 | | | | 0.82 | 0.26 | |
| | | ( 3.45) | ( 2.06) | | | | ( 4.71) | ( 1.93) | |
| | | [ 1.37] | [ 0.73] | | | | [ 2.30] | [ 0.72] | |
| | | | | -1.43 | | | | | -3.04 |
| | | | | ( -2.22) | | | | | ( -3.35) |
| | | | | [ -3.14] | | | | | [ -8.77] |
| 0.11 | 0.75 | | | | 0.11 | 0.93 | | | |
| ( 0.51) | ( 3.59) | | | | ( 0.42) | ( 5.46) | | | |
| [ 0.25] | [ 1.62] | | | | [ 0.32] | [ 2.61] | | | |
| 0.14 | | 0.61 | 0.29 | | 0.12 | | 0.81 | 0.26 | |
| ( 0.62) | | ( 3.24) | ( 1.63) | | ( 0.44) | | ( 4.55) | ( 1.96) | |
| [ 0.31] | | [ 1.33] | [ 0.63] | | [ 0.33] | | [ 2.26] | [ 0.73] | |
| 0.08 | 0.72 | | | -1.22 | -0.05 | 0.90 | | | -2.67 |
| ( 0.32) | ( 3.47) | | | ( -1.71) | ( -0.15) | ( 4.91) | | | ( -2.34) |
| [ 0.17] | [ 1.57] | | | [ -2.67] | [ -0.14] | [ 2.52] | | | [ -7.51] |
| 0.12 | | 0.66 | 0.21 | -1.40 | -0.05 | | 0.79 | 0.23 | -2.67 |
| ( 0.49) | | ( 3.58) | ( 1.15) | ( -1.99) | ( -0.15) | | ( 4.23) | ( 1.75) | ( -2.33) |
| [ 0.27] | | [ 1.43] | [ 0.46] | [ -3.05] | [ -0.14] | | [ 2.22] | [ 0.65] | [ -7.51] |

**Table 9**
**Intensity of Negative and Positive Follow-up Jumps**
This table reports the results for the following logit regressions

$$P(J^{F*}_{t+1} = 1|U_t) = \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$
$$P(J^{F*}_{t+1} = 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+U_t\beta)}}$$

where $J^{F*}_{t+1} = J^{F-}_{t+1}$, negative follow-on jump in Panel A, $J^{F*}_{t+1} = J^{F+}_{t+1}$, positive follow-on jump, in Panel B, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}^-_t/\sigma(\bar{J}^-), \bar{J}^+_t/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}^-_t$ is the past intensity of negative jumps, $\bar{J}^+_t$ is the past intensity of positive jumps, $D_t$ is the diffusive variance, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$. The coefficient estimates for $\beta$ are reported in the first row, and the corresponding t-statistics are reported in the parentheses. The average marginal effects, $\overline{P_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^{F*}_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the square brackets. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

A. $J^{F-}_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.55 | | | | | 0.30 | | | | |
| ( 2.32) | | | | | ( 1.49) | | | | |
| [ 0.71] | | | | | [ 0.75] | | | | |
| | 0.58 | | | | | 0.97 | | | |
| | ( 2.49) | | | | | ( 5.42) | | | |
| | [ 0.74] | | | | | [ 2.44] | | | |
| | | 0.56 | 0.14 | | | | 0.86 | 0.26 | |
| | | ( 2.44) | ( 0.63) | | | | ( 4.63) | ( 1.83) | |
| | | [ 0.72] | [ 0.18] | | | | [ 2.14] | [ 0.64] | |
| | | | | -0.50 | | | | | -2.99 |
| | | | | ( -0.76) | | | | | ( -3.14) |
| | | | | [ -0.64] | | | | | [ -7.73] |
| 0.37 | 0.42 | | | | 0.17 | 0.96 | | | |
| ( 1.32) | ( 1.63) | | | | ( 0.58) | ( 5.29) | | | |
| [ 0.47] | [ 0.54] | | | | [ 0.43] | [ 2.42] | | | |
| 0.40 | | 0.51 | 0.01 | | 0.17 | | 0.84 | 0.26 | |
| ( 1.46) | | ( 2.10) | ( 0.02) | | ( 0.59) | | ( 4.45) | ( 1.88) | |
| [ 0.52] | | [ 0.65] | [ 0.01] | | [ 0.43] | | [ 2.11] | [ 0.66] | |
| 0.37 | 0.41 | | | -0.31 | 0.03 | 0.93 | | | -2.57 |
| ( 1.25) | ( 1.59) | | | ( -0.49) | ( 0.10) | ( 4.76) | | | ( -2.12) |
| [ 0.47] | [ 0.53] | | | [ -0.40] | [ 0.09] | [ 2.33] | | | [ -6.48] |
| 0.41 | | 0.53 | -0.04 | -0.51 | 0.03 | | 0.82 | 0.23 | -2.58 |
| ( 1.41) | | ( 2.22) | ( -0.16) | ( -0.71) | ( 0.10) | | ( 4.15) | ( 1.67) | ( -2.11) |
| [ 0.53] | | [ 0.68] | [ -0.05] | [ -0.66] | [ 0.09] | | [ 2.07] | [ 0.59] | [ -6.49] |

**Table 9** (Cont'd)

B. $J^{F+}_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.33 | | | | | 0.02 | | | | |
| ( 1.19) | | | | | ( 0.04) | | | | |
| [ 0.30] | | | | | [ 0.01] | | | | |
| | 1.15 | | | | | 0.68 | | | |
| | ( 3.57) | | | | | ( 1.35) | | | |
| | [ 1.03] | | | | | [ 0.20] | | | |
| | | 0.78 | 0.60 | | | | 0.53 | 0.26 | |
| | | ( 2.57) | ( 2.44) | | | | ( 1.00) | ( 0.62) | |
| | | [ 0.70] | [ 0.54] | | | | [ 0.16] | [ 0.08] | |
| | | | | -2.51 | | | | | -3.10 |
| | | | | ( -2.80) | | | | | ( -1.19) |
| | | | | [ -2.46] | | | | | [ -0.94] |
| -0.31 | 1.28 | | | | -0.24 | 0.72 | | | |
| ( -0.84) | ( 3.54) | | | | ( -0.33) | ( 1.40) | | | |
| [ -0.27] | [ 1.15] | | | | [ -0.07] | [ 0.21] | | | |
| -0.30 | | 0.84 | 0.69 | | -0.22 | | 0.58 | 0.26 | |
| ( -0.81) | | ( 2.71) | ( 2.60) | | ( -0.30) | | ( 1.05) | ( 0.60) | |
| [ -0.27] | | [ 0.75] | [ 0.62] | | [ -0.06] | | [ 0.17] | [ 0.07] | |
| -0.54 | 1.15 | | | -2.34 | -0.64 | 0.70 | | | -3.19 |
| ( -1.49) | ( 3.97) | | | ( -2.58) | ( -0.71) | ( 1.30) | | | ( -1.09) |
| [ -0.54] | [ 1.15] | | | [ -2.34] | [ -0.19] | [ 0.21] | | | [ -0.96] |
| -0.52 | | 0.83 | 0.54 | -2.40 | -0.63 | | 0.56 | 0.25 | -3.18 |
| ( -1.46) | | ( 3.16) | ( 2.28) | ( -2.65) | ( -0.70) | | ( 0.99) | ( 0.59) | ( -1.09) |
| [ -0.53] | | [ 0.84] | [ 0.55] | [ -2.41] | [ -0.19] | | [ 0.17] | [ 0.08] | [ -0.96] |

