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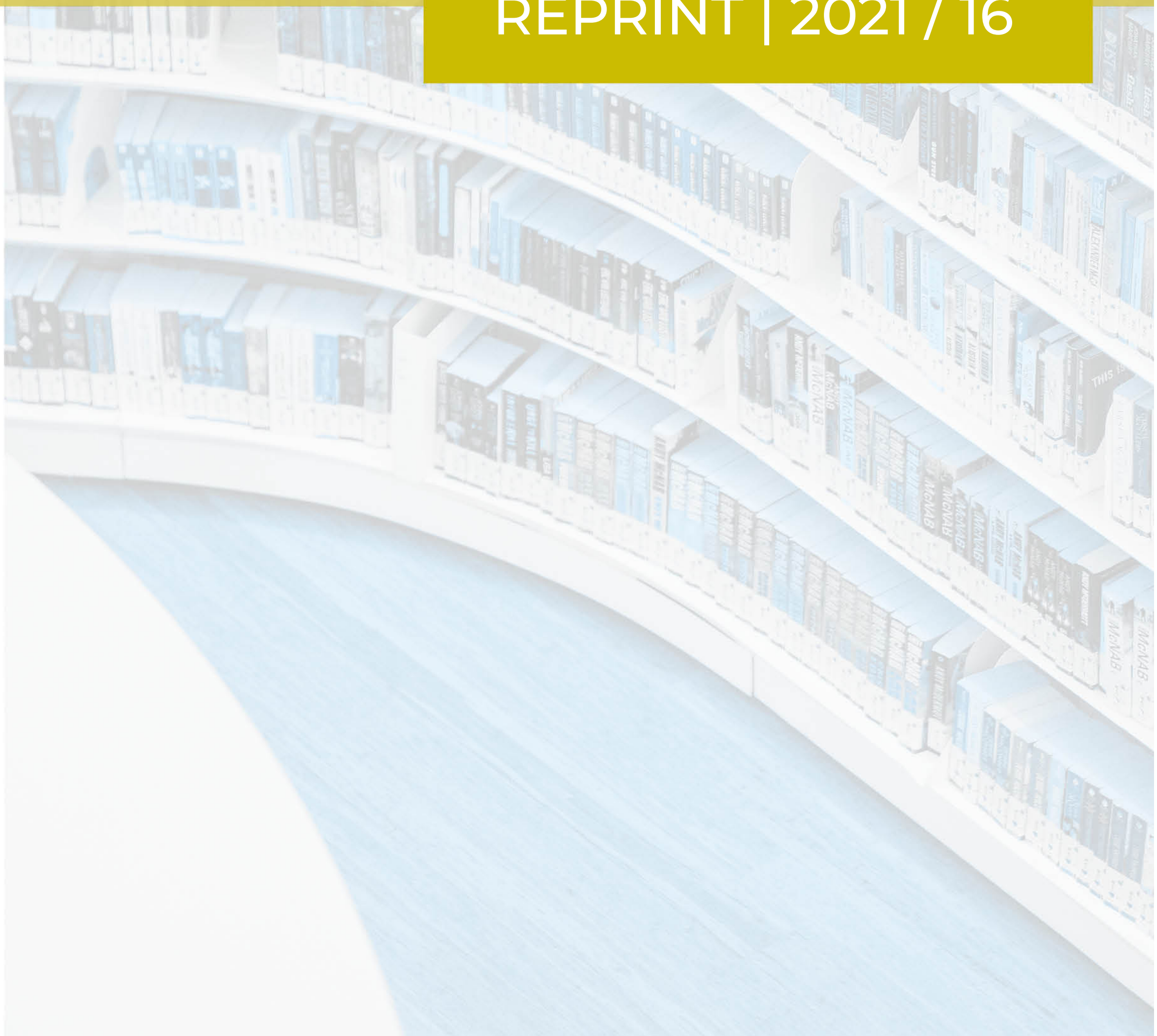

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Market Instability and Technical Trading at High Frequency: Evidence from NASDAQ Stocks

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Abstract

The promotion of financial stability is the mission of central banks and market authorities. This mission is more difficult to accomplish when trading activity is associated with financial instability in the form of intraday price jumps. While the literature has widely shown that exogenous news releases trigger these jumps, very little is known about the consequences of endogenous technical trading on market instability. Using high-frequency 5-minute data on 460 NASDAQ stocks from February to September 2017, we provide new evidence that sharp price movements during the day are also triggered by technical trading around special market configurations. When technical trading activity dominates, intraday price jumps are detected more frequently, and their direction becomes significantly predictable, particularly in small caps and in the energy sector. Our results support the view that the explanations for intraday market instability are not limited to news releases.

JEL: C12, C14, G12, G14

Keywords: Market instability, Jumps, Volatility, Trading signals, Technical analysis, High-frequency data, NASDAQ, Sectoral analysis, Small-cap stocks.

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1. Introduction

Central bank authorities have historically taken monetary policy measures to intervene in and stabilize the economy. As indicated by MacDonald et al. (2015), their mandate has more recently been extended to financial stability, the promotion of which is more difficult when asset prices jump frequently, quickly, and significantly. Price jumps not only are helpful for explaining periods of market instability (see, e.g., Bates, 2000) but also reveal why risk-averse investors shun assets exposed to sharp unforeseeable price comovements (Eraker et al., 2003).

While the role of news announcements in amplifying jumps has been well documented (Dewachter et al., 2014), the impact of trading activity *by itself* has not been examined thoroughly to understand the characteristics of jumps and, hence, the associated consequences for market stability. Whether or not market instability, in the form of intraday price jumps, is more likely to occur and more easily identified around specific trading patterns remains an open question. On the financial side, jumps have been recognized by market professionals for years. Better known as *gaps*, jumps are defined as unfilled spaces or intervals during which no trading takes place. Although jumps are popular among practitioners, they have not been studied in depth at the high frequency level in *combination* with trading configurations and robust statistical methods.

The theories behind trading configurations and jump detection share a common ground: both question the efficient market hypothesis (EMH) proposed by Fama (1970). On the one hand, the study of trading patterns through technical analysis contradicts the random walk hypothesis since it consists of studying past prices and volumes to predict future price changes, disregarding company fundamentals (Edwards et al. 2013; Zhu and Zhou, 2009). On the other hand, price jump theory does not consider the random walk process as a reliable stochastic process for explaining stock price movements (Tankov and Voltchkova, 2009). Despite this commonality and to the best of our knowledge, the information conveyed by trading patterns and jumps has always been studied separately (see, e.g., Fama and Blume, 1966; Jensen and Benington, 1970; Blume et al., 1994, Lo et al., 2000; Wang and Chan, 2009; Wang and Wu, 2015, and Cervelló-Royo et al., 2015).

Among the most well-known studies on trading configurations through technical analysis, Neely (2002) follows the approach of LeBaron (1999) to show that the abnormally high returns derived from the use of simple trading configurations, such as moving averages, cannot be explained by official interventions in the foreign exchange market since they precede them. There is also evidence of the substantial profitability of technical trading rules for some periods according to Hsu et al. (2016). Most recently, Ivanova et al. (2021) have shown that these substantial excess returns in forex markets are not explained by the higher risk implied by the use of trading rules. None of the many examined models account for technical profitability. This failure lends support to nonrisk explanations, such as adaptive markets or limits to arbitrage.

The broader implication of trading signals is confirmed by Huang (2008) when assessing extreme uncertainty and further by Neely et al. (2014) in characterizing the equity risk premium. Most interestingly, Zhu and Zhou (2009) develop a theoretical framework for the impact of trading signals on asset allocation, revealing that trading based on moving averages becomes more profitable around central banks' market rate decisions when price uncertainty increases and market stability is at stake. These market conditions are precisely characterized by more frequent volatility spikes. Such bouts of volatility, called jumps, are nevertheless latent, and their identification requires the use of robust identification techniques. Various econometric methods of identification have been developed, as further detailed in the next section (see, e.g., Barndorff-Nielsen and Shephard, 2006; Andersen et al., 2007, and Todorov and Tauchen, 2011).

The prevailing evidence suggests that the occurrence of jumps in asset prices is explained by news. Lee (2012), who uses high-frequency data for 23 stocks of the Dow Jones Industrial Average (DJIA) index, finds that jumps are likely to occur shortly after macroeconomic information releases, such as Federal Reserve announcements, nonfarm payroll reports, and jobless claims, as well as market index jumps. Both the study of Lahaye et al. (2011) and that of Dewachter et al. (2014), which use intraday data on exchange rates, confirm these findings.

Boudt and Petitjean (2014) focus more on the trading dynamics around jumps, which are found to coincide with a significant increase in trading costs and demand for immediacy, amplified by new releases. Liquidity supply, nevertheless, remains high, and there is strong evidence of resilience. Liquidity shocks in the number of trades are a key driver behind the occurrence of a jump, which was first identified by Giot et al. (2010) for the US market and confirmed by Shahzad et al. (2014) for Australian stocks.

To the best of our knowledge and despite these significant advances, there has been no study on market instability in the form of price jumps around trading configurations and no estimation of their joint dynamics at high-frequency trading scales. Some critical questions of interest remain unanswered. Is market instability more likely to occur and more easily identified when technical trading dominates, i.e., when herding and mimicking behaviors by market practitioners are more prevalent? Are the size and direction of the resulting jumps better predicted under these market conditions? Does market instability around trading signals depend on the underlying stock or sector? We aim to address these questions in this paper.

Our paper is also related to studies that explore jump dynamics in financial markets. Among these studies, Liu et al. (2019) develop a model for predicting the occurrences and signs of price jumps. Using vector autoregressive (VAR) analysis and Granger-causality tests, Omura et al. (2018) investigate the presence of lead-lag relationship between convenience yield, realized volatility and jumps. Ouadghiri and Uctum (2016) and Xu et al. (2011) examine jump dynamics in the foreign exchange markets and foreign equity option markets, respectively.

