Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks

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Abstract

We study the dynamics of liquidity around jumps by identifying their exact intraday timing and retrieve all macroeconomic and firm-specific news for the 30 constituents of the Dow Jones Industrial Average index. We match around a third of the jumps with macroeconomic news announcements, while five per cent of the jumps are associated with firm-specific news. Jumps are found to coincide with a significant increase in trading costs and demand for immediacy, amplified by the release of news. Liquidity supply remains nevertheless high and there is rather strong evidence of resilience. Liquidity shocks in the effective spread and the number of trades are the key drivers behind the occurrence of a jump. Compared with macroeconomic news, the arrival of firm-specific news increases the probability of a jump twice as much. Finally, order imbalance appears to be the most informative liquidity variable with respect to price discovery, especially after the arrival of news.

Keywords: High-frequency data, liquidity, news, price jumps, volatility.

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1 Introduction

In finance, the study of liquidity dynamics around intraday jumps is of utmost importance for several reasons. Not only jumps play an important role in periods of market stress (Bates 2000; Duffie et al. 2000) but they also make markets incomplete since jump risk cannot easily be hedged away. As indicated by Pan (2002), this in turn can lead investors to demand a larger premium to carry these risks as risk averse investors are arguably expected to shun investments with sharp unforeseeable co-movements, all else being equal (Eraker et al. 2003). In addition, higher moments of asset return distributions and the related implied volatility smile are better explained when jumps are considered (Bates 1996; Bakshi et al. 1997; Andersen et al. 2002; Carr and Wu 2007). Finally, discontinuous price changes are recognized as an essential component in many practical financial applications. For example, jumps have distinctly different implications for the valuation of derivatives (Merton 1976a; Merton 1976b), risk measurement and management (Duffie and Pan 2001), as well as asset allocation (Jarrow and Rosenfeld 1984).

In spite of the relevance of the topic, there are just a few empirical studies about the dynamics of liquidity around intraday jumps. To complement the literature in this area of research, we carry out an original intraday event study of abnormal levels of spreads, trading volume, number of trades, mean trade size, order imbalance and depth around jumps for the 30 DJIA constituents between July 2007 and December 2009. We relate our findings to the four key dimensions of liquidity, namely, trading quantity, trading speed, trading cost, and price impact. Together, they measure liquidity, i.e. the ability to trade large quantities quickly at low cost with little price impact.

Regarding NYSE stocks, only two event-type studies focus on liquidity dynamics around large price movements, but none considers the four liquidity dimensions and none looks at jumps. Lee et al. (1993) study the reaction of spreads to earnings announcements and find that for 230 randomly chosen firms spreads in 1988 increase dramatically in the half hour containing the earning announcement, and remain wider for up to one day, while quoted depths return to nonannouncement levels after three hours. Brooks (1994) condition their study on completely unanticipated events such as the death of a CEO. For the period 1989 through 1992, they document that these events lead to wider spreads and higher volume that remain significant for over one hour. In this paper, we take a different approach since we condition the analysis of liquidity dynamics around jumps directly on the event times identified by the intraday jump detection test of Lee and Mykland (2008).

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The only study of liquidity dynamics around jumps is done by Jiang et al. (2011) who study the effect of macroeconomic news announcements on jumps in the U.S. Treasury market. Contrary to Jiang et al. (2011), we correct for seasonality in our median-based event study and explicitly test for the impact of jumps on liquidity. We also deal with large U.S. stocks and include all information arrivals leading to jumps. While macroeconomic events obviously affect individual firms, individual stock prices are also affected by sudden unexpected firm-specific information that can force an abrupt revaluation of the firms stock. Therefore, conditioning the intraday analysis on macro news does not completely capture the liquidity response by market participants to jumps in stock prices since many jumps are not directly associated with macro news (Lahaye et al., 2011). Bollerslev et al. (2008) indeed show that firm-specific news events are the dominant effect in terms of their immediate price impact at the individual stock level. Lee and Mykland (2008) even note that for individual equities, the majority of jumps occur with unscheduled news and their magnitudes are comparable to those that occur with earnings announcements.