# Table 10
## Intensity of Signed Out-of-the-Blue and Follow-up Jumps

This table reports the results for the following logit regressions

$$
\begin{aligned}
P(J^{*s}_{t+1} = -1|U_t) &= \frac{1}{1 + e^{-(\beta_0^- + U_t\beta)}} \\
P(J^{*s}_{t+1} = 0|U_t) &= \frac{1}{1 + e^{-(\beta_0^+ + U_t\beta)}} - \frac{1}{1 + e^{-(\beta_0^- + U_t\beta)}} \\
P(J^{*s}_{t+1} = 1|U_t) &= 1 - \frac{1}{1 + e^{-(\beta_0^+ + U_t\beta)}}
\end{aligned}
$$

where $J^{*s}_{t+1} = J^{Os}_{t+1}$, the signed out-of-the-blue jump, in Panel A, $J^{*s}_{t+1} = J^{Fs}_{t+1}$, the signed follow-on jump, in Panel B, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}^-_t/\sigma(\bar{J}^-), \bar{J}^+_t/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}^-_t$ is the past intensity of negative jumps, $\bar{J}^+_t$ is the past intensity of positive jumps, $D_t$ is the diffusive variance, and $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$. The coefficient estimates for $\beta$ are reported in the first row, and the corresponding t-statistics are reported in the parentheses. The average marginal effects for a negative jump, $\overline{P^{*-}_{U_i}} = \sum_{t=1}^{T-1} \partial P(J^{*s}_{t+1} = -1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the square brackets. The average marginal effects for a positive jump, $\overline{P^{*+}_{U}} = \sum_{t=1}^{T-1} \partial P(J^{*s}_{t+1} = 1|U_t)/\partial U_{it}/(T-1)$, multiplied by 1000, are reported in the curly braces. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

A. $J^{Os}_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| 0.27 | | | | | 0.39 | | | | |
| ( 2.05) | | | | | ( 2.42) | | | | |
| [ 0.70] | | | | | [ 1.22] | | | | |
| {-0.30} | | | | | {-0.23} | | | | |
| | -0.07 | | | | | 0.08 | | | |
| | ( -0.53) | | | | | ( 0.54) | | | |
| | [ -0.18] | | | | | [ 0.26] | | | |
| | { 0.08} | | | | | {-0.05} | | | |
| | | -0.22 | 0.14 | | | | 0.01 | 0.12 | |
| | | ( -1.47) | ( 0.95) | | | | ( 0.08) | ( 0.77) | |
| | | [ -0.56] | [ 0.36] | | | | [ 0.04] | [ 0.38] | |
| | | { 0.24} | {-0.15} | | | | {-0.01} | {-0.07} | |
| | | | | -0.08 | | | | | -0.26 |
| | | | | ( -0.71) | | | | | ( -1.69) |
| | | | | [ -0.21] | | | | | [ -0.80] |
| | | | | { 0.09} | | | | | { 0.15} |
| 0.42 | -0.30 | | | | 0.39 | 0.00 | | | |
| ( 2.77) | ( -1.86) | | | | ( 2.39) | ( 0.02) | | | |
| [ 1.08] | [ -0.76] | | | | [ 1.21] | [ 0.01] | | | |
| {-0.46} | { 0.32} | | | | {-0.23} | {-0.00} | | | |
| 0.41 | | -0.31 | -0.02 | | 0.43 | | -0.13 | 0.18 | |
| ( 2.63) | | ( -2.02) | ( -0.12) | | ( 2.58) | | ( -0.67) | ( 1.18) | |
| [ 1.04] | | [ -0.81] | [ -0.05] | | [ 1.34] | | [ -0.39] | [ 0.56] | |
| {-0.44} | | { 0.34} | { 0.02} | | {-0.25} | | { 0.07} | {-0.11} | |
| 0.42 | -0.30 | | | 0.01 | 0.40 | -0.03 | | | -0.23 |
| ( 2.69) | ( -1.85) | | | ( 0.04) | ( 2.33) | ( -0.16) | | | ( -1.48) |
| [ 1.08] | [ -0.76] | | | [ 0.01] | [ 1.23] | [ -0.08] | | | [ -0.71] |
| {-0.46} | { 0.32} | | | {-0.01} | {-0.23} | { 0.02} | | | { 0.13} |
| 0.42 | | -0.32 | -0.02 | 0.03 | 0.44 | | -0.16 | 0.18 | -0.24 |
| ( 2.61) | | ( -2.02) | ( -0.11) | ( 0.23) | ( 2.53) | | ( -0.85) | ( 1.18) | ( -1.53) |
| [ 1.07] | | [ -0.83] | [ -0.04] | [ 0.08] | [ 1.36] | | [ -0.50] | [ 0.55] | [ -0.74] |
| {-0.45} | | { 0.35} | { 0.02} | {-0.04} | {-0.26} | | { 0.09} | {-0.10} | { 0.14} |

**Table 10** (Cont'd)

B. $J^{Fs}_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}_t^-$ | $\bar{J}_t^+$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}_t^-$ | $\bar{J}_t^+$ | $D_t$ |
| 0.17 | | | | | 0.26 | | | | |
| ( 1.00) | | | | | ( 1.40) | | | | |
| [ 0.22] | | | | | [ 0.66] | | | | |
| {-0.15} | | | | | {-0.08} | | | | |
| | -0.09 | | | | | 0.85 | | | |
| | ( -0.54) | | | | | ( 4.94) | | | |
| | [ -0.12] | | | | | [ 2.12] | | | |
| | { 0.08} | | | | | {-0.25} | | | |
| | | 0.10 | -0.21 | | | | 0.74 | 0.22 | |
| | | ( 0.53) | ( -1.10) | | | | ( 4.17) | ( 1.56) | |
| | | [ 0.13] | [ -0.27] | | | | [ 1.86] | [ 0.56] | |
| | | {-0.09} | { 0.19} | | | | {-0.22} | {-0.07} | |
| | | | | 0.04 | | | | | -0.34 |
| | | | | ( 0.29) | | | | | ( -1.99) |
| | | | | [ 0.06] | | | | | [ -0.84] |
| | | | | {-0.04} | | | | | { 0.10} |
| 0.30 | -0.26 | | | | 0.10 | 0.83 | | | |
| ( 1.53) | ( -1.25) | | | | ( 0.41) | ( 4.79) | | | |
| [ 0.39] | [ -0.33] | | | | [ 0.25] | [ 2.10] | | | |
| {-0.27} | { 0.23} | | | | {-0.03} | {-0.24} | | | |
| 0.33 | | 0.03 | -0.35 | | 0.10 | | 0.73 | 0.23 | |
| ( 1.67) | | ( 0.15) | ( -1.67) | | ( 0.43) | | ( 3.98) | ( 1.60) | |
| [ 0.43] | | [ 0.04] | [ -0.45] | | [ 0.26] | | [ 1.83] | [ 0.57] | |
| {-0.30} | | {-0.03} | { 0.32} | | {-0.03} | | {-0.21} | {-0.07} | |
| 0.34 | -0.27 | | | 0.10 | 0.06 | 0.83 | | | -0.26 |
| ( 1.65) | ( -1.32) | | | ( 0.79) | ( 0.23) | ( 4.64) | | | ( -1.14) |
| [ 0.43] | [ -0.35] | | | [ 0.13] | [ 0.15] | [ 2.09] | | | [ -0.64] |
| {-0.30} | { 0.24} | | | {-0.09} | {-0.02} | {-0.24} | | | { 0.07} |
| 0.35 | | 0.01 | -0.35 | 0.08 | 0.06 | | 0.72 | 0.23 | -0.26 |
| ( 1.74) | | ( 0.05) | ( -1.63) | ( 0.55) | ( 0.25) | | ( 3.89) | ( 1.62) | ( -1.14) |
| [ 0.45] | | [ 0.01] | [ -0.44] | [ 0.10] | [ 0.15] | | [ 1.81] | [ 0.58] | [ -0.64] |
| {-0.32} | | {-0.01} | { 0.31} | {-0.07} | {-0.02} | | {-0.21} | {-0.07} | { 0.07} |