Our approach extends and complements these studies in several ways. First, unlike Liu et al. (2019), we directly test for the arrival times of jumps and link the jump occurrences to trading signals, rather than explaining them via lagged realized measures. In our setup, the trading activity is the *signal* that alters the jump-type tail responses for which investors can evaluate their positions. Moreover, while Omura et al. (2018) extract the jump component of realized volatility as a factor to predict convenience yield, we treat jumps as *target variable* that represents the realized risk at the marketplace. Compared to Ouadghiri and Uctum (2016), we study U.S. stock market and link jump occurrences to trading signals rather than to macro news. The key methodological task of Xu et al. (2011) is to introduce a foreign equity option pricing model that captures stochastic volatility and jumps. In contrast, our focus is on the realized risk side that is embedded solely in the jumps of underlying assets (i.e., stocks). We detect the arrival times of these risk episodes from the data and assess whether or not they are triggered by trading signals.

Methodologically, we first test whether or not market instability, as estimated by the size and direction of jumps, may be anticipated in periods when trading is essentially driven by technical signals, i.e., when herding and mimicking behaviors by market practitioners are more prevalent. While the existing literature reveals that jumps are associated with exogenous events, we show that market instability is driven by endogenous high-frequency trading activity around specific configurations. We then test whether market instability around trading signals depends on the underlying stock or sector. This is arguably the case when there is no, little or uncertain information about a company's business fundamentals or when firm-level economic interactions within sectors are sparse (Hou, 2017, among others). In these situations, market prices reflect economic fundamentals less smoothly, and market stability is more sensitive to technical trading. This is arguably the case for younger, smaller, intangibles-dependent companies in heterogeneous and versatile industries.[1]

If trading analysis permits the anticipation of the occurrence or direction of those jumps, then this could be considerably informative for avoiding periods of market instability. We find evidence that supports this hypothesis. Focusing on the NASDAQ stock market, we contribute to a better understanding of market instability and trading while distinguishing large stocks, medium-sized stocks and small stocks in eleven industries and extending the selection of trading configurations beyond the use of moving averages, which often constitute the only rules used in the above-cited papers.

The remainder of the paper is organized as follows. We outline the methodology in the next section. In Section 3, we describe our data. Section 4 presents the empirical results, and Section 5 concludes the paper.

2. Methodology

To explore the relationship between market instability and technical trading, we divide our analysis into three stages: (i) the econometric detection of jumps, (ii) the extraction of trading signals, and (iii) the implementation of statistical tests to determine the joint regularities between jumps and trading signals.

2.1. Jump detection

The use of robust tests to detect jumps is essential to assess the stochastic features of irregular jump arrivals. Although several tests have been developed to identify the presence of jumps in low-frequency data,[2] the most direct way to identify jumps is by using intraday data. The first major contribution to the detection of jumps using intraday data is that of Barndorff-Nielsen and Shephard (2006), who developed a jump-robust measure of integrated variance called realized bipower variation (RBV).[3] Lee and Mykland (2008) exploit the properties of the RBV and develop an alternative nonparametric test that yields both the direction and size of detected jumps at the intraday level. More importantly, Lee and Mykland's (2008) test allows for the identification of the exact timing of the jump, which we adopt in our study.

Let us define a price jump as a significant discontinuity in a price series, following Boudt and Petitjean (2014). The definition of a "significant discontinuity" requires the use of an underlying model. Following Andersen et al. (2007) and Lee and Mykland (2008), we assume that the observed log price, p, is generated by a continuous time Brownian semi-martingale process with finite activity jumps:

$$dp(s) = \mu(s)dt + \sigma(s)dW(s) + \kappa(s)dq(s), \tag{1}$$

where $\mu(s)$ is the drift term with a continuous and locally finite variation sample path, $\sigma(s)$ is a strictly positive spot volatility process, and $W(s)$ is a standard Brownian motion. The

[1] For example, the assumptions made about growth rates in sales or earnings are often highly uncertain for these firms, making technical trading more attractive to them due to the lack of a robust valuation method based on economic fundamentals. This is in line with Shynkevich (2012), who finds that the continuance of existing trends, i.e., the momentum on which technical trading heavily relies, 'is generally believed to be stronger among small firms and price movements in stocks with smaller capitalization have been found to be more predictable'. This has been documented by Lo and MacKinlay (1988), Hong et al. (2000), Jegadeesh and Titman (2001), Hong and Stein (1999), and Asness (1997).

[2] See Wang (1995), Aït-Sahalia (2002), Carr and Wu (2003), Johannes (2004), Johannes et al. (2009), among others.

[3] See, e.g., Becker et al. (2009), Giot et al. (2010) and Wright and Zhou (2009), who test for the jump component in daily volatility.

component $\kappa(s)dq(s)$ corresponds to the pure jump component, where $dq(s) = 1$ if there is a jump at time s and 0 otherwise, and $\kappa(s)$ is the jump size.

The jump test of Lee and Mykland (2008) allows for the detection of the exact timing and size of a price jump within a day in a computationally simple way. Intuitively, instantaneous returns are increments of Brownian motion in the absence of jumps after standardizing for local volatility. Standardized returns that are too extreme to plausibly come from a standard Brownian motion must reflect jumps.

More formally, let us assume that we have T days of M equally spaced intraday returns and denote the i-th return of day t as $r_{t,i} \equiv p(t+i/M) - p(t+(i-1)/M)$, where $i = 1, ..., M$. The associated test statistic for jumps in $r_{t,i}$ is the absolute return standardized with a jump-robust estimate of local volatility

$$\sigma_{t,i} = \sqrt{\int_{t+(i-1)/M}^{t+i/M} \sigma^2(s)ds}.$$

Lee and Mykland (2008) use a rolling window of observations to estimate local volatility. This approach has the disadvantage of being highly dependent on the size of the window used in estimating volatility. On the one hand, if the window size used is too large, then it may not be able to capture time-varying volatility. On the other hand, if the window size used is too small, then the test result may be influenced by intraday seasonality. Boudt et al. (2011) show that precise estimates of $\sigma_{t,i}$ can be obtained by approximating the intraday volatility $\sigma_{t,i}$ as the product of a jump-robust estimate of the average daily volatility ξ_t, together with an intraday volatility factor, $f_{t,i}$. The associated test statistic for jumps in $r_{t,i}$ is the absolute return standardized with a jump-robust estimate of the average daily volatility ξ_t, together with an intraday volatility factor, $f_{t,i}$:

$$J_{t,i} = \frac{|r_{t,i}|}{\xi_t f_{t,i}}. \tag{2}$$

Lee and Mykland (2008) propose estimating ξ_t as the square root of the average of the realized bipower variation (RBV) because RBV converges, under weak conditions, to the integrated variance, i.e., for $M \to \infty$, such that

$$RBV_t(M) \equiv \mu_1^{-2} \sum_{i=2}^{M} |r_{t,i}||r_{t,i-1}| \xrightarrow{p} \int_{t-1}^{t} \sigma^2(s)ds, \tag{3}$$

where $\mu_1 = \sqrt{2/\pi} \simeq 0.79788$ (Barndorff-Nielsen and Shephard, 2006). For $f_{t,i}$, we use the corresponding truncated maximum likelihood periodicity estimate recommended by Boudt et al. (2011). The estimation scheme omits returns that might contain jumps to avoid biased estimates of the periodicity.[4]

Under the null hypothesis of no jumps, the test statistic $J_{t,i}$ follows approximately the same distribution as the absolute value of a standard normal variable, and its sample maximum is Gumbel distributed. Lee and Mykland (2008) propose rejecting the null of the no jump effect on $r_{t,i}$ if

$$J_{t,i} > G^{-1}(1-\alpha)S_n + C_n, \tag{4}$$

where $G^{-1}(1-\alpha)$ is the $(1-\alpha)$ quantile function of the standard Gumbel distribution, $C_n = (2\log n)^{0.5} - \frac{\log(\pi)+\log(\log n)}{2(2\log n)^{0.5}}$ and $S_n = \frac{1}{(2\log n)^{0.5}}$, with n being the total number of observations (i.e., $M \times T$). With a probability α of type I error, we reject the null of no jump if $J_{t,i} > S_n\beta^* + C_n$ with β^* such that $\exp(-\exp^{-\beta^*}) = 1-\alpha$; i.e., $\beta^* = -\log(\log(1-\alpha))$. This

[4]See Boudt et al. (2011) for further details about the periodicity filters and the importance of adjusting for periodicity when testing for intraday jumps.

conservative procedure should be expected to find only α spurious jumps in a given sample of n observations. We therefore obtain the binary variable $I_{t,i}$ as follows:

$$I_{t,i} = \left\{ \begin{array}{l} 1, \text{ if } J_{t,i} > G^{-1}(1-\alpha) S_n + C_n \\ 0, \text{ else} \end{array} \right\} \tag{5}$$

In our main empirical analysis, we use the modified intraday jump detection test given in Equation (2) and rely on the decision rule defined in Equation (5) using the 5-minute sampling frequency. This sampling frequency is appropriate to filter out the presence of market microstructure noise while preserving the high-frequency signal.[5]

2.2. Trading signals

Having outlined our baseline jump identification scheme, we turn to the specification of trading signals. We consider the following benchmark technical indicators: the double crossover method (DXM), the relative strength index (RSI), the moving average convergence divergence (MACD), and volume.

2.2.1 DXM

The DXM developed by Murphy (1999) is based on the use of simple moving averages (SMAs), which represent almost 50% of the trading rules used by practitioners (see, e.g., Shynkevich, 2012). We can express the basic form of SMA as follows:

$$SMA_\tau = \frac{1}{k} \sum_{j=0}^{k-1} p_{\tau-j}, \tag{6}$$

where p is the price level at time τ, and k represents the total number of price observations.

There are two SMAs with different lengths in the DXM. A shorter length characterizes a faster trend, while a longer length corresponds to a slower trend. Crossings between them result in a change of direction in the price trend. A bullish crossover occurs when the shorter moving average crosses above the longer moving average, implying buying pressure and potentially leading to market instability in the form of downward price jumps. A bearish crossover occurs when the shorter moving average crosses below the longer moving average, implying selling pressure and potentially leading to market instability in the form of downward price jumps. The DXM indicator can then be written as follows:

$$DXM_\tau = \left\{ \begin{array}{l} 1, \text{ if } SMA_{short,\tau} - SMA_{long,\tau} > 0 \text{ and } SMA_{short,\tau-1} - SMA_{long,\tau-1} < 0 \\ -1, \text{ if } SMA_{short,\tau} - SMA_{long,\tau} < 0 \text{ and } SMA_{short,\tau-1} - SMA_{long,\tau-1} > 0 \\ 0 \quad \text{else,} \end{array} \right\} \tag{7}$$

where DXM_τ is interpreted as a buy/long signal when it is equal to 1 and a sell/short signal when it is equal to -1. In this scheme, no action is taken when its value is 0.

