Online Annex 3.1. Identifying Idiosyncratic Jumps in Stock Returns

With the advent of high-frequency data in financial economics, various methodologies for detecting price jumps or extreme return movements have emerged. This chapter adopts the thresholding technique for identifying jumps in our intraday dataset. Initially proposed by Mancini (2001) and subsequently popularized by Bollerzev et al. (2013), this technique has become a standard in the literature surrounding jump detection (Pelger, 2020; Aleti and Bollerzev, 2024). The core principle of the thresholding technique involves computing a time-varying threshold and classifying any intraday return whose absolute value exceeds this threshold as a jump.

We apply this technique to a sample of securities, utilizing intraday returns on selected dates between 2007 and 2024. The time-of-day (TOD) indicator, as outlined by Bollerzev et al. (2013), is calculated for each stock. This TOD indicator serves as an input for the threshold beyond which a stock return is considered a jump, whereby the indicator accounts for the fact that trading dynamics vary throughout the day. The TOD for the largest exchange traded fund tracking the S&P 500 index (SPY), illustrated in Online Annex Figure 3.1, panel 1, reflects a typical U-shaped pattern, indicative of the heightened volatility typically observed at the beginning and end of the trading day. Subsequently, we compute the time-varying threshold for each day utilizing the bipower variation[1]. Online Annex Figure 3.1, panel 2, depicts the thresholds and returns of SPY for three consecutive days in March 2020. Notably, on March 12, 2020—sometimes referred to as Black Thursday—the thresholding technique identifies two jumps for SPY.

By applying this methodology over the sample period, we derive a jump frequency for each year. Online Annex Figure 3.1, panel 3 (solid blue line), illustrates a downward trend in the jump frequency, decreasing from approximately 0.9 percent for 2007 to 0.5 percent for 2024. These estimates align closely with findings by Pelger (2020), who analyzed a panel of 332 stocks from 2004 to 2016. While less than 1 percent of price movements qualify as jumps, they account for a disproportionately significant share of realized variation[2]—approximately 10 percent (Online Annex Figure 3.1, panel 4, solid orange line) —underscoring their critical role in the analysis of stock price dynamics.

Jumps can be categorized as systematic and idiosyncratic jumps. Systematic jumps pertain to market-wide events, such as inflation data releases or monetary policy meetings. We employ two distinct techniques to identify idiosyncratic jumps. The first identifies idiosyncratic jumps as those occurring in individual stocks that do not coincide with jumps in large, liquid passive ETFs tracking the S&P 500 index (SPDR S&P 500 ETF Trust - SPY). The second technique involves regressing each stock's returns against SPY returns. By extracting the residuals from these regressions and applying the thresholding technique, we directly obtain a measure of idiosyncratic jumps. Both techniques yield similar results, as shown in Online Annex Figure 3.1, panels 3 and 4 (dotted and dashed lines).

[1] The bipower variation is an empirical estimate of the integrated volatility of a financial asset over a period, excluding the effects of jumps.

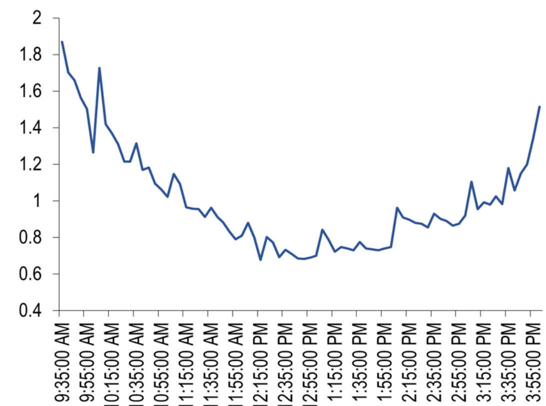
[2] The realized variation is an empirical estimate of the total variance of a financial asset over a period and provides a measure of total volatility, capturing both the continuous and jumps components of price movements.

Online Annex Figure 3.1. Jumps detection technique, frequency, and variation proportion.

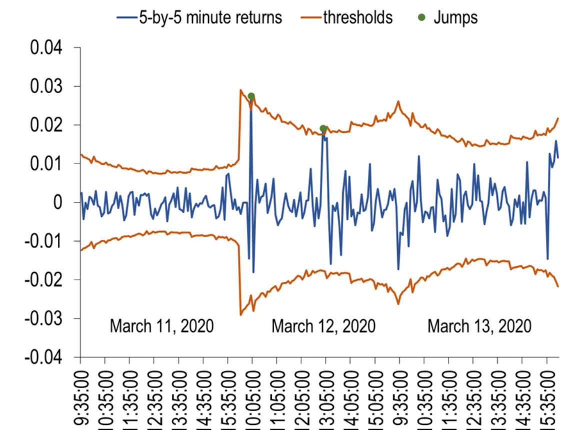
Higher volatility at the start and the end of the day leads to a U-shaped time-varying threshold ...

... that tends to be higher when broader market conditions are more stressed.

1. Time of day indicator for SPY



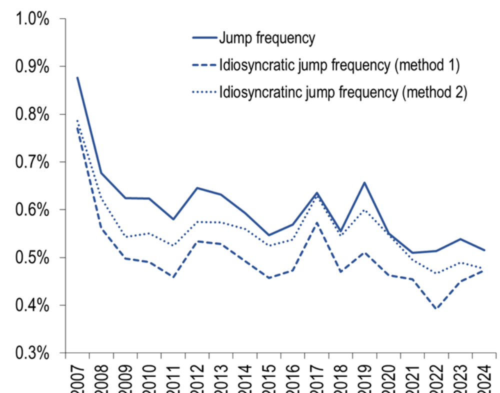
2. SPY returns and jumps detection thresholds in March 2020



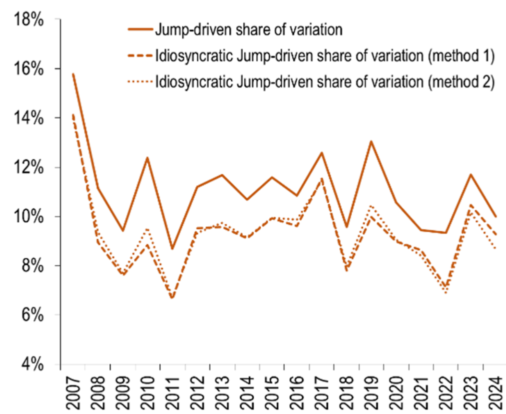
While the jumps in stock returns have become less frequent over the past two decades ...

... they do account for a relatively large share of the return variation

3. Jumps and Idiosyncratic Jumps frequency (Percent)



4. Share of Variation due to Jumps and Idiosyncratic jumps (Percent)



Sources: Bloomberg Finance L.P.; and IMF staff calculations.

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