To the best of our knowledge, no event study has been carried out on the U.S. stock market to analyze the link between intraday liquidity dynamics and properly identified intraday jumps, whatever the type of information arrivals. To complement the nonparametric event study, we implement a parametric analysis to assess the contribution of both liquidity shocks and news in both the occurrence of jumps and the price discovery process. Not only we analyze the dynamics of liquidity around all jumps by identifying their exact intraday timing, but we also retrieve all macroeconomic news announcements (prescheduled or not) as well as all firm-specific news provided by the Dow Jones and Reuters News Services. We are therefore able to study the impact of news on liquidity around the detected jumps. We match around a third of the jumps with macroeconomic news announcements, while five per cent of the jumps are associated with firm-specific news. A large majority of the jumps are therefore expected to result from pure market liquidity variations.

If we characterize liquidity by market width, jumps do worsen market liquidity conditions. If trading quantity and immediacy are considered, the picture is different. The demand for immediate execution increases sharply around jumps. If we zoom in on the drivers behind this volume surge, we show that both the number of trades and the mean trade size jump up. At the same time, depth (at the best bid-offer) does not withdraw from the market. We show that positive (negative) jumps are associated with even thicker sell side (buy side). Such findings suggest that jumps depend mainly on the elevated trading aggressiveness of one side of the market, and not on the traders reluctance to provide liquidity on the opposite side of the book. In fact, a greater demand for liquidity, rather than a weak liquidity supply, is associated with extreme price changes. As such, jumps do not seem to be due to an endogenous deficient provision of market liquidity. We also present evidence of significant resilience after the occurrence of a jump, whatever the liquidity measures under consideration.

Regarding the release of news around jumps, we find that news arrivals amplify the rise in both trading costs and demand for immediacy. However, the release of news does not really affect neither order imbalance nor liquidity provision: liquidity providers do not respond to the increase in trading costs and demand for immediacy by providing less liquidity, keeping order imbalance relatively unchanged.

We further indicate that liquidity shocks in the effective spread and the number of trades are the key drivers behind the occurrence of a jump. Compared with macroeconomic news, the arrival of firm-specific news is also identified as a stronger news driver behind the occurrence of jumps. Finally, several liquidity variables are shown to contribute to price discovery. This contribution is nevertheless not much affected by the occurrence of jumps. The post-news price discovery process is more informative, but mainly limited to order imbalance. Overall, order imbalance appears to be the most informative liquidity variable with respect to price discovery, especially after the arrival of news.

The remainder of the paper is organized as follows. In Section 2, we explain the procedure used to detect price jumps. In Section 3, we describe the data and provide summary statistics. In Section 4, we define our event study methodology. In Section 5, we report and interpret the empirical results. We conclude in Section 6.

2 Jump detection

To learn about the stochastic features of irregular jump arrivals and their associated market information, it is critical to use robust tests to detect jumps. A variety of formal tests have been developed to identify the presence of jumps, most of them being typically designed for the analysis of low frequency data.[1] However, the most natural and direct way to learn about jumps is by studying high frequency or intraday data. The earliest contributions in the identification of jumps using intraday data include Barndorff-Nielsen and Shephard (2004, 2006) who developed a jump robust measure of integrated variance called realized bipower variation

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

(RBV). It has been used by Becker et al. (2009), Giot et al. (2010) and Wright and Zhou (2009), among others, to test for a jump component in daily volatility. Exploiting the properties of RBV, Lee and Mykland (2008) developed an alternative non-parametric test which yields both the direction and size of detected jumps at the intraday level, allowing characterization of jump size distribution as well as stochastic jump intensity. Most importantly, the test allows for identification of the exact timing of the jump.