[5] At higher frequencies (such as 1 second or 15 seconds), microstructure noise dominates and typically generates a difference between the observed price series and the underlying efficient prices. For a discussion, see e.g., Hansen and Lunde (2006). The use of a lower sampling frequency, however, prevents us from disentangling the jumps from Brownian motion. As highlighted by Aït-Sahalia and Jacod (2004), jumps disappear when sampling is too sparse because of time averaging. Considering these aspects, we rely on a 5-minute sampling frequency for our empirical analysis, and this choice is consistent with the literature on high-frequency financial econometrics. For instance, Novotný and Urga (2018) use a 5-minute sampling frequency to test for cojumps between the components of the Dow Jones Industrial Average 30 index. Novotný et al. (2015) also work at the 5-minute sampling frequency to investigate trading opportunities for price jump clustering in FX markets. Similarly, Griffin et al. (2003) study NASDAQ stocks based on a 5-minute sampling frequency.

This DXM indicator given in (7) has three different time frames. The first variant (DXM_{Short}) is on a daily basis, accounting for the 1-hour SMA and the 1-day SMA. The second variant (DXM_{Mid}) considers mid-term trends, with the 14-day SMA and the 50-day SMA. Finally, the use of 50-day and 100-day SMAs replicates the popular rule, i.e., the *Golden and Death Crosses* (DXM_{Long}), which is very commonly used to identify long-term market trends.

2.2.2 RSI

To proceed further, we follow Chong and Ng (2008) and compute the RSI momentum indicator as follows:

$$RSI_\tau = 100 - (\frac{100}{1 + RS_\tau}), \tag{8}$$

with

$$RS_\tau = \frac{N_{UP}}{N_{DOWN}}, \tag{9}$$

where N_{UP} and N_{DOWN} refer to the N-day average positive price variation and N-day average negative price variation, respectively, and N is the signal length traditionally set at 14 periods (Chong and Ng, 2008). Characterizing the direction of price movement, positive and negative price variations are defined by the indicator functions UP_τ and $DOWN_\tau$, respectively, as follows:

$$UP_\tau = \left\{ \begin{array}{c} 0, \text{ if } p_\tau - p_{\tau-1} < 0 \\ p_\tau - p_{\tau-1}, \text{ else} \end{array} \right\}, \tag{10}$$

$$DOWN_\tau = \left\{ \begin{array}{c} 0, \text{ if } p_\tau - p_{\tau-1} > 0 \\ p_\tau - p_{\tau-1}, \text{ else} \end{array} \right\}. \tag{11}$$

Intuitively, we see that the RSI is close to 100 when the N-day average positive price variation is much higher than the N-day average negative price variation and close to 0 when it is the opposite. While the RSI indicator can oscillate between 0 and 100, the range from 30 to 70 is considered normal for a stock. When the RSI goes below 30 and above 70, the price momentum has reached an extreme, and the price trend is likely to reverse. The stock is then considered *oversold* in the first case and *overbought* in the second, implying selling and buying pressure, respectively, potentially leading to market instability in the form of price jumps.

The use of the standard parameters is justified on the grounds that technical analysis may work partly due to the "belief" in a self-fulfilling prophecy (Menkhoff, 1997). As indicated in Equation (12), we identify buy and sell areas when $RSILevel_\tau = 1$ and $RSILevel_\tau = -1$, respectively. That is,

$$RSILevel_\tau = \left\{ \begin{array}{l} 1, \text{ if } RSI_\tau > 70 \\ -1, \text{ if } RSI_\tau < 30 \\ 0, \text{ else} \end{array} \right\}. \tag{12}$$

This implies that buy signals occur when the $RSILevel_\tau = -1$ and the RSI crosses above the 30 level. In contrast, sell signals occur when the $RSILevel_\tau = 1$ and the RSI crosses below the 70 level.

2.2.3 MACD

As a complementary metric, we utilize the moving/average convergence-divergence (MACD) indicator, which is a centered price momentum oscillator that is based on the difference between two exponential moving averages (EMAs) of the security's closing price at time τ, P_τ. The computation of the exponential moving averages (EMAs) is as follows:

$$EMA_{k,\tau} = \frac{2}{k}\left(P_\tau - EMA_{k,\tau-1}\right) + EMA_{k,\tau-1}, \tag{13}$$

where k refers to the number of time periods across which the average is computed. The standard values for k are 12 and 26 (Chong and Ng, 2008). Overbought and oversold areas of the MACD are defined by using high threshold values, i.e., 1.5 and -1.5, respectively, beyond which only 5% of all MACD values are located in our sample. That is, we have

$$MACDLevel_\tau = \left\{ \begin{array}{l} 1,\ \text{if } MACD_\tau > 1.5 \\ -1,\ \text{if } MACD_\tau < 1.5 \\ 0,\ \text{else} \end{array} \right\}. \tag{14}$$

When the MACD goes below -1.5 and above 1.5, the price momentum has reached an extreme, and thus, the price trend is likely to reverse. The stock is then considered *oversold* in the first case and *overbought* in the second, implying selling and buying pressure, respectively, potentially leading to market instability in the form of price jumps.

To determine buy and sell signals more precisely, we use crossings, as was the case for the SMAs and the RSI. In particular, we use the signal line indicator ($Signal_\tau$) corresponding to the 9-period EMA of the MACD indicator itself. Buy signals occur when the *MACD level* at time τ is -1 and the MACD crosses above the signal line; *MACDX* at time τ is 1 in such a case. Correspondingly, sell signals occur when the *MACD level* at time t is $+1$ and the MACD crosses below the signal line, i.e., *MACDX* at time τ is -1. Taken together, the decision rule for MACD can be written as follows:

$$MACDX_\tau = \left\{ \begin{array}{l} 1,\ \text{if } MACD_\tau - Signal_\tau > 0 \text{ and } MACDLevel_\tau = -1 \\ -1,\ \text{if } MACD_\tau - Signal_\tau < 0 \text{ and } MACDLevel_\tau = +1 \\ 0,\ \text{else} \end{array} \right\}. \tag{15}$$

2.2.4 Volume

As a final measure, we compute the Z-score in volume to make it comparable across different stocks. This gives us the following statistic:

$$Z_{vol,\tau} = \frac{(vol_\tau - \overline{vol})}{\sigma_{vol}}, \tag{16}$$

where the average and standard deviation are computed over the sample available at time $\tau - 1$. We identify abnormally high and low levels in volume when the Z-score is above 2 and below -2, respectively.[6] That is,

[6] We follow Degenhardt and Auer (2018), who suggest that a higher threshold (i.e., 2.5) is more appropriate when volatility is higher on average. They suggest that the higher 2.5 threshold used by Maberly and Pierce (2004) is only "justified by the higher volatility of the Japanese market in comparison to the US market". Hence, we choose a threshold equal to 2.

$$VOLLevel_\tau = \left\{ \begin{array}{l} 1, \text{ if } Z_{vol,\tau} > 2 \\ -1, \text{ if } Z_{vol,\tau} < -2 \\ 0, \text{ else} \end{array} \right\}. \tag{17}$$

After introducing the techniques used to identify price jumps and trading signals, in the next section, we outline our testing procedure to estimate conditional probabilities.

2.3. Conditional probabilities based on jumps and trading signals

In this section, we estimate the probability of the occurrence of a jump, conditional on a *triggering event*. The identification of a trading signal constitutes the *triggering event* in our study. Relying on the methodology of Lahaye et al. (2011), the conditional probability can then be simply written as follows:

$$p(jump_\tau | event_i) = \frac{p(jump_\tau \text{ and } event_i)}{p(event_i)}, \tag{18}$$

where the window length τ ranges between the values -3 and +3, i.e., between 15 minutes before and after the jump using a 5-minute timescale; i denotes the trading signal i among those explained in the previous section. We compare this conditional probability with the unconditional probability of a jump as well as with the unconditional probability of observing the trading signal at the 5-minute timescale.

To generate testable hypotheses based on conditional probabilities, we further run a two-sample t-test for equal means for every 5-minute timescale in the event window. This allows us to test for the null hypothesis under which the average value of the trading signal *with* jumps is equal to the average value of the trading signal *without* jumps. This test is applied to the RSI, the MACD and the Z-score in volume. Following Dewachter et al. (2014), the corresponding null and alternative hypotheses can be written as follows:

$$\begin{aligned} &H_0 : Indicator_{\tau,(\text{with jump})} = Indicator_{(\text{no jump})} \\ &H_1 : Indicator_{\tau,(\text{with jump})} \neq Indicator_{(\text{no jump})} \end{aligned} \tag{19}$$

where window length τ ranges between -3 and +3, i.e., between 15 minutes before and after the jump using a 5-minute timescale. If the null hypothesis is rejected, then jumps are related to "abnormal" values of the technical indicator. This implies that jumps are more likely to occur when there are trading signals. Hence, we attempt to test for jump arrivals conditional on trading signals, which is much more relevant from a risk management perspective than studying the reverse conditional probability.

3. Data

Our sample consists of the individual stocks of 460 companies traded on the NASDAQ stock exchange, covering the period between February 22, 2017, and September 5, 2017, i.e., 136 trading days. We extract the raw data from Thomson Reuters, and our empirical analysis is carried out at a 5-minute frequency during market trading hours, i.e., from 9:30 EST to 16:00 EST. We, therefore, have slightly more than 4,800,000 observations, which correspond to almost 10,500 observations per stock on average. Before conducting our tests, we process the data and apply several filters (such as IPO assessments, sufficient analyst coverage, and liquidity) to select the companies. Table 1 presents the summary statistics for market cap and trading volume.