## Table 11
## Size of Out-of-the-Blue and Follow-up Jumps

This table reports the results for the following OLS regressions

$$Z^*_{t+1} = \gamma_0 + U_t\gamma + \varepsilon_{t+1}$$

where $Z^*_{t+1} = Z^O_{t+1}$, the out-of-the-blue jump size in Panel A, $Z^*_{t+1} = Z^F_{t+1}$, the follow-on jump size in Panel B, $U_t = (Y_t/\sigma(Y), \bar{J}_t/\sigma(\bar{J}), \bar{J}^-_t/\sigma(\bar{J}^-), \bar{J}^+_t/\sigma(\bar{J}^+), D_t/\sigma(D))$ with $\sigma(\cdot)$ indicating the standard deviation, $Y_t$ is the relative level of the index, $\bar{J}_t$ is the past jump intensity, $\bar{J}^-_t$ is the past intensity of negative jumps, $\bar{J}^+_t$ is the past intensity of positive jumps, $D_t$ is the diffusive variance, and $\gamma = (\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5)'$. The coefficient estimates for $\gamma$ multiplied by 1000 are reported in the first row, and the corresponding t-statistics adjusted for heteroscedasticity are reported in the parentheses. The results for the S&P 500 index (SPX) and the NASDAQ composite index (NDX) are reported in the left and right panels, respectively.

A. $Z^O_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| -9.15 | | | | | -27.43 | | | | |
| ( -1.80) | | | | | ( -4.72) | | | | |
| | 3.31 | | | | | 1.53 | | | |
| | ( 0.73) | | | | | ( 0.26) | | | |
| | | 2.54 | 1.30 | | | | 0.18 | 1.54 | |
| | | ( 0.52) | ( 0.26) | | | | ( 0.03) | ( 0.50) | |
| | | | | -48.39 | | | | | -40.20 |
| | | | | ( -2.99) | | | | | ( -1.38) |
| -14.31 | 10.30 | | | | -29.61 | 6.84 | | | |
| ( -2.43) | ( 2.02) | | | | ( -5.17) | ( 1.75) | | | |
| -14.45 | | 5.43 | 6.83 | | -29.73 | | 6.77 | 1.05 | |
| ( -2.36) | | ( 1.17) | ( 1.15) | | ( -5.20) | | ( 1.71) | ( 0.37) | |
| -14.94 | 9.96 | | | -49.65 | -28.49 | 3.77 | | | -35.27 |
| ( -2.85) | ( 2.08) | | | ( -3.41) | ( -3.59) | ( 1.08) | | | ( -2.20) |
| -14.89 | | 6.25 | 5.40 | -49.76 | -28.60 | | 3.95 | 0.38 | -35.23 |
| ( -2.79) | | ( 1.49) | ( 1.10) | ( -3.35) | ( -3.60) | | ( 1.04) | ( 0.16) | ( -2.20) |

B. $Z^F_{t+1}$

| SPX | | | | | NDX | | | | |
|---|---|---|---|---|---|---|---|---|---|
| $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ | $Y_t$ | $\bar{J}_t$ | $\bar{J}^-_t$ | $\bar{J}^+_t$ | $D_t$ |
| -11.73 | | | | | -0.50 | | | | |
| ( -1.12) | | | | | ( -0.05) | | | | |
| | 9.33 | | | | | -9.76 | | | |
| | ( 1.31) | | | | | ( -1.17) | | | |
| | | 1.18 | 7.89 | | | | -7.94 | -4.34 | |
| | | ( 0.18) | ( 1.16) | | | | ( -1.13) | ( -0.97) | |
| | | | | -110.49 | | | | | -105.74 |
| | | | | ( -4.57) | | | | | ( -3.61) |
| -21.43 | 21.34 | | | | 4.68 | -10.52 | | | |
| ( -1.89) | ( 2.52) | | | | ( 0.52) | ( -1.22) | | | |
| -26.71 | | 4.32 | 19.82 | | 3.83 | | -8.55 | -4.36 | |
| ( -1.94) | | ( 0.90) | ( 2.10) | | ( 0.44) | | ( -1.19) | ( -0.98) | |
| -18.42 | 14.98 | | | -107.40 | -13.27 | -5.07 | | | -116.06 |
| ( -2.06) | ( 2.92) | | | ( -5.15) | ( -1.40) | ( -0.83) | | | ( -4.18) |
| -15.70 | | 12.85 | 4.78 | -113.30 | -13.74 | | -4.01 | -2.42 | -115.49 |
| ( -1.81) | | ( 2.37) | ( 1.16) | ( -5.30) | ( -1.37) | | ( -0.73) | ( -0.89) | ( -4.47) |