Let us define the event of interest as a jump in a firm's stock price. In essence, a price jump is a significant discontinuity in a price series. To define what is meant by 'significant discontinuity', we need an underlying price model. Following Andersen et al. (2007) and Lee and Mykland (2008), we assume that the observed log-prices p are generated by a continuous time Brownian semi-martingale process with finite activity jumps:

$$dp(s) = \mu(s)ds + \sigma(s)dW(s) + \kappa(s)dq(s), \tag{2.1}$$

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

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

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

Lee and Mykland (2008) use a rolling window of observations to estimate the local volatility. This approach has the disadvantage of being highly dependent on the size of window used in estimating volatility. 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, 2012) 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 $f_{t,i}$:

$$J_{t,i} = \frac{|r_{t,i}|}{\xi_t f_{t,i}}. \tag{2.2}$$

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

$$RBV_t(M) = \mu_1^{-2} \sum_{i=2}^{M} |r_{t,i}||r_{t,i-1}| \xrightarrow{p} \int_{t-1}^{t} \sigma^2(s)ds, \tag{2.3}$$

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.[2]

Under the null 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 to reject the null of no jump effect on $r_{t,i}$ if

$$J_{t,i} > G^{-1}(1-\alpha)S_n + C_n, \tag{2.4}$$

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 $S_n = \frac{1}{(2\log n)^{0.5}}$, 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 conservative procedure is expected to find only α spurious jumps in a given sample of n observations. In the empirical analysis on the 30 Dow Jones Industrial Average constituents for the period July 2007-December 2009, we set $\alpha = 0.1$ and sample returns at the 2-minute frequency.

Recent studies by Andersen et al. (2010), Andersen et al. (2012) and Bajgrowicz and Scaillet

[2]The periodicity factor is estimated using the default implementation in the R package highfrequency (Cornelissen et al., 2013). See Boudt et al. (2011, 2012) for further details about the periodicity filters and the importance of adjusting for periodicity when testing for intraday jumps.

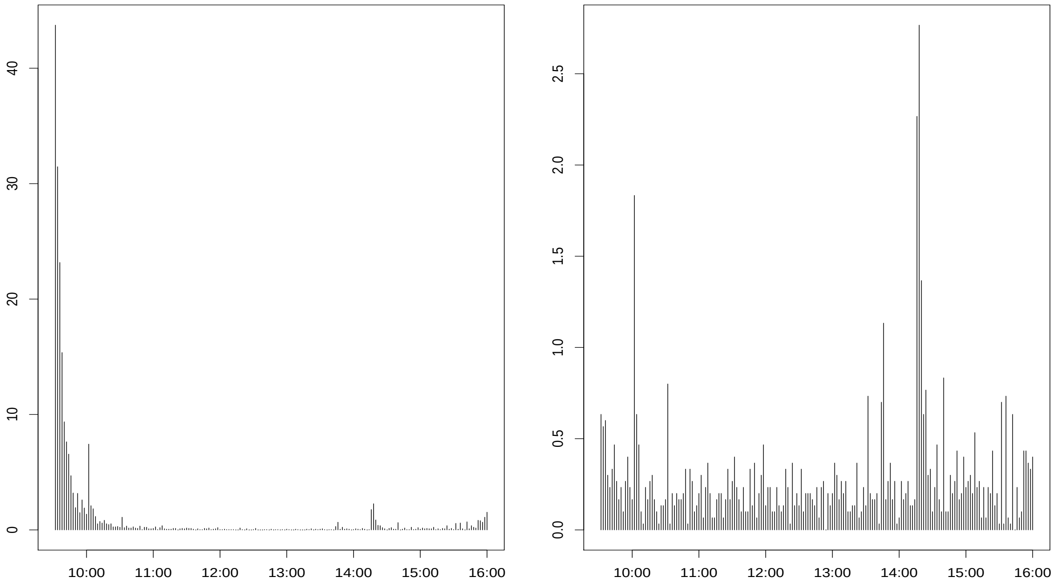
(2011) on a similar data set show that the 2-minute sampling frequency strikes a balance between using fine-grained sampling and avoiding market microstructure noise. In fact, on the one hand, a high sampling frequency is needed to disentangle the jumps from the Brownian motion: when sampling too sparsely, jumps disappear because of time averaging, as illustrated by Aït-Sahalia and Jacod (2004). On the other hand, at ultra high frequencies, microstructure effects cause a difference (called microstructure noise) between the observed price series and the underlying efficient price following the process in (2.1). While microstructure noise is well-known to impact the accuracy of integrated variance estimators (e.g. Hansen and Lunde 2006), Boudt et al. (2011) show that one should not be too worried about the impact of microstructure noise on the size of the Lee-Mykland test statistic. The intuition for this is that, in the presence of i.i.d. normal microstructure noise with variance σ_ϵ^2 (and independent of the efficient price process), the variance of the no jump component of the return $r_{t,i}$ is $\sigma_{t,i}^2 + 2\sigma_\epsilon^2$ instead of $\sigma_{t,i}^2$. Since, the realized bipower variation then estimates the integrated variance plus the total noise variation, the Lee-Mykland test still has good size properties. The power of the Lee-Mykland test reduces as the variance of the microstructure noise increases, since relatively small jumps are more difficult to detect. Finally, another reason for not being too concerned about the microstructure noise is that the analysis is conducted on very liquid large capitalization stocks and, as noted by Bajgrowicz and Scaillet (2011), that, because of the emergence of electronic and high-frequency trading, volume has increased significantly over the past years, making previous recommendations concerning the maximum frequency to avoid microstructure noise too conservative.