Table 1. Market cap and trading volume

	Average Market Cap	Average Daily Volume	# Stocks
Full sample	USD 15.32 B	USD 1.87 M	460
Large-Cap (LC)	USD 60.10 B	USD 4.77 M	100
Mid-Cap (MC)	USD 4.56 B	USD 1.23 M	168
Small-Cap (SC)	USD 0.99 B	USD 0.71 M	192

Notes: The cross-sectional average of market capitalization was computed on September 5, 2017, while the cross-sectional average daily volume corresponds to the cross-sectional mean of the average volume observed for each stock between February 22, 2017, and September 5, 2017.

In addition to these considerations, we decompose the aggregated sample into eleven industries, consisting of basic industries, capital goods, consumer durables, consumer nondurables, consumer services, energy, finance, health care, public utilities, technology and transportation. We use the same (four) trading signals and identify jumps using the same robust identification procedure. For each sector, we then estimate the conditional probabilities of observing jumps, given the trading signals. We finally assess the magnitudes, probabilities and directions of conditional jump events.

Regarding the activity of detected jumps, there are approximately 118 jumps on average per stock in the sample at the 5-minute frequency. At the daily level, 86 days out of 136 contained at least one jump. The cross-sectional median for the average size of these 5-minute jumps is equal to -4.07%. While the frequency of jumps is equal to 1.13% across all observations, jumps occur more frequently for LC stocks than SC stocks: 0.60% of all 5-minute observations correspond to jumps for LC stocks, while the fractions become 0.92% and 1.63% for MC and SC stocks, respectively. It is worth emphasizing that the same trend holds at the daily level. For SC stocks, 95.8% of the days are exposed to at least one jump, while the fraction decreases to 65.6% and 29.4% for MC and LC stocks, respectively.

Table 2 further reports the descriptive statistics for returns and jumps based on the three market cap categories. Interestingly, we notice that as market capitalization shrinks, the amplitude of jumps becomes larger, and a similar pattern is also observed for the standard deviation. For example, the average downward jump for SC stocks is 7%, which is considerably relevant at the 5-minute frequency, showing how relevant the detection of jumps is for trading practices. For LC, MC, and SC stocks, the contribution of jumps to the standard deviation of returns is approximately 65.0%, 76.5%, and 76.8%, respectively. These values suggest that jumps explain a large part of the total volatility. It is also noticeable that kurtosis falls dramatically from over 267 to an excess of 18 when jumps are removed.[7]

[7] It is worth mentioning that the returns of LC, MC and SC stocks are not necessarily normally distributed, even in the absence of jumps in the data. One reason behind this pattern is the presence of another driving force, which is the stochastic volatility component. While Brownian shocks exhibit diffusive variation, sharp changes in stochastic volatility are still likely to trigger fat tails. The jump detection test that we use in our paper, however, controls for the potential effect of stochastic volatility. Therefore, even though the distributions of LC, MC and SC stock returns may reveal heavy tails (with our without jumps, due to stochastic volatility), we detect jumps (conditional on trading signals) by accounting for stochastic volatility. Therefore, our model consideration (model 1) is compatible with high-frequency data (i.e., both stochastic volatility and jumps generate return distributions). We thank the referee for pointing out this important issue.

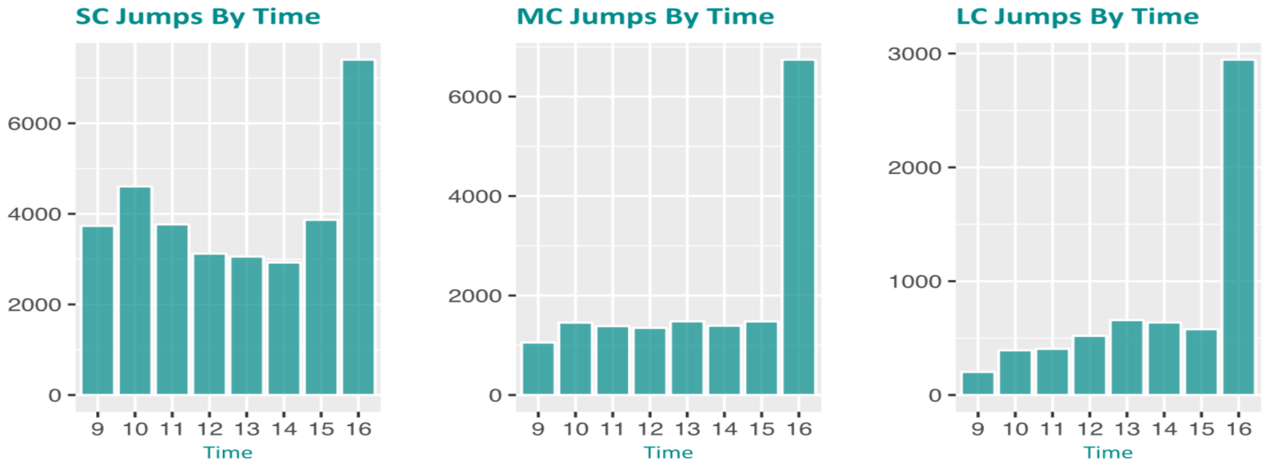
Table 2. Cross-sectional median statistics of returns and jumps

All stocks	***Mean***	***St. Dev.***	***Skewness***	***Kurtosis***
Raw Returns	0.00%	0.73%	-0.41	266.97
Jumps	-4.07%	3.88%	-1.44	5.76
Up Jumps	0.85%	0.44%	1.85	6.49
Down Jumps	-5.91%	3.93%	-1.56	5.13
Returns excl. jumps	0.00%	0.18%	-0.22	17.93
Large Caps (LC)	***Mean***	***St. Dev.***	***Skewness***	***Kurtosis***
Raw Returns	0.00%	0.37%	0.35	191.31
Jumps	-3.62%	2.24%	-0.89	4.27
Up Jumps	0.67%	0.30%	1.56	4.78
Down Jumps	-4.72%	2.21%	-1.24	3.91
Returns excl. jumps	0.00%	0.13%	-0.32	15.82
Median Caps (MC)	***Mean***	***St. Dev.***	***Skewness***	***Kurtosis***
Raw Returns	0.00%	0.74%	-0.02	288.91
Jumps	-3.81%	4.31%	-1.30	5.32
Up Jumps	0.72%	0.37%	1.71	5.55
Down Jumps	-5.36%	4.20%	-1.38	4.97
Returns excl. jumps	0.00%	0.17%	-0.47	19.53
Small Caps	***Mean***	***St. Dev.***	***Skewness***	***Kurtosis***
Raw Returns	0.00%	0.94%	-0.18	264.79
Jumps	-4.54%	4.81%	-1.88	7.49
Up Jumps	1.05%	0.57%	2.24	8.49
Down Jumps	-7.00%	5.11%	-1.88	6.01
Returns excl. jumps	0.00%	0.22%	-0.06	17.76

Notes: The table reports the median statistics *across stocks* for the period between February 22, 2017, and September 5, 2017. Jumps are identified by the testing procedures described in the main text, following the approach of Andersen et al. (2007), with the periodicity correction introduced by Boudt et al. (2011).

To facilitate the understanding of jump patterns in the data, Figure 1 further displays that the last hour of trading contributes significantly to the total number of jumps, irrespective of the market cap of the stock. However, this is particularly the case for MC and LC stocks, with 41.3% and 46.5% of jumps occurring during the last hour, respectively, in comparison to 22.8% for SC stocks.

Figure 1. Number of jumps during the trading day



Notes: The figure displays the number of jumps at an hourly frequency during the trading hours across the 136 days included in the sample and for the small-cap (SC), medium-cap (MC) and large-cap (LC) stocks.

4. Empirical Analysis

In this section, we conduct our empirical analysis and explore jump dynamics around trading signals extracted based on four methods: DXM, RSI, MACD and volume. To examine the joint interactions between jumps and trading signals, we carry out a set of event studies, assess the (un)conditional probabilities, and run t-tests of equal means. We employ our method separately for each category of stocks based on their market caps.

4.1. DXM

We start by looking into the moving average patterns. The events based on simple moving averages (SMA) correspond to *crossings* between them. As explained in Section 2, we investigate three specific types of crossings: DXM_{Short}, DXM_{Mid}, and DXM_{Long}. It is important to note that each of these crossings represents a different heterogeneous event, under which we closely analyze their associated relationship with the detected intraday jumps.

Table 3 indicates that DXM_{Short} events occur quite often, i.e., in 16.41% of all the 5-minute intervals. The probability of occurrence is much lower for both DXM_{Mid} and DXM_{Long} events, with 2.54% and 1.01%, respectively. These DXM events are nevertheless all equally likely to occur on 5-minute positive return intervals compared to those on 5-minute negative return intervals. This is not the case for intraday 5-minute jumps, which are twice as likely to occur during the 5-minute negative return intervals. We also notice that they occur once every 500 minutes on average (since the probability is 1.13%).

Table 3. DXM events and unconditional probabilities of occurrence

Event	DXM_{Short}	DXM_{Mid}	DXM_{Long}	*Jumps*
P(Event)	16.41%	2.54%	1.01%	1.13 %
P(Event) on + Ret	7.93%	1.18%	0.50%	0.39%
P(Event) on – Ret	8.48%	1.31%	0.49%	0.74%

Notes: DXM_{Short} is the crossing between the 1-hour SMA and the 1-day SMA. DXM_{Mid} is the crossing between the 14-day SMA and the 50-day SMA; DXM_{Long} is the crossing between the 50-day SMA and the 100-day SMA. P(Event) is the unconditional probability of occurrence of the event. *P(Event) on + Ret* is the unconditional probability of occurrence of the event when the 5-minute return is positive. *P(Event) on – Ret* is the unconditional probability of occurrence of the event when the 5-minute return is negative.

In Table 4, we report the probability of the occurrence of a jump, given the triggering trading signal, which corresponds to one of the three crossings explained above. In comparison to the unconditional probability of a jump (close to 1% in Table 3), the conditional probabilities reveal that jumps are much more likely to occur when one SMA crosses the other, especially in regard to medium- and long-term SMA maturities. Algorithmic trading strategies may imply automatic reactions to SMA crossings through the closing of positions to take profits or cut losses. We also observe that jumps are twice as likely when the crossings of SMAs send a *sell* signal (*Down Cross*), i.e., when the shorter SMA crosses below the longer SMA.