**Table 12**
**Simulation Analysis of Jump Detection Biases**
This table reports the results for the following logit regression based on the simulated data

$$
\begin{aligned}
P(J_{t+1} &= 1|U_t) = \frac{1}{1+e^{-(\beta_0+\beta_1 U_t)}} \\
P(J_{t+1} &= 0|U_t) = 1 - \frac{1}{1+e^{-(\beta_0+\beta_1 U_t)}},
\end{aligned}
$$

where $J_t = 1$ if there is a jump at day $t$, zero otherwise, $U_t = D_t/\sigma(D)$ with $\sigma(\cdot)$ indicating the standard deviation, and $D_t$ is the diffusive variance. The data are simulated from the model

$$
\begin{aligned}
dS_u &= \left(\mu - \frac{1}{2}D_u^*\right)du + \sqrt{D_u^*}dw_{1,u} + Z_u dN_u \\
d\ln D_u^* &= (\theta - \kappa \ln D_u^*)du + \eta dw_{2,u},
\end{aligned}
$$

where $S_u$ is the log asset price, $D_u^*$ is the diffusive variance, $w_{1,u}$ and $w_{2,u}$ are standard Brownian motions with correlation $\rho$, $N_u$ is a counting process, and $Z_u$ is the jump size. The jump intensity is specified as $\lambda_u^* = \lambda_0^* + \lambda^* D_u^*$, and sizes of the jumps are bootstrapped from the actual data. The parameters estimated in Andersen et al. (2002) on the S&P index are used: $\mu = 0.0304$, $\theta = -0.012$, $\kappa = 0.0145$, $\eta = 0.1153$, and $\rho = -0.6127$. The table reports the 5th percentile, 50th percentile, and 95th percentile of the average jump intensity, $\tilde{J} = \sum_{t=1}^{T} J_t/T$, power and size in percentage, the coefficient estimate for $\beta_1$, the t-statistic for $\beta_1$, the average marginal effect, $\overline{P_U} = \sum_{t=1}^{T-1} \partial P(J_{t+1} = 1|U_t)/\partial U_t/(T-1)$, and $\lambda = \overline{P_U}/\sigma(D)$, from 100 samples, for various values of $\lambda_0^*$ and $\lambda^*$.

| | $\lambda_0^* = 0.01, \lambda^* = 0$ | | | $\lambda_0^* = 0.005, \lambda^* = 0.015$ | | | $\lambda_0^* = 0, \lambda^* = 0.03$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | P5 | P50 | P95 | P5 | P50 | P95 | P5 | P50 | P95 |
| $\tilde{J} \times 10^3$ | 7.40 | 8.69 | 9.94 | 9.20 | 11.07 | 12.71 | 11.45 | 13.38 | 15.31 |
| power | 61.22 | 66.44 | 73.39 | 62.32 | 68.50 | 73.77 | 63.50 | 69.53 | 74.57 |
| size | 0.15 | 0.21 | 0.29 | 0.15 | 0.22 | 0.28 | 0.14 | 0.21 | 0.30 |
| $\beta_1$ | -0.66 | -0.30 | -0.10 | -0.10 | 0.04 | 0.15 | 0.00 | 0.13 | 0.20 |
| t-statistic | -3.95 | -2.27 | -1.00 | -1.16 | 0.49 | 2.34 | 0.07 | 2.28 | 4.13 |
| $\overline{P_U} \times 10^3$ | -6.12 | -2.56 | -0.92 | -1.09 | 0.37 | 1.63 | 0.06 | 1.59 | 2.59 |
| $\lambda \times 10^3$ | -8.50 | -4.01 | -1.24 | -1.84 | 0.54 | 2.78 | 0.02 | 2.55 | 4.30 |

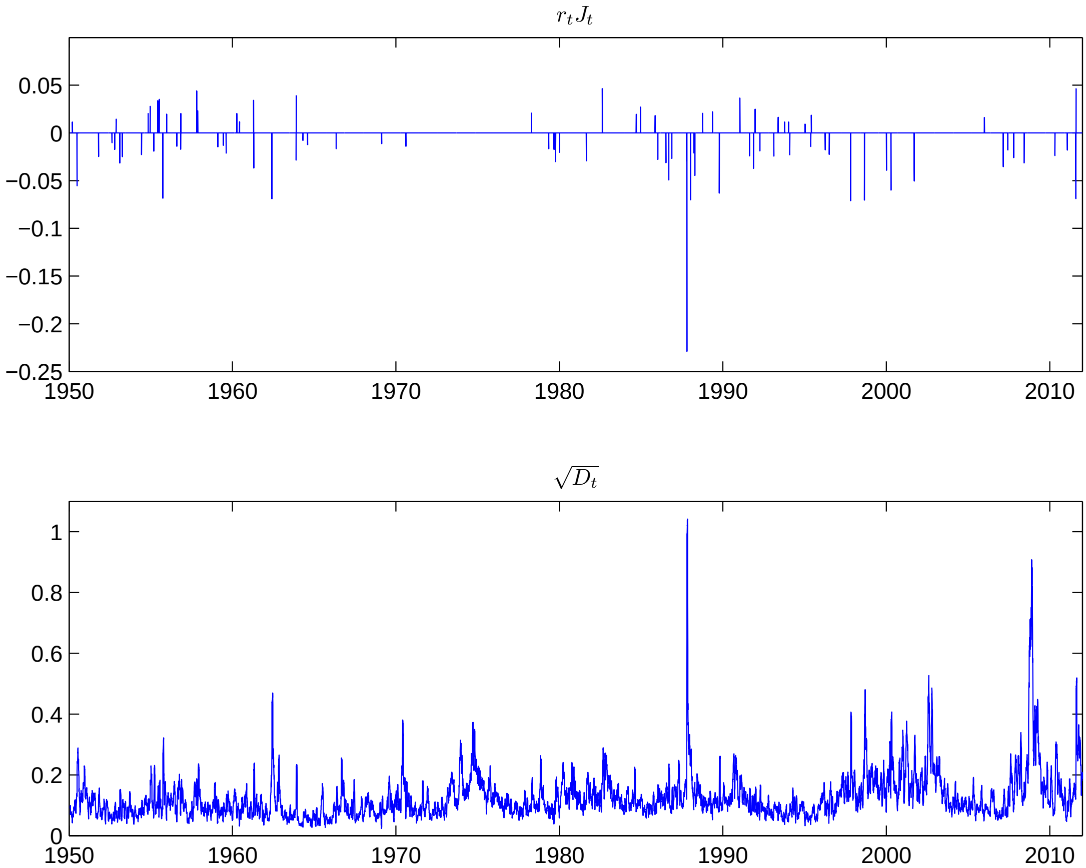


**Figure 1. SPX jumps and diffusive volatility**

The top panel shows the time-series plot of jump sizes, $r_t J_t$, and the bottom panel shows the time-series plot of diffusive volatility, $\sqrt{D_t}$, of the S&P 500 index (SPX).