3 Data

Tick-by-tick records of transactions and quotations on the 30 Dow Jones Industrial Average constituents (as of January 1, 2008) are extracted from the Trades and Quotes (TAQ) database provided by the NYSE for the period July 2007-December 2009.[3] There are 628 trading days over these 2.5 years. Prior to the analysis, the data is cleaned using the step-by-step procedure proposed in Barndorff-Nielsen et al. (2010) and implemented in the R package highfrequency (Cornelissen et al. 2013). Data are sampled at a two-minute frequency. Days with more than 25% of zero returns are excluded from the analysis. At the 2-minute frequency, 1627 jumps were detected. Like in Bos et al. (2012), we find that sampling at a lower frequency reduces

[3]The tickers of the stocks in the sample are: AA, AIG, AXP, BA, C, CAT, DD, DIS, GE, GM, HD, HON, HPQ, IBM, INTC, JNJ, JPM, KO, MCD, MMM, MO, MRK, MSFT, PFE, PG, T, UTX, VZ, WMT, XOM.

Figure 1: Average number of jumps detected per stock per intraday 2-minute interval when jumps are detected using the non-adjusted test statistic $|r_{t,i}|/\xi_t$ (left figure) versus the periodicity adjusted test statistic $|r_{t,i}|/(f_{t,i}\xi_t)$.



(a) Without adjusting the test statistic for periodicity (b) With adjusting the test statistic for periodicity

the number of jumps detected. At the 4, 6, 8 and 10 minute sampling frequency, 547, 320, 202 and 154 jumps were detected, respectively. Between 50 and 60% of these lower frequency jumps correspond to time intervals in which the test on 2-minute returns detected jumps.

A key feature of the implementation of the Lee-Mykland test given in (2.2) is the adjustment of the average daily volatility for intraday periodicity. Ignoring periodicity leads to an overdetection of jumps for the intraday times when volatility is periodically high (typically, at the opening and closing of markets) and to an underdetection of jumps when periodicity is low (typically, at lunch time). In Figure 1, we plot the intraday distribution of detected jumps when using the periodicity adjusted test statistic $|r_{t,i}|/(\xi_t f_{t,i})$ (right plot) versus the unadjusted test statistic $|r_{t,i}|/\xi_t$. The adjustment for periodicity makes a very significant difference. After adjustment, most of the jumps are in the 10:00 - 10:02 am interval and 14:14-14:20 interval.[4] Those intervals correspond to the intraday times when most of the macroeconomic news scheduled during the day are released.