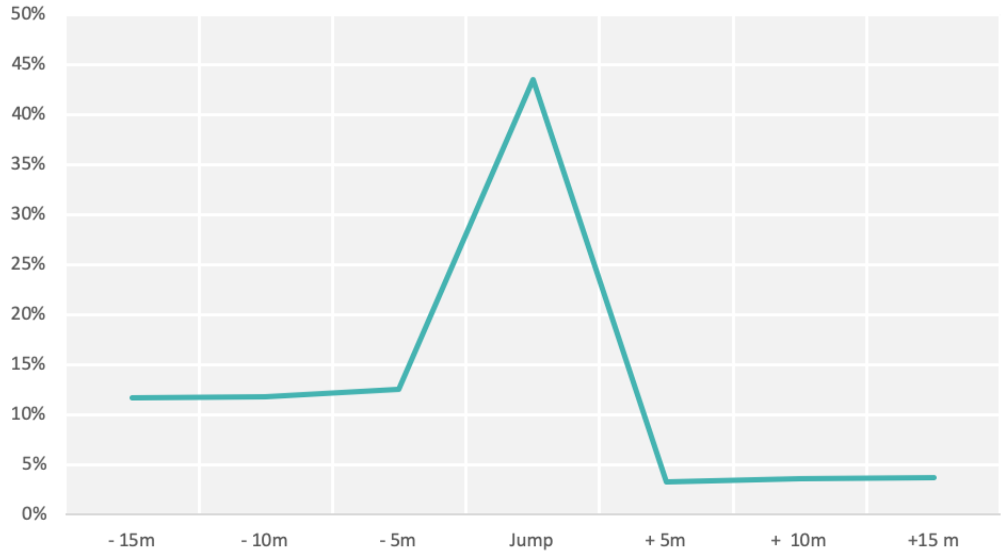
Table 4. DXM events and conditional probabilities of a jump

Event	DXM_{Short}	DXM_{Mid}	DXM_{Long}
P(Jump| DXM)	43.48%	57.47%	55.84%
P(Jump| DXM) on Up Cross	14.81%	20.58%	20.02%
P(Jump| DXM) on Down Cross	28.67%	36.89%	35.82%

Notes: DXM_{Short} is the crossing between the 1-hour SMA and the 1-day SMA. DXM_{Mid} is the crossing between the 14-day SMA and the 50-day SMA; DXM_{Long} is the crossing between the 50-day SMA and the 100-day SMA. *P(Jump| DXM)* is the probability of occurrence of the event conditional on DXM occurring, i.e., the crossing of two SMAs. *P(Jump| DXM) on Up Cross* is the probability of occurrence of the event conditional on DXM occurring when the shorter SMA crosses above the longer SMA (buy signal). *P(Jump| DXM) on Down Cross* is the probability of occurrence of the event conditional on DXM occurring when the shorter SMA crosses below the longer SMA (sell signal).

In addition to these patterns provided by Tables 3 and 4, Figure 2 further illustrates how the probability of a jump evolves during the event window related to DXM_{Short}. As crossing occurs, the probability falls heavily after 5 minutes. From a financial perspective, when these crossings are realized, they arguably mark a substantial change in the *trend*, reassuring practitioners about the future direction of the market.

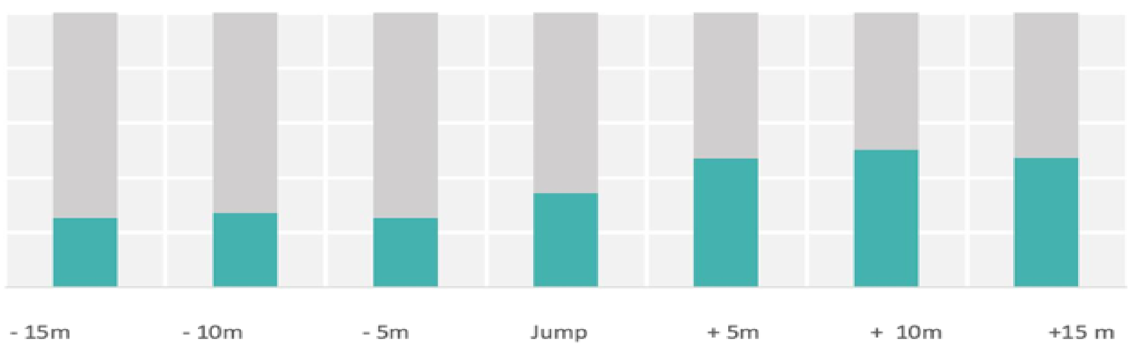
Figure 2. Probability of a jump in the DXM event window



Notes: The figure line represents the probability of a jump during the event window, where (DXM_{Short}) is the crossing between the 14-day SMA and the 50-day SMA.

We further observe in Figure 3 that the direction of jumps changes substantially during the event window. Before the occurrence of crossings, the probability of a jump arrival is more than twice as high for downward jumps than for upward jumps. After the crossings, nevertheless, we observe equal odds (50/50), implying an equal chance of occurrence. This may reflect the relatively fast elimination of the potential profitability in using trading signals for volatility trading strategies.

Figure 3. Direction of jumps in the DXM event window



Notes: (DXM_{Short}) is the crossing between the 14-day SMA and the 50-day SMA. % of upward jumps in green and % of downward jumps in gray.

4.2. RSI

After assessing the regularities via SMA, we now proceed by using the measure RSI to uncover the relationship between jumps and trading signals at the intraday level. We consider four events related to the RSI. The first event (RSIX70) refers to the RSI indicator crossing above the threshold value of 70, employed as the entry point into the *overbought area*. Alternatively, the second event (RSIX30) corresponds to when the RSI crosses below the threshold value of 30, under which the *oversold area* is identified. During the third and fourth events, the RSI value is simply above 70 and below 30, respectively. In these four cases, we examine the time during which the RSI remains in the overbought and oversold areas.

Table 5 reports the probability of occurrence for these four types of event classes. The probabilities indicate that stock prices, on average, remain in the overbought area (RSI>70) in four 5-minute return intervals out of 100. We observe that the probabilities in the oversold and overbought areas are similar.

Table 5. Probability of the occurrence of RSI-related events

Event	RSIX70	RSIX30	RSI>70	RSI<30	Jumps
P(Event)	1.14%	1.56%	4.42%	4.58%	1.13 %

Notes: The table reports the unconditional probabilities for each of the RSI-related events identified at the 5-minute interval for 136 days and across 460 stocks. RSIX70 (RSIX30) refers to the RSI indicator crossing above (below) the threshold value of 70 (30). RSI>70 (RSI<30) means that the RSI value is above 70 (below 30).

We further present in Table 6 the probability of a jump conditional on the occurrence of one of the four RSI-induced events. At the 5-minute frequency, jumps are four times more likely to be detected when stock prices enter the oversold area (RSIX30). In one case out of four, there is a jump when the RSI crosses below 30. When the crossing is over 70, however, the probability occurs only 6.38% of the time.

Table 6. Conditional probabilities of a jump given the occurrence of RSI-related events

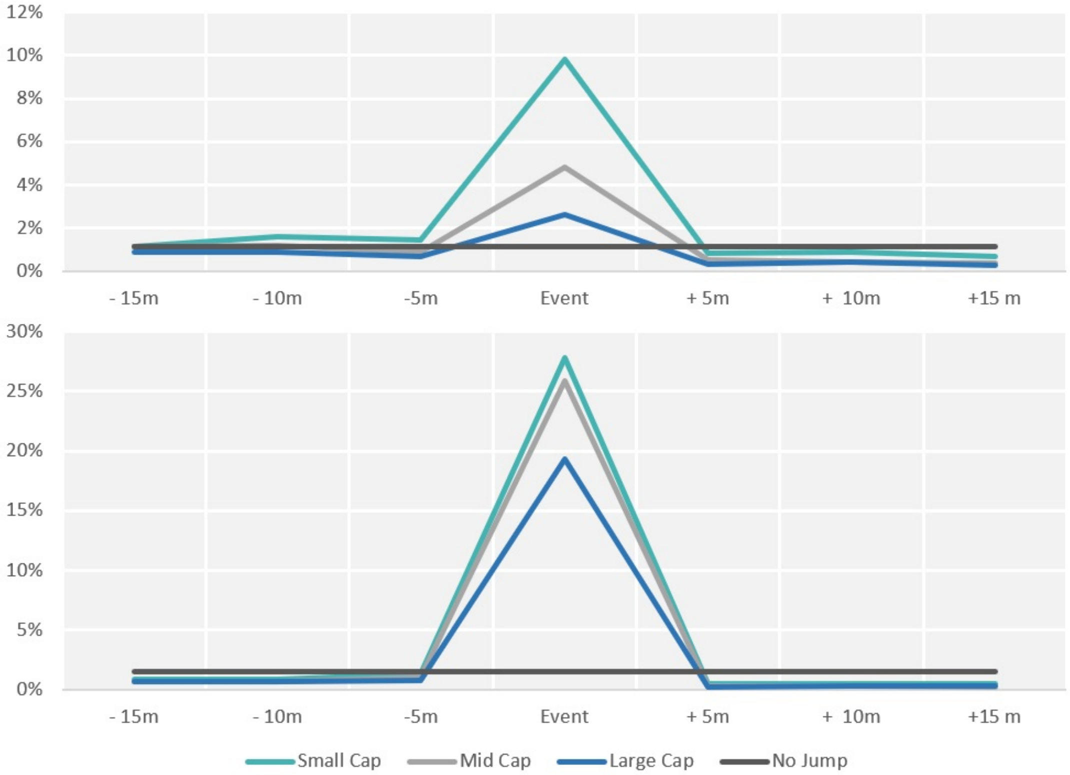
Event	RSIX70	RSIX30	RSI>70	RSI<30
P(Jump| Event)	6.38%	25.35%	2.29%	9.85%
% (+Jump| Event)	100.00%	0.00%	98.68%	0.31%
% (-Jump| Event)	0.00%	100.00%	1.32%	99.69%

Notes: The table reports the conditional probabilities for each of the RSI-related events identified at the 5-minute interval for 136 days and across 460 stocks. RSIX70 (RSIX30) refers to the RSI indicator crossing above (below) the threshold value of 70 (30). RSI>70 (RSI<30) means that the RSI value is above 70 (below 30).