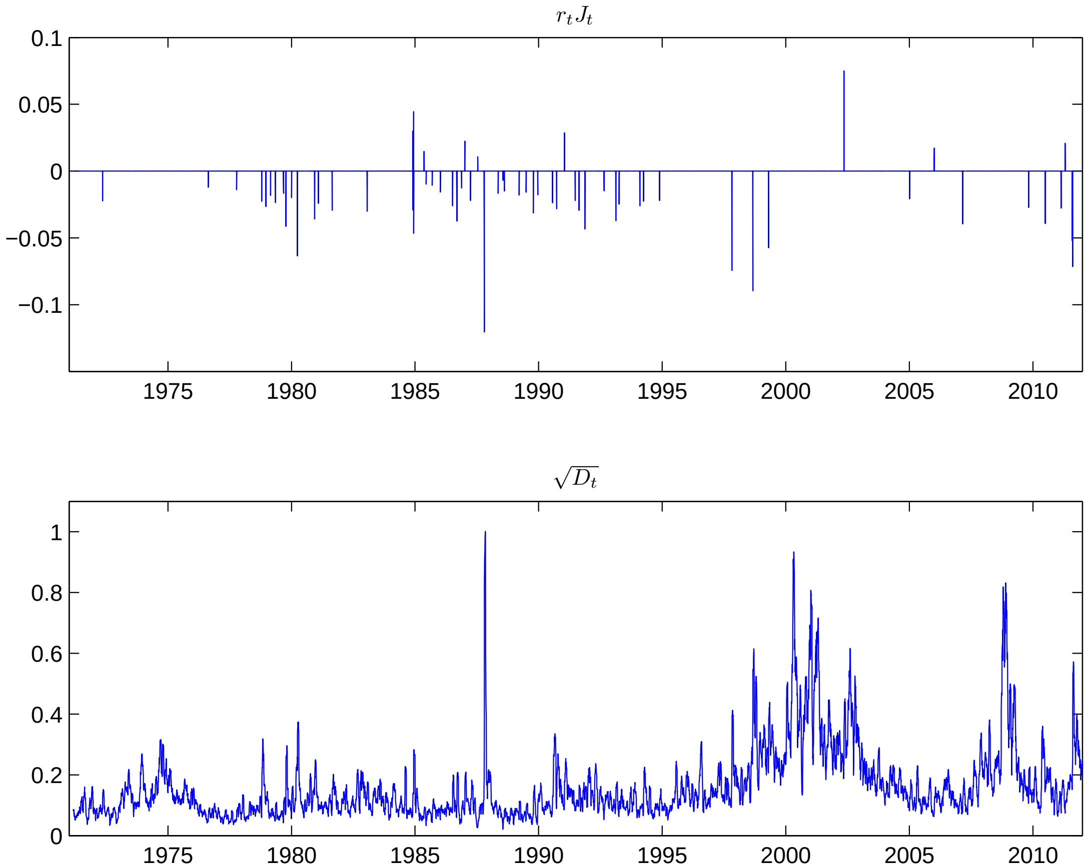


**Figure 2. NDX jumps and diffusive volatility**

The top panel shows the time-series plot of jump sizes, $r_tJ_t$, and the bottom panel shows the time-series plot of diffusive volatility, $\sqrt{D_t}$, of the NASDAQ composite index (NDX).

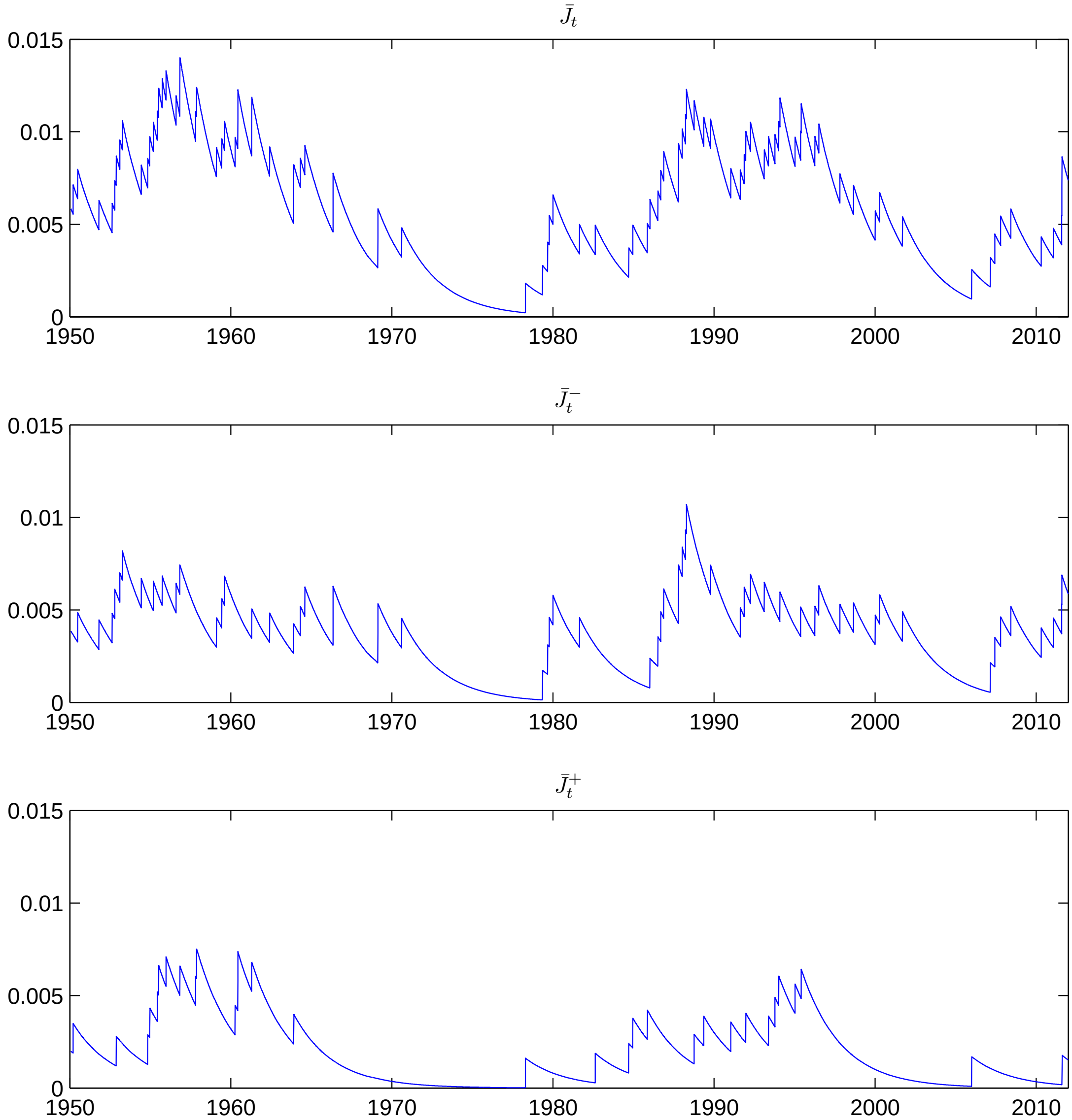


**Figure 3. SPX past jump intensities**

This figure shows the time-series plots of the exponential moving average of jump intensities of the S&P index (SPX). The top panel is for the total jump intensity, $\bar{J}_t$, the middle panel is for the intensity of negative jumps, $\bar{J}_t^-$, and the bottom panel is for the intensity of positive jumps, $\bar{J}_t^+$.