[4]Throughout the paper, we use the EST time zone.

Out of 1627 jumps, 630 jumps occur within 10 minutes of the announcement time of US macroeconomic news. Using the Dow Jones and Reuters News Services, we include all scheduled announcements as well as all the unscheduled macro news identified by a search on an extensive set of keywords.[5] 215 macroeconomic news are released within the 2-minute price jump. 239 (versus 300) macro news are released within 9 minutes after (versus before) the 2-minute price jump interval. Many jumps thus correspond to multiple news items.

In addition, we study the association between jumps and firm-specific Dow Jones and Reuters news. Using the same 10-minute window filter, we match jumps with firm-specific news and identify 90 associations, which is in line with Bajgrowicz and Scaillet (2011). For 23 jumps, there is a news item in the 2-minute jumps interval. 25 (versus 52) firm-specific news are released within 9 minutes after (versus before) the 2-minute price jump interval.

For the analysis of liquidity around jumps, we need to match the trades and quotes data sets. Similar to Chordia et al. (2000), the direction of each transaction is determined by the widely-used Lee and Ready (1991) algorithm.[6] Our data is sampled at a two-minute frequency. On a similar data set, Andersen et al. (2012) show that this frequency strikes a balance between using fine-grained sampling and avoiding market microstructure noise. For each interval i, we observe NT_i transactions and Q_i quotes.[7] Let $p_{i,k}$, $ask_{i,k}$ and $bid_{i,k}$ be respectively the transaction price, (best) ask quote price, and (best) bid quote price associated to the kth trade in interval i. In addition, let $size_{i,k}$, $askdepth_{i,k}$ and $biddepth_{i,k}$ be the trade size, ask depth (i.e. number of shares displayed at the best offer quote price), and bid depth (i.e. number of shares displayed at the best bid quote price) associated to the kth trade in interval i. Finally, define $ask_{i,(k)}$ and $askdepth_{i,(k)}$ (resp. $bid_{i,(k)}$ and $biddepth_{i,(k)}$) as the price and depth for the kth best ask (bid) quote in interval i (without necessarily corresponding to any trade).

[5] The keywords are: Budget Deficit, Business Inventories, Consumer Confidence, Capacity Utilization, US Credit, Consumer Prices, Durable Goods, Existing Home Sales, Fed Credit, Fed and Funds, Fed Funds Rate, Fed GDP, Factory Orders, Fed Rate, GDP Deflator, Housing Starts, Industrial a Production, Leading Indicators, NAPM, Nonfarm Payroll Employment, Personal and Consumption, Personal and Income, Producer and Price and Index, Trade and Balance, Unemployment and Claims, Unemployment Rate, US Construction, US GDP, US M1, US M2, US M3, US Retail Sales. Jiang et al. (2011) apply the same 10-minute window jumps-news matching rule for the U.S. Treasury Market. In previous studies on stock markets, the relationship is only studied at the daily level, whereby the test consists in identifying whether jumps occur on days with news or not (Bajgrowicz and Scaillet, 2011; Lee, 2012).

[6] As a number of papers in the literature points out, this algorithm is a standard and accurate method for signing transactions (see, e.g. Hvidkjaer 2006). This algorithm performs best for NYSE transactions: 93% of transactions are correctly classified in the sample examined in Lee and Radhakrishna (2000) while Finucane (2000) and Odders-White (2000) report 85% of accurate trade directions.

[7] For simplicity of notation, we omit henceforth the index for the day t.