In the overbought area, there is a 2.29% chance of a jump occurring, which is again significantly lower than the probability of occurrence of a jump when stock prices are in the oversold area. This may indicate that discontinuous changes in volatility are more frequent when stock prices face downward pressure. Interestingly, jumps exacerbate the *momentum* in the trend. For example, in the oversold area, there is a 99.69% chance that jumps occurring in this area push the price further down. The direction of the jumps in these zones is, therefore, highly predictable.

To facilitate visual inspection, Figure 4 shows the evolution of the conditional probabilities during the RSIX70 and RSIX30 event windows with respect to market capitalization. The noticeable pattern is that the smaller the market capitalization is, the more likely that the crossing of the RSI leads to a jump. Differences between market cap groups are the largest when the RSI crosses above the threshold of 70. Both event windows display the same patterns.

Figure 4. Size-based conditional probabilities in RSIX70 and RSIX30 event windows



Notes: For each market cap group of stocks, the curve represents the probability of a jump during the RSIX70 and RSIX30 event windows. The black line represents the unconditional probability of a jump.

On a daily basis, the results indicate that the conditional probability of one jump is rather constant across events (Table 7). Quite remarkably, there appears to be a 38.17% chance of observing a jump on a day where the RSI is above 70 without any crossing. The regularity of staying in the "overbought" or "oversold" area is, in fact, a source of jump risk. Although the probabilities of observing exactly two jumps (instead of 1 jump) are four times lower, they exhibit the same regular pattern across events. Notice the high probability equal to 8.06% of observing 3 or more jumps on a day where the RSI is in the oversold area.

Table 7. Conditional daily probability of jumps given the occurrence of RSI-related events

Event	RSIX70	RSIX30	RSI>70	RSI<30
Daily P(1 Jump| Event)	38.57%	33.02%	38.17%	34.44%
Daily P(2 Jumps| Event)	10.76%	11.53%	10.06%	11.58%
Daily P(3+ Jumps| Event)	3.28%	5.92%	4.11%	8.06%

Notes: Table 7 reports the conditional daily probabilities of jumps under different RSI-related rules.

Table 8 suggests that the occurrence of jumps is associated with the levels of the RSI. Specifically, the t-test of equal means reveals the practical usefulness of the RSI to predict jumps at a high sampling frequency. Abnormally low levels of the RSI are identifiable at the time of the event. When jumps arrive, the average RSI reaches a level of 37.31, compared to the average jump-free level of 50.69. From a statistical perspective, differences between this scenario and the *no jump* scenario are significant starting from five minutes before the event and remain significant at 1% even ten minutes after the event.

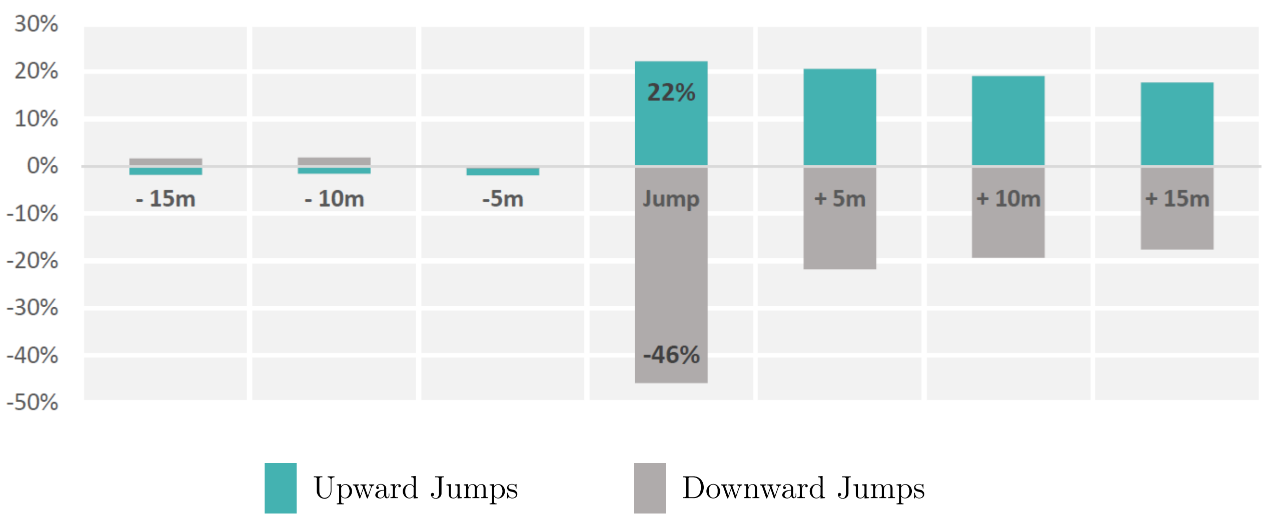
Table 8. Intraday t-tests of equal means for RSI events

Event	No Jump	-15 min	-10 min	- 5 min	On Jump	+5 min	+10 min	+15 min
Mean	50.69	50.67	50.71	49.85	37.31	49.98	50.35	50.53
St. Dev.	10.86	13.02	13.31	13.73	23.63	16.07	15.00	14.20
Sig.		-	-	$***$	$***$	$***$	$***$	$*$

Notes: The t-test compares the average RSI values on "no jump" days with the average values of the indicator during the event window on days with jumps. $***$, $**$, and $*$ indicate 1% , 5% and 10% significance levels, respectively.

We can also assess the link between RSI values and upward and downward jumps separately (Figure 5). On the one hand, *downward* jumps occur when the RSI values are 46% below their normal levels, i.e., their levels when there is no RSI-induced event. On the other hand, the RSI values are only 22% higher than their normal levels, on average, when *upward jumps* are detected from the data. Except for this strong asymmetry, there is no other noticeable difference before or after the jump during the event window. In fact, when jumps are present, there is a rather persistent impact on the RSI since its level remains 20% away from its average level observed in the absence of jumps.

Figure 5. Intraday variations in RSI values



Notes: The figure displays that the intraday variations in the RSI values are centered on upward and downward jumps.

4.3. MACD

We proceed with the MACD measure, which enters the overbought area in 0.03% of all the 5-minute return intervals, while it enters the oversold area in 0.09% of the time (Table 9). There is a low probability that intraday MACD goes into the overbought and oversold areas.

In comparison to the RSI, the time duration in which the MACD remains in the sell and buy areas appears to be quite short when MACD level>1 and MACD level<-1, respectively.

Table 9. Unconditional intraday probabilities of occurrence of MACD-related events

Event	MACDLevel1	MACDLevel-1	MACDLevel>1	MACDLevel<-1	Jumps
P(Event)	0.03%	0.09%	0.45%	0.55%	1.13 %

Notes: The table reports the unconditional probabilities for MACD-related level events identified at the 5-minute interval during 136 days and across 460 stocks. MACDLevel1 and MACDLevel-1 imply that the MACD enters the overbought and oversold areas, respectively. MACDLevel>1 is the fraction during the MACD remaining in the overbought area. MACDLevel<-1 is the time during which the MACD remains in the oversold area.

To compare the probabilities with the other hitherto analyzed technical indicators, Table 10 includes the probability of a jump conditional on the occurrence of one of the four MACD-induced events. At the 5-minute frequency, we observe that jumps are much more likely to occur when the MACD enters the oversold area (MACDLevel-1) relative to the case when it goes into the overbought area. As expected, downward jumps are very likely to occur in the former case, with a probability equal to 67.90%. The probability of a jump is also 10 times more likely when the MACD remains in the oversold area, with a probability of 12.34% versus 1.28% in the overbought area. Overall, the direction of the jump is particularly predictable when the MACD enters or remains in the oversold area.

Table 10. Conditional intraday probabilities of jumps given the occurrence of MACD-induced events

Event	MACDLevel1	MACDLevel-1	MACDLevel>1	MACDLevel<-1
P(Jump| Event)	3.20%	68.04%	1.28%	12.34%
P(+Jump| Event)	2.69%	0.14%	0.71%	0.74%
P(-Jump| Event)	0.50%	67.90%	0.56%	11.60%

Notes: P(Jump| Event) is the conditional probability of a jump given the occurrence of four MACD-related level events. P(+Jump| Event) is the conditional probability of an upward (positive) jump, while P(-Jump| Event) is the conditional probability of a downward (negative) jump. MACDLevel1 and MACDLevel-1 imply that the MACD enters the overbought and oversold areas, respectively. MACDLevel>1 and MACDLevel<-1 indicate that the MACD is in the overbought and oversold areas, respectively.

On a daily basis, the probability patterns appear to resemble those previously identified for the RSI (Table 11). The probability levels are close to those observed for the RSI and similar crossing events.

Table 11. Conditional daily probabilities of jumps under different MACD levels

Event	MACDLevel1	MACDLevel-1	MACDLevel>1	MACDLevel<-1
Daily P(1 Jump| Event)	42.12%	35.55%	39.65%	36.86%
Daily P(2 Jumps| Event)	10.84%	13.52%	11.34%	11.91%
Daily P(3+ Jumps| Event)	4.58%	5.36%	5.24%	7.06%

Notes: Table 11 reports the conditional daily probabilities of jumps given the occurrence of MACD-related events during the day. MACDLevel1 and MACDLevel-1 imply that the MACD enters the overbought and oversold areas, respectively. MACDLevel>1 and MACDLevel<-1 indicate that the MACD is already in the overbought and oversold areas, respectively.

Several patterns emerge as we look at the crossings between the MACD and signal line (Table 12). First, the probability of a jump on an intraday basis is 2.43% when there is a sell signal, which implies that the MACD is in the *overbought* area and crosses below the signal line. Second, in contrast, the probability is more than twice as high (5.30%) when there is a buy signal, i.e., when the MACD is in the *oversold* area and crosses above the signal line, pointing to the end of the bearish market. At the daily level, there is an approximately 57% chance that a jump occurs when there is a crossing.