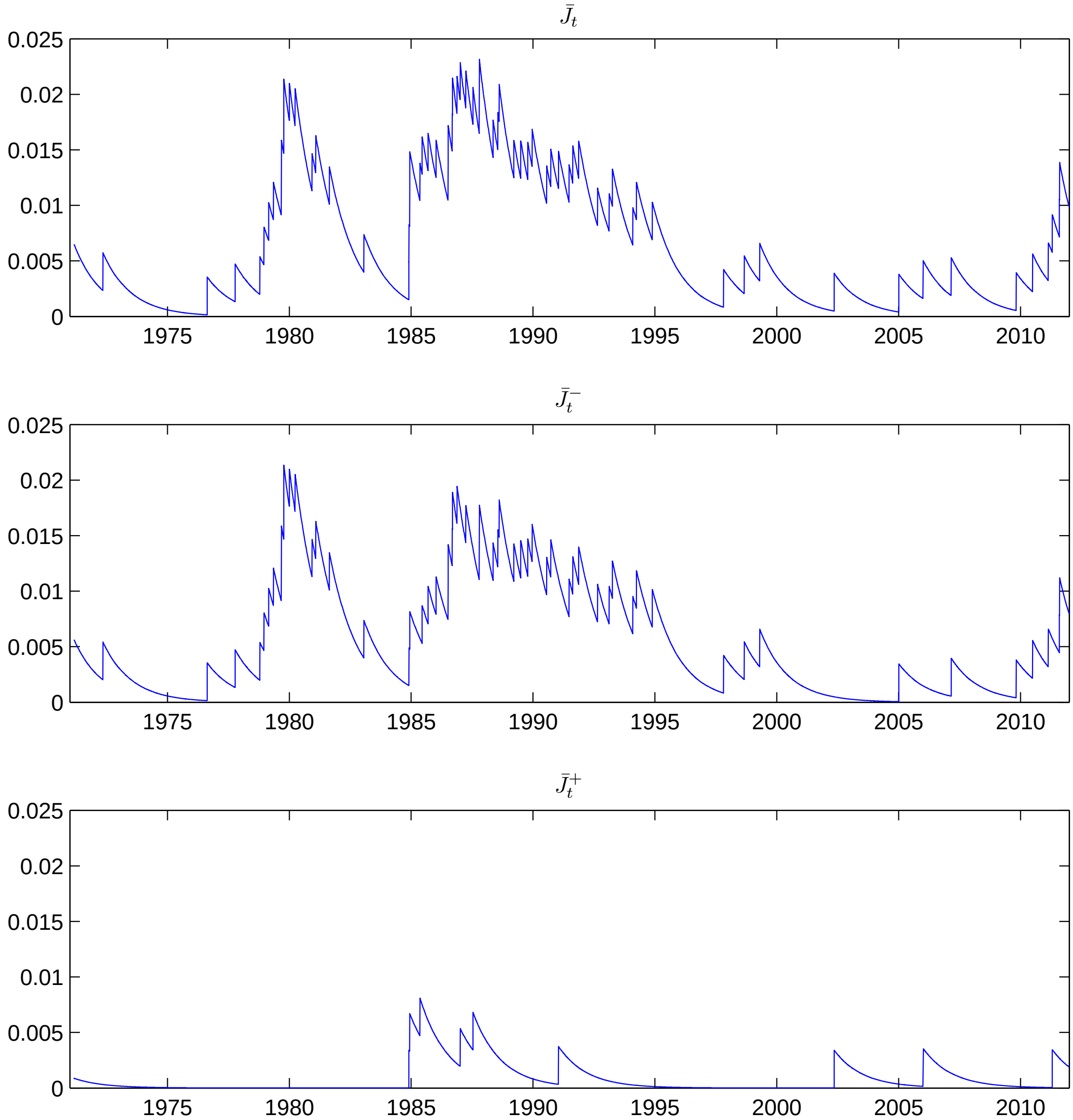


**Figure 4. NDX past jump intensities**

This figure shows the time-series plots of the exponential moving average of jump intensities of the NASDAQ composite index (NDX). The top panel is for the total jump intensity, $\bar{J}_t$, the middle panel is for the intensity of negative jumps, $\bar{J}_t^-$, and the bottom panel is for the intensity of positive jumps, $\bar{J}_t^+$.

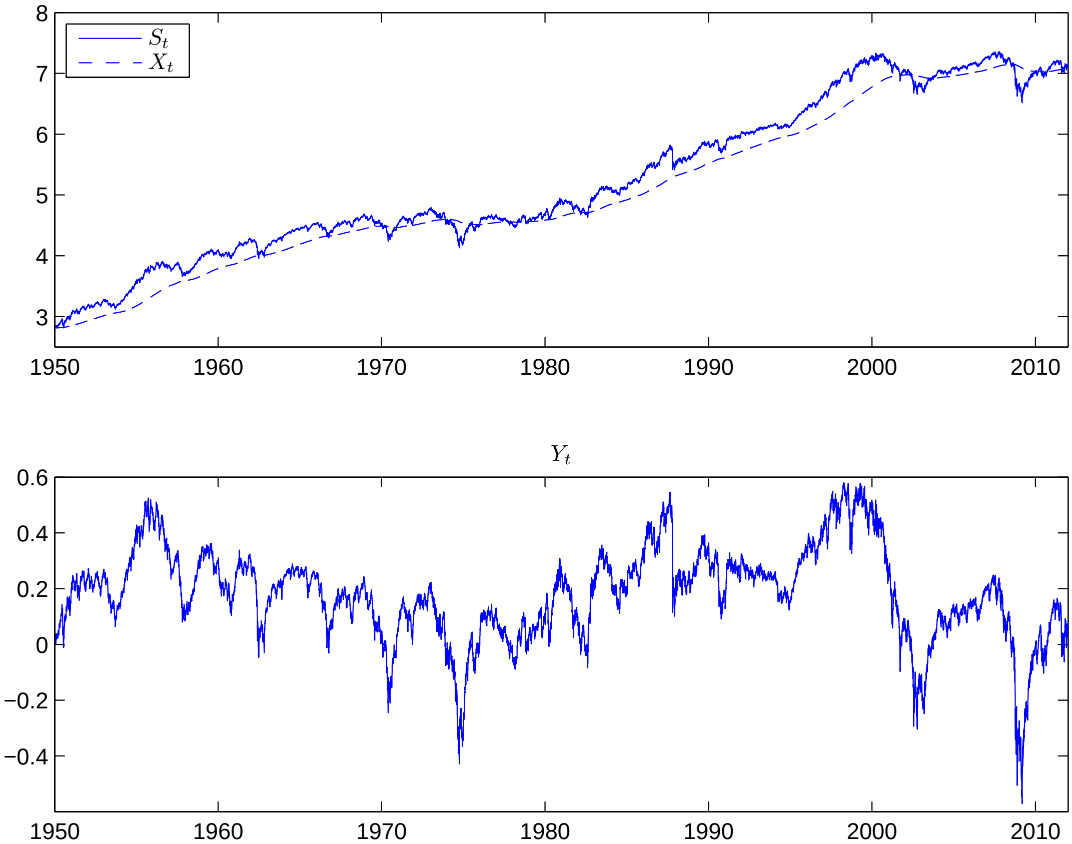


**Figure 5. SPX relative level**

The top panel shows the time-series plot of the index level in log scale, $S_t$, and its exponential moving average, $X_t$, and the bottom panel shows the relative stock price level, $Y_t$, of the S&P 500 index (SPX).