We measure tightness by the proportional quoted bid-ask spread (QS) and the proportional effective spread (ES). For the kth quote:

$$QS_{i,k} = (ask_{i,k} - bid_{i,k})/[\frac{1}{2}(ask_{i,k} + bid_{i,k})]. \tag{3.1}$$

Half the quoted spread represents the cost of liquidity before a transaction for a quantity of shares not exceeding the available depth (at best bid-offer). Quoted spreads are prone to overestimating trading costs, since market orders are frequently price improved, i.e. they trade within the quotes. QS is therefore complemented by ES, which measure actual trading costs. ES is defined as twice the absolute value of the difference between the execution price and the midpoint of the prevailing quoted spread. For the kth transaction,

$$ES_{i,k} = [2D_{i,k}(p_{i,k} - \frac{1}{2}(ask_{i,k} + bid_{i,k}))]/\frac{1}{2}(ask_{i,k} + bid_{i,k}), \tag{3.2}$$

where $D_{i,k}$ stands for the direction of the kth trade in interval i (+1 and -1 for buy and sell orders respectively).

For both spreads, we obtain two-minute observations by calculating the size-weighted average over the interval. Size-weighted proportional quoted spreads (QSPRD) are weighted by the depth available at the prevailing quotes while size-weighted proportional effective spreads (ESPRD) are weighted by the number of shares traded:

$$QSPRD_i = \frac{\sum_{k=1}^{Q_i} QS_{i,k}(askdepth_{i,k} + biddepth_{i,k})}{\sum_{k=1}^{Q}(askdepth_{i,k} + biddepth_{i,k})} \tag{3.3}$$

and

$$ESPRD_i = \frac{\sum_{k=1}^{NT_i} ES_{i,k} size_{i,k}}{\sum_{t=1}^{NT_i} size_{i,k}}, \tag{3.4}$$

where Q_i is the number of quotes in interval i and NT_i is the number of trades.

Depth is looked at by measuring the quantity of shares available at the best bid and offer. More precisely, mean depth is measured by computing the sum of the average depth at the bid and at the ask over all quotes within a two-minute interval.

$$DPTH_i = BDPTH_i + ADPTH_i, \tag{3.5}$$

with

$$BDPTH_i = \frac{1}{Q}\sum_{k=1}^{Q} biddepth_{i,k}, \tag{3.6}$$

and similarly for mean ask depth. Depth imbalance (DI) is computed as follows:

$$DI_i = \frac{(ADPTH_i - BDPTH_i)}{DPTH_i} \tag{3.7}$$

In addition to tightness and depth, we also measure trading volume (VOLU) by the total value of all the shares traded over interval i:

$$VOLU_i = \sum_{k=1}^{NT_i} Size_{i,k}, \tag{3.8}$$

where $Size_{i,k}$ is the number of shares for trade k in interval i. Trading volume can then be decomposed into two components: The number of trades over interval i (NT_i) and the average trade size over interval i, given by $ATS_i = \frac{1}{NT_i} VOLU_i$. Finally, we also take order imbalance (OI) into account, which is estimated as the value of shares of buyer-initiated trades less the value of shares of seller-initiated trades (scaled by total trading volume):

$$OI_i = \frac{\sum_{k=1}^{NT_i} D_{i,k} Size_{i,k}}{VOLU_i}, \tag{3.9}$$

where $D_{i,k}$ is 1 if the kth trade of interval i was a buy, -1 if it was a sell.

Table 1 shows some summary statistics for all the liquidity variables described above. The statistics are reported separately for days with jumps and days without jumps. At first sight, the median liquidity on days without jumps does not look fundamentally different than the median liquidity on days with jumps. However, these samples are unmatched, with possibly very different values of 'normal' liquidity (i.e. liquidity under the null of no effect of jumps on liquidity). It is therefore difficult to draw any conclusion from this table regarding the effect of jumps on liquidity. To carry out such an analysis, we use an event study methodology defined in the next Section. We complement it with a regression analysis to assess the role of liquidity shocks in both jumps and price discovery, while controlling for the arrival of news as well.