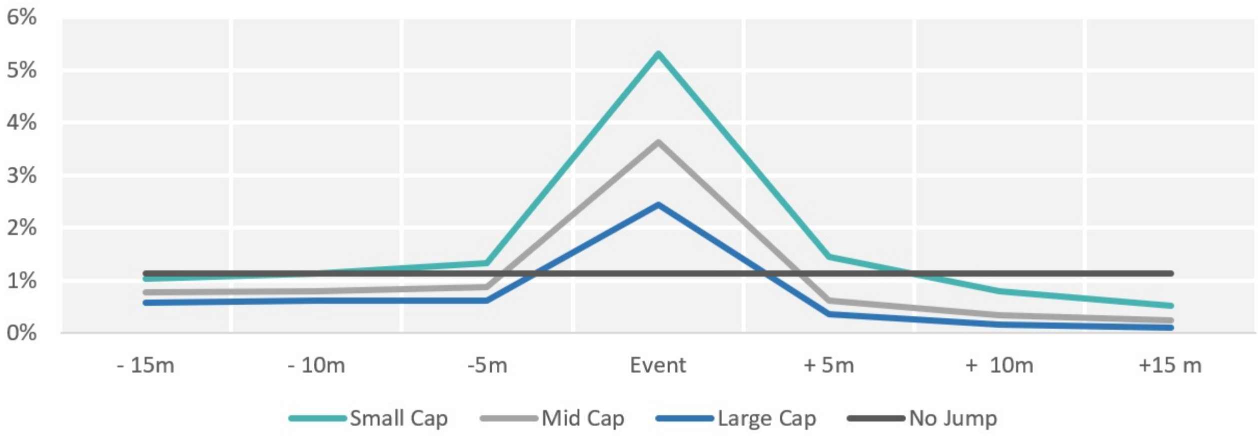
Table 12. Conditional jump probabilities given MACD-based crossing events

Event	Intraday crossings	Daily crossings
P(Jumps| MACDX1)	2.43%	57.94%
P(Jumps| MACDX-1)	5.30%	56.60%

Notes: Table 12 reports the conditional intradaily and daily probabilities of jumps given the occurrence of MACD-related events during the day.

Figure 6 displays the variations in the conditional probabilities during the event window related to the crossing between the MACD and the signal line, i.e., when (MACDX = 1) or (MACDX = -1). We report the results for the three market cap groups of stocks. Confirming the findings for the RSI, we observe that the smaller the market capitalization is, the more likely the crossing is to lead to a jump. The peak is preceded and followed by a rapid rise and decline in the conditional probability of a jump, as it goes below the unconditional probability after 5 minutes (as indicated by the black line).

Figure 6. Conditional probabilities of a jump given MACD and the signal line



Notes: For each market cap group of stocks, the curve represents the probability of a jump during the event window characterized by an upward crossing (MACDX1) or a downward crossing (MACDX-1) between the MACD and the signal line. The dark gray line represents the unconditional probability of a jump.

Finally, Table 13 indicates that the occurrence of jumps varies due to different levels of MACD. Analogous to the characteristics with the RSI, the highest difference can be quite precisely detected at the time of the event, with -0.23 versus 0.01 when there is a jump and when there is no jump, respectively. From a statistical perspective, these differences with the "no jump" scenario are significant during the whole event window.

Table 13. Intraday t-tests of equal means for MACD crossing events

Event	No Jump	-15 min	-10 min	- 5 min	On Jump	+5 min	+10 min	+15 min
Mean	0.01	0.01	0.01	0.00	-0.23	-0.02	-0.01	0.00
St. Dev.	0.28	0.25	0.26	0.28	0.77	0.47	0.44	0.42
Sig.		$***$	$***$	$***$	$***$	$***$	$***$	$***$

Notes: The t-test compares the average RSI values on "no jump" days with the average values of the indicator during the event window on days with jumps. $***$, $**$, and $*$ indicate the 1% , 5% and 10% significance levels.

4.4. Z-score in volume

Focusing on the volume-jump interactions, we report in Table 14 the unconditional probability of jump occurrences for each volume-induced event. The results suggest that on an intraday basis, there are only 800 observations for which the Z-score goes two standard deviations below the standardized mean (VoLLevel-1), with a probability equal to 0.01%. Volume remains *abnormally high* in 4.74% of all the 5-minute return intervals and *abnormally low* in 0.02% of the cases. On a daily basis, the findings also indicate that the volume probabilities are rather low. Nevertheless, there is still an 8.82% chance that a day exhibits a volume higher than two standard deviations.

Table 14. Unconditional intraday probabilities of the occurrence of volume-related events

Event	VoLLevel1	VoLLevel-1	VoLLevel>1	VoLLevel>-1	Jumps
Intraday P(Event)	2.91%	0.01%	4.74%	0.02%	1.13 %
Daily P(Event)	1.39%	1.21%	8.82%	1.15%	56.47%

Notes: The table reports the unconditional probabilities for volume-related level events identified at the 5-minute interval during 136 days and across 460 stocks. VOLLevel1 and VOLLevel-1 imply that standardized volume goes 2 standard deviations above and below the standardized mean, respectively, within 5 minutes. VOLLevel>1 denotes the percentages of 5-minute intervals that display an abnormally high volume level. VOLLevel<-1 denotes the percentages of 5-minute intervals that display an abnormally low volume level.

Table 15 shows that the probability of a jump is related to *abnormal volumes.* When volumes are extremely *high*, the probability of a jump increases with a conditional probability of 2.99% versus an unconditional probability of 1.13% (as reported in Table 14). These extremely *high* volumes tend to be associated with a rather even distribution of up and down jumps (1.82% versus 1.17%). When trading volume is very low, the probability of observing a jump decreases. This finding is consistent with the fact that low levels of trading activity result in low market volatility, which, in turn, decreases the likelihood of observing jumps in stock prices. Furthermore, the distribution of jumps becomes more uneven, with negative jumps being more likely to occur in the data.

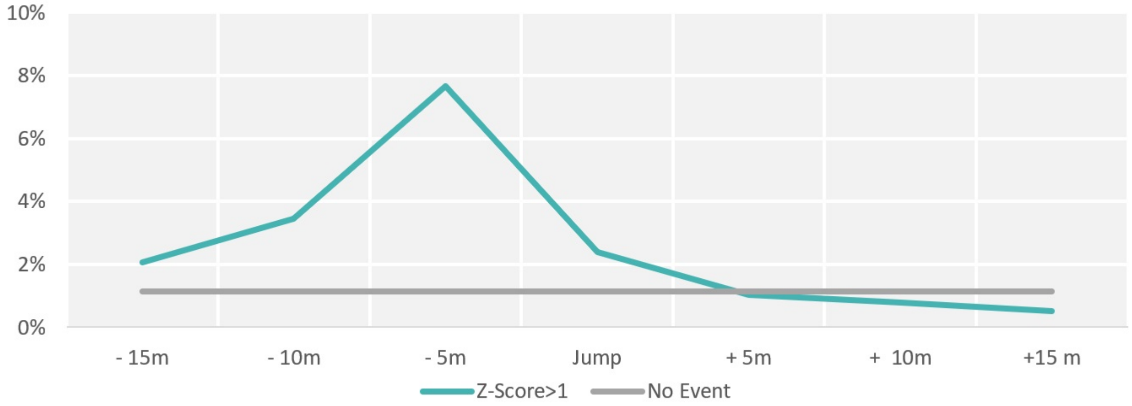
Table 15. Conditional intraday probabilities of jumps given the occurrence of volume-induced events

Event	VoLLevel1	VoLLevel-1	VoLLevel>1	VoLLevel>-1
P(Jump| Event)	2.99%	1.82%	2.39%	1.78%
P(+Jump| Event)	1.82%	0.00%	1.42%	0.13%
P(-Jump| Event)	1.17%	1.82%	0.97%	1.65%

Notes: P(Jump| Event) is the conditional probability of a jump given the occurrence of four volume-related events. P(+Jump| Event) is the conditional probability of an upward jump, while P(-Jump| Event) is the conditional probability of a downward jump. VOLLevel1 and VOLLevel-1 imply that standardized volume goes 2 standard deviations above and below the standardized mean, respectively, within 5 minutes. VOLLevel>1 is the percentage of 5-minute intervals that display such an abnormally high-volume level. VOLLevel<-1 is the percentage of 5-minute intervals that display such an abnormally low volume level.

The Z-score in volume exhibits a considerably unique feature in Figure 7. The probability of having a jump is the highest 5 minutes before the Z-score in volume goes above 2. In fact, there is a 7.67% probability that a jump occurs before volume increases to abnormally high levels. As a feedback mechanism, this may reflect that jumps lead to a larger degree of trading volume.

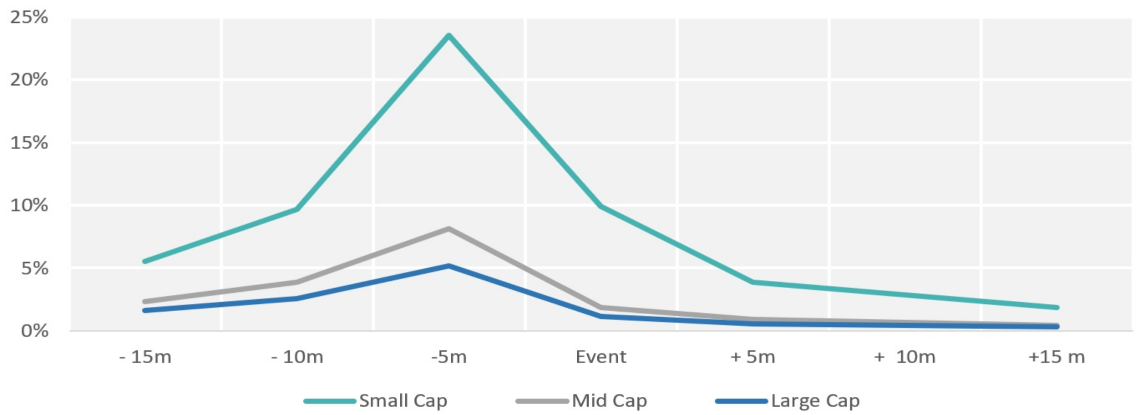
Figure 7. Conditional jump probabilities characterized by a positive shock in volume



Notes: The curve represents the probability of a jump during the event window, where the event is a positive shock in volume (VoLLevel1); i.e., standardized volume goes above a two-standard-deviation positive shock within 5 minutes. The gray line indicates the unconditional probability of a jump.