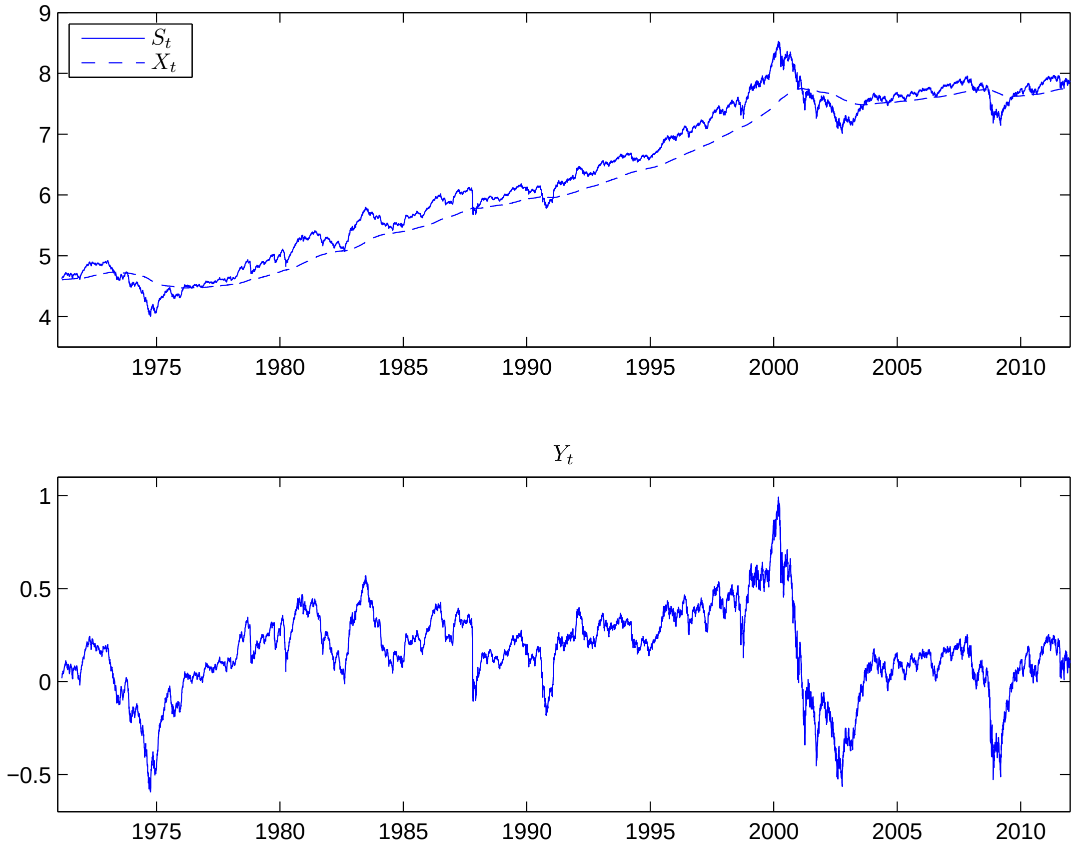


**Figure 6. NDX relative level**

The top panel shows the time-series plot of the index level in log scale, $S_t$, and its exponential moving average, $X_t$, and the bottom panel shows the relative stock price level, $Y_t$, of the NASDAQ composite index (NDX).

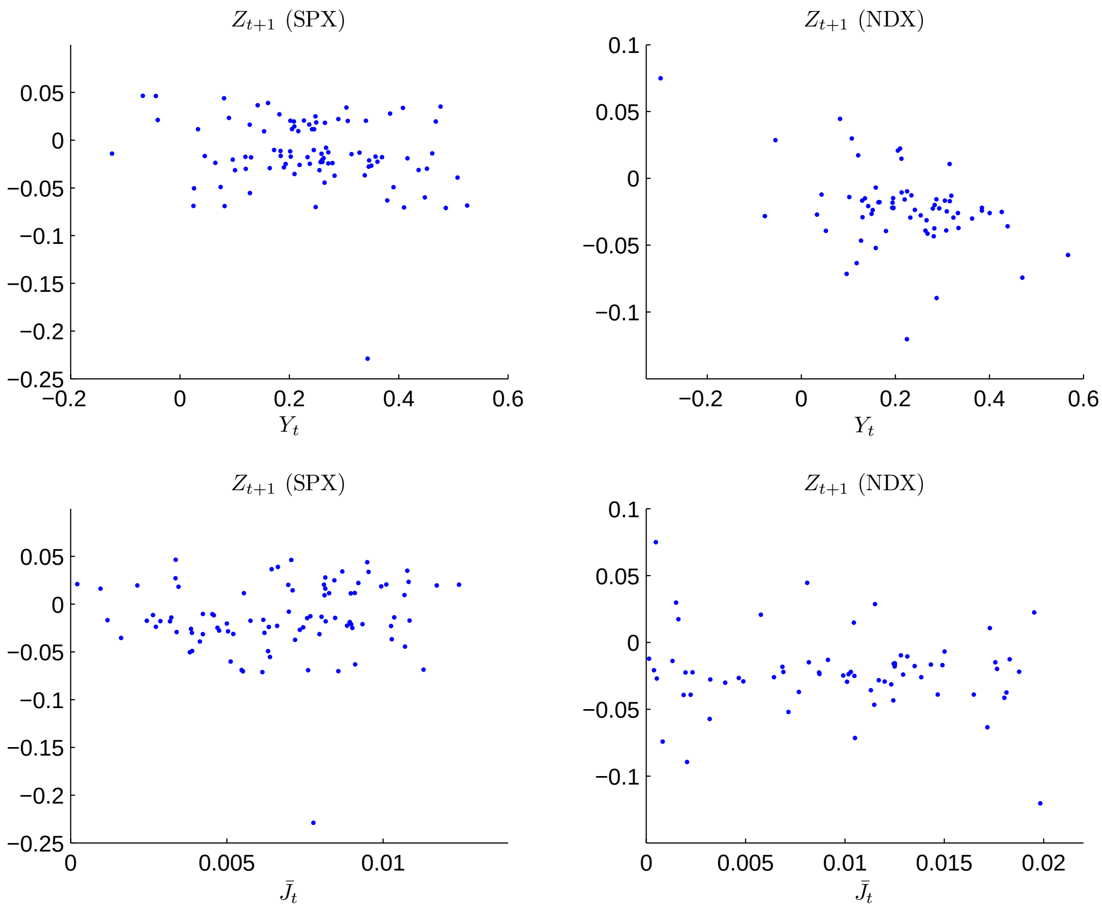


**Figure 7. Jump size vs. relative level and past jump intensity**

This figure shows the scatter plots of the jump size $Z_{t+1}$ against the relative stock price level $Y_t$ and the past jump intensity $\bar{J}_t$. The left panels are for the S&P 500 index (SPX), and the right panels are for the NASDAQ composite index (NDX).