These results hold irrespective of the market capitalization of the stocks, as indicated in Figure 8. The predictive power nevertheless increases quite significantly when market capitalization decreases. For small caps, there is a 23.52% chance of pinning down a jump, while the probability decreases to 5.20% for large caps. On a daily basis, Table 16 confirms the previous findings relying on other trading signals: probability levels are close to those observed for the RSI and the MACD, and they are comparable across event types.

Figure 8. Size-specific conditional jump probabilities characterized by a positive shock in volume



Notes: For each market cap group of stocks, the curve represents the probability of a jump during the event window, where the event is a positive shock in volume (VoLLevel1); i.e., the standardized volume goes above a two-standard-deviation positive shock within 5 minutes. The dark gray line indicates the unconditional probability of a jump.

Table 16. Conditional daily probability of jumps given the occurrence of volume-related events

Event	VOLLevel1	VOLLevel-1	VOLLevel>1	VOLLevel<-1
Daily P(1 Jump| Event)	35.55%	38.69	37.76%	39.89%
Daily P(2 Jumps| Event)	13.52%	13.65%	12.22%	12.80%
Daily P(3+ Jumps| Event)	5.36%	8.84%	4.88%	8.06%

Notes: Table 16 reports the conditional daily probabilities of jumps given the occurrence of MACD-related events during the day.

Regarding the tests of equal means, Table 17 presents evidence in favor of a strong interdependence between volume and volatility. As the table reveals, when the window is centered on the jump, we observe abnormally high volumes 5 minutes prior to the occurrence of the jump. There is a 1.85-standard-deviation increase in volume 5 minutes before the jump arrivals compared to estimations when there is no jump in the data. The results indicate that there is a persistent and statistically significant increase in abnormal volume even 15 minutes before the jump, and the correction only occurs 15 minutes following the jump arrivals. Overall, there is a strong feedback mechanism between jumps and volume; peaks in volume lead to spikes in volatility, as suggested by Wang and Wu (2015), and the opposite holds, as clearly indicated in Figure 8.

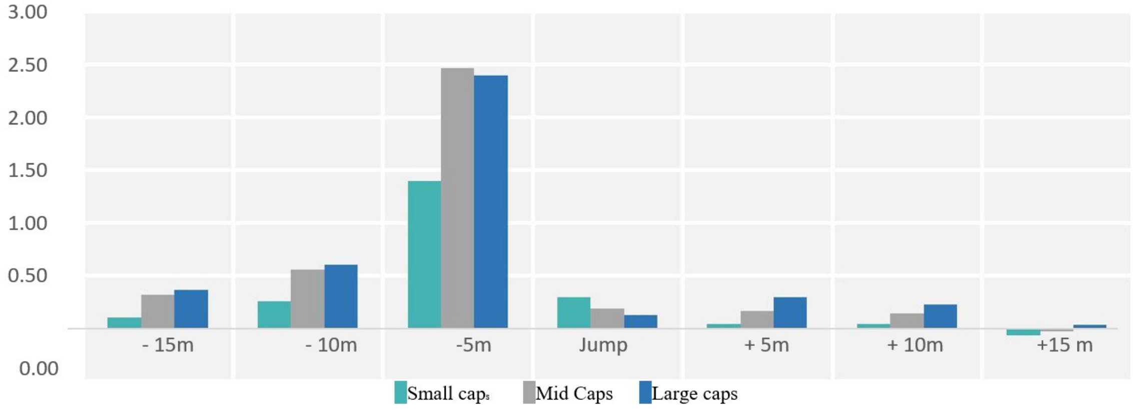
Looking at the intraday regularities, Figure 9 displays the "abnormal" rise in volume 5 minutes before the occurrence of jumps for each market cap group of stocks. While the probability of a jump conditional on an elevated level in volume is the highest for small caps (see Figure 8), the average excess level in volume is the lowest. A decrease in capitalization raises the sensitivity of the stock to changes in volume. In contrast, large caps require higher abnormal levels of volume for a jump to occur 5 minutes later. The average excess volume that could predict a jump for large caps is 2.39 standard deviations away from its normal level, i.e., when there is no jump.

Table 17. Intraday t-tests of equal means for volume-related events

Event	No Jump	-15 min	-10 min	- 5 min	On Jump	+5 min	+10 min	+15 min
Mean	0.00	0.21	0.39	1.85	0.23	0.09	0.08	-0.05
St. Dev.	0.52	0.83	1.14	3.60	1.49	1.17	1.43	0.58
Sig.		$***$	$***$	$***$	$***$	$***$	$***$	$***$

Notes: The t-test compares the average Z-score values in trading volume on "no jump" days with the average values of the indicator during the event window on days with jumps. $***$, $**$, and $*$ indicate the 1% , 5% and 10% significance levels.

Figure 9. Intraday variations in volume centered on jumps



Notes: For each cap-based group of stocks, the figure reports the intraday variations in the volume Z-score relative to its average intraday value when there is no jump, with the window centered on the jump.

4.5. Sectoral analysis

In the previous sections, we assess the relationship between jumps and trading signals using three classes of market capitalization. As a complementary check, we also examine sector characteristics. The timing of price adjustments to events arguably varies across sectors, mostly due to firm-level interactions (see, e.g., Hou and Moskowitz, 2005; Hou, 2007; DellaVigna and Pollet, 2007). In our context, we conjecture that price adjustments are less sudden when firm interactions within sectors are "denser", generating a stronger connection between market activity and technical trading. For sectors in which the adjustment is faster so that firm interactions within sectors are "sparser", one may instead anticipate a weaker connection. We are thus interested in examining whether such sector differences are critical in uncovering jump dynamics conditional on the extracted trading signals.

We proceed by decomposing the aggregated sample into eleven industries, consisting of basic industries, capital goods, consumer durables, consumer nondurables, consumer services, energy, finance, health care, public utilities, technology and transportation. We use the same four trading signals and identify jumps using the same robust identification procedure. For each sector, we then estimate the conditional probabilities of observing jumps, given the trading signals. We finally assess the magnitudes, probabilities and direction of conditional jump events.[8]

[8]For the sake of brevity, we discuss only the main findings here. Our Supplementary Data Appendix presents the entire set of empirical results of our sectoral analysis.

Our results reveal that moving average crossings considerably increase the likelihood of observing intraday jumps, and this evidence is prevalent for all sectors. We further observe that the percentage of upward and downward jumps tends to stabilize when crossings happen. This regularity turns out to be a common feature in the data across sectors except for consumer durables. Departing from other sectors, the energy sector exhibits a high positive jump ratio (approximately 57.6%) within the event windows. In terms of reaction timing, the probability of jumps (reaching up to 70%) substantially decreases following the arrivals of crossings rather than before the conditioning events. This pattern holds quite well for all eleven industries, pointing to the relatively homogeneous behavior of jump-event activities across all sectors.

In comparison to moving averages, the use of the RSI signals reveals that the direction of jumps across sectors can be predicted in-sample for a large proportion of jumps, i.e., in 90% of the cases. In fact, we obtain the largest percentages for sectors such as basic industries, energy and consumer durables. In the other sectors, trading signals are still able to determine the direction of the jumps with reasonable power, with the finance sector being the least predictable. The magnitude of shocks related to RSI signals is particularly large during bearish episodes, while market corrections appear to be fast. There is also evidence of overreaction in "bullish" periods, with the exception of the energy sector.

In the case of MACD events, the average probability of occurrence is quite low. In the sample, the MACD falls below or above its common range in 0.56% of the cases. The only industries where MACD signals tend to occur more frequently are basic industries, for which the conditional probability is approximately 1.83%. Across all sectors, most of the jumps tend to occur when the MACD is below its lower bound. Compared to the other trading signals, we observe a relatively low probability of a jump after the MACD crossings. The conditional probabilities of observing jumps are nevertheless still fairly high at approximately 37.2%.

We complete our sectoral investigation by evaluating the Z-score in volume. With an average probability of 8.6%, we find that the Z-score can effectively anticipate a jump 5 minutes before its arrival time. The prediction level is the highest for the energy sector (13.4%), while the lowest conditional probabilities are obtained for public utilities (6.3%). Interestingly, the lack of volume tends to create *negative* jumps in the data, particularly for public utilities and technology.

Our testing procedures by sector suggest that the energy sector displays the highest level of predictability in regard to identifying the *direction* of jumps, conditional on the occurrence of conventional trading signals. More broadly, we observe similar characteristics with respect to the link between jumps and trading signals across all sectors. The arrivals and directions of jump-type extreme volatility tend to vary with technical patterns.

5. Concluding Remarks

Market authorities have increasingly been concerned about financial stability, and the frequent occurrence of quick and significant asset price jumps makes their mandates more difficult to fulfill. Prior research finds evidence that price jumps are associated with exogenous news announcements. We extend the literature by showing that endogenous technical trading conveys information as well.

We find robust evidence that the occurrence of jumps is related to technical indicators. The size and direction of jumps are more easily predicted when we use trading signals as conditioning events. Such evidence remains stable, as we assess the dynamics separately by sector. Jump dynamics around trading signals also depend on market capitalization. In particular, the joint dynamics of intraday jumps and technical trading activity are particularly strong when valuation is more ambiguous, as is the case for smaller caps. As such, trading stocks around technical trading signals leads to higher jump risk (and, thus, instability), particularly in regard to trading smaller caps.

Our results show that trading volume is the most effective in predicting jumps. When volume is low, the probability of a jump is smaller in comparison to periods for which trading volume is substantially higher. We find evidence that jumps that are associated with extremely low volumes typically push prices downward. Conditional on the occurrence of trading signals, jump events have, therefore, some well-specified direct effects on the way stock prices vary over time. The predictive power of abnormal volume is also stronger for smaller caps since variations in volume for large caps need to be more radical for jumps to occur. These findings are confirmed at the sector level, with the direction of jumps being the most predictable in the energy sector.

Is it possible for market participants and policymakers to prevent *unintended consequences* of technical trading? Can portfolio managers diversify trading-driven jump risk via, for instance, sector rotation? What type of market monitoring, if any, is required by central bankers? These questions, which we leave open for future research, are important to thoroughly explore the financial implications of endogenous tail risk.

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