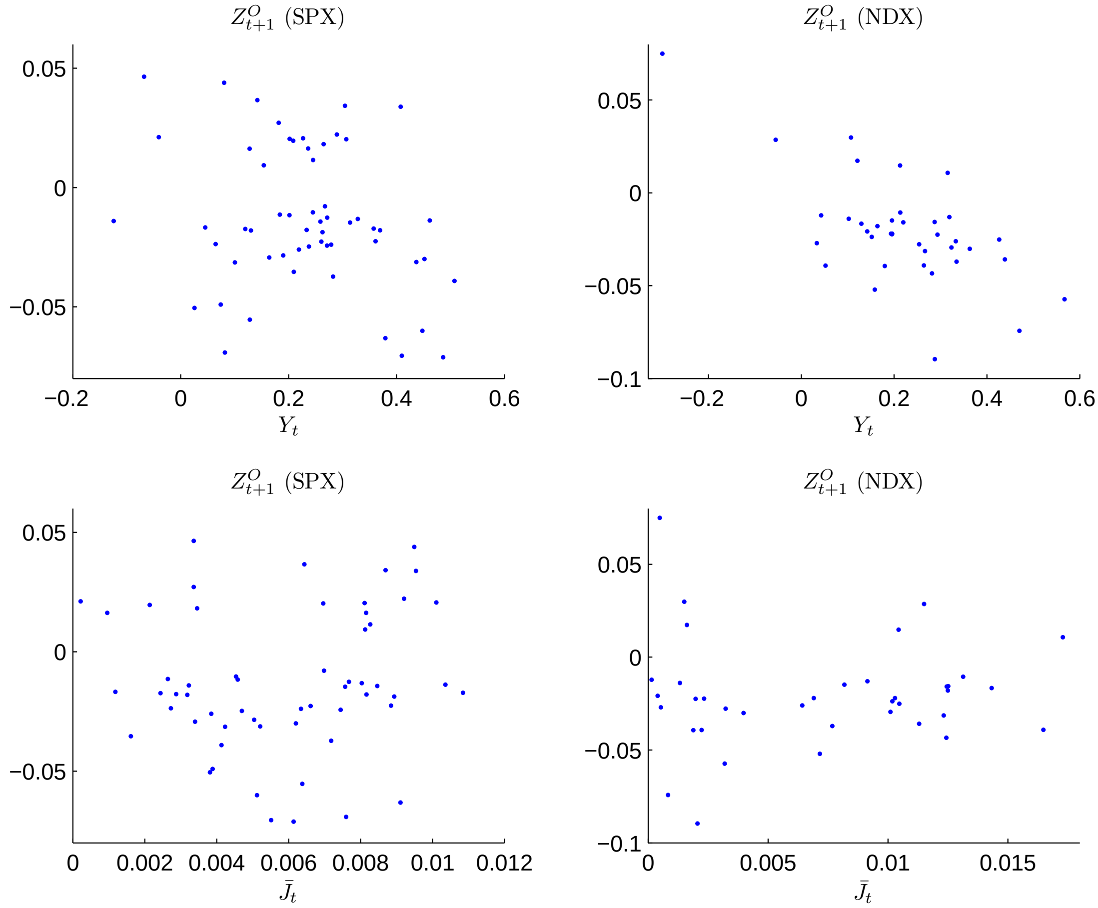


**Figure 8. Size of out-of-the-blue jumps vs. relative level and past jump intensity**

This figure shows the scatter plots of the size of out-of-the-blue jumps $Z^O_{t+1}$ against the relative stock price level $Y_t$ and the past jump intensity $\bar{J}_t$. The left panels are for the S&P 500 index (SPX), and the right panels are for the NASDAQ composite index (NDX).

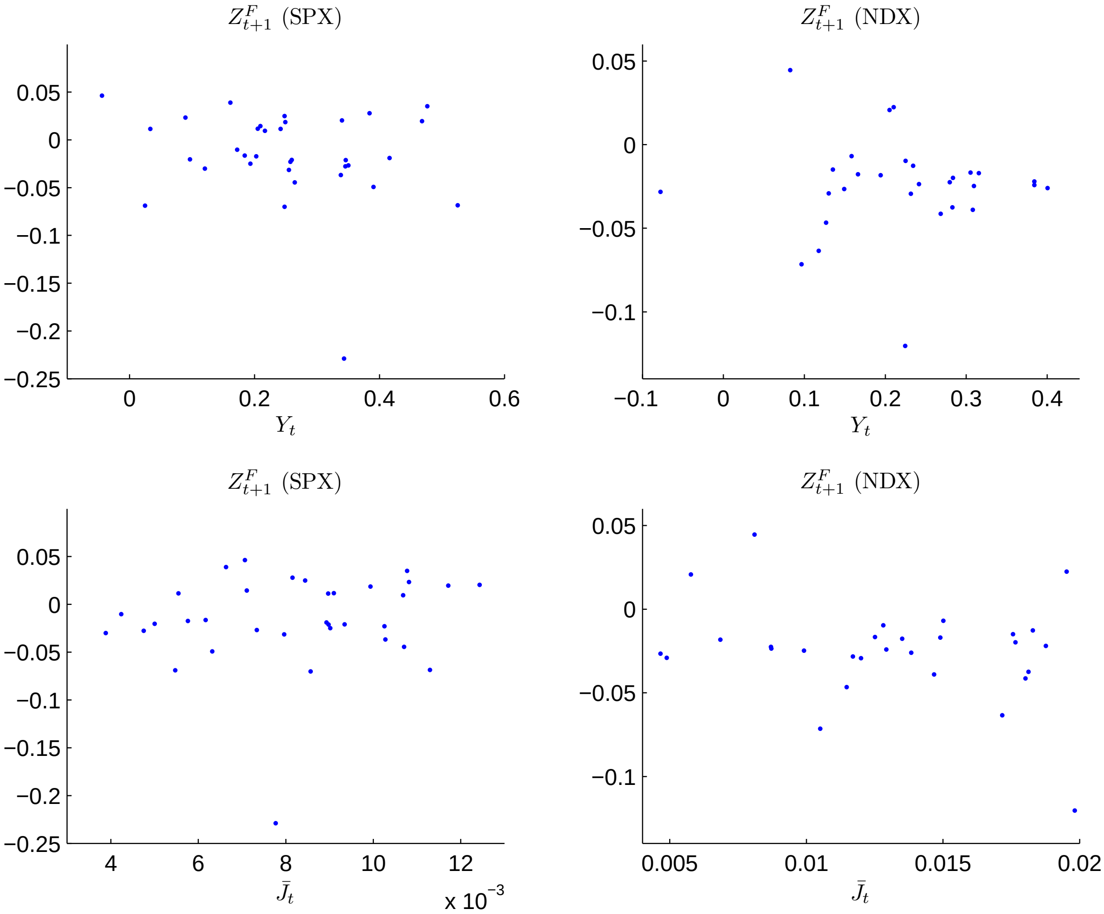


**Figure 9. Size of follow-on jumps vs. relative level and past jump intensity**
This figure shows the scatter plots of the size of follow-on jumps $Z^F_{t+1}$ against the relative stock price level $Y_t$ and the past jump intensity $\bar{J}_t$. The left panels are for the S&P 500 index (SPX), and the right panels are for the NASDAQ composite index (NDX).