Table 1: Summary statistics

	Returns (in%)	QSPRD (in%)	ESPRD (in%)	VOLU	ATS	NT	OI* (in %)	DPTH	ADPTH	BDPTH	DI* (in%)
Days without jumps (14994 days)											
min	-24.36	0.01	0.00	100.00	100.00	1.00	0.00	0.00	0.00	0.00	0.00
med	0.00	0.04	0.04	7900.00	459.09	17.00	36.11	91.57	43.65	44.01	17.08
mean	-0.00	0.05	0.06	19049.04	752.11	20.90	41.00	758.28	377.62	380.65	21.42
max	28.72	8.54	11.33	18189800.00	2733800.00	120.00	100.00	2269018.61	1279274.21	1855903.13	99.65
Days with jumps (1481 days)											
min	-17.63	0.01	0.00	100.00	100.00	1.00	0.00	2.00	1.00	1.00	0.00
med	0.00	0.04	0.04	8200.00	465.62	17.00	36.13	85.92	40.45	41.10	18.27
mean	0.00	0.05	0.06	20163.25	725.17	22.19	41.05	537.12	270.15	266.97	22.76
max	17.44	2.84	14.83	4468334.00	246160.00	120.00	100.00	367331.08	352897.90	162450.59	99.56

Returns are 2-minute log returns. $QSPRD$ is the 2-minute size-weighted proportional quoted spread. $ESPRD$ is the 2-minute size-weighted proportional effective spread. $VOLU$ measures trading volume, i.e. the total value of all the shares traded over 2 minutes. NT is the total number of transactions over 2 minutes. ATS is the average size of a transaction (i.e. $VOLU/NT$) over a 2-minute interval. OI^* is the absolute order imbalance computed over 2 minutes. $ADPTH$ and $BDPTH$ are respectively the average depth at the ask and at the bid observed over 2 minutes. $DPTH$ is the sum of $ADPTH$ and $BDPTH$. DI^* is the absolute depth imbalance. All statistics are computed over the 30 stocks included in the sample covering the July 2007-December 2009 time period.

4 Methodology

To study the impact of jumps on liquidity, we perform intraday event studies on different measures of liquidity. The null hypothesis of the event study is that: *Jumps have no effect on liquidity*. The alternative is: *Liquidity around a price jump is abnormally low or high.* The null will be tested by running multiple event studies on the different measures of liquidity described in Section 3. Our event study method proceeds in five steps: 1. Define the event and event window; 2. Collect a sample of event occurrences; 3. Standardize liquidity measures; 4. Aggregate individual events; 5. Evaluate hypothesis.

Definition of the event and event window. The period over which we study the effect of the price jump on liquidity is called the event window. It is centered around the 2-minute interval in which the jump has occurred. It contains further the 60 minutes before and after that jump interval. Observations of liquidity measures will be indexed in event time using τ, which indicates the number of minutes relative to the jump. Defining $\tau = 0$ as the intraday time of the jumps, $i + \tau$ indicates the τ-th minute counting from i. The full event window is represented by all even integer $\tau \in [-60, 60]$. The length of this window provides a trade-off between the ability to capture the full effect of a jump, demanding a longer window, and the ability to include jumps that occur near the beginning or closing of the trading day.[8]

Event occurrences. The Lee and Mykland jump test presented in Section 2 detects 1627

[8] It would not be meaningful to construct event windows containing observations from different days, due to overnight trading.

Table 2: Summary statistics for the joint distribution of jumps and news releases

		Positive jumps				*Negative jumps*			
			No News	Macro News	Firm News		No news	Macro News	Firm News
Number of Jumps	Total	465	331	117	22	374	280	82	16
	10:30-11:30	89	68	18	4	78	67	7	4
	11:30-12:30	82	65	14	5	74	58	11	6
	12:30-13:30	75	66	6	3	66	56	10	1
	13:30-14:30	148	78	65	7	136	80	54	4
	14:30-15:30	71	54	14	3	20	19	0	1
Jump Size	Min	0.122	0.122	0.215	0.257	-17.626	-17.626	-9.097	-2.133
(in%)	Median	0.604	0.525	1.029	0.792	-0.544	-0.513	-0.995	-0.673
	Max	28.723	17.435	28.723	6.899	-0.171	-0.171	-0.307	-0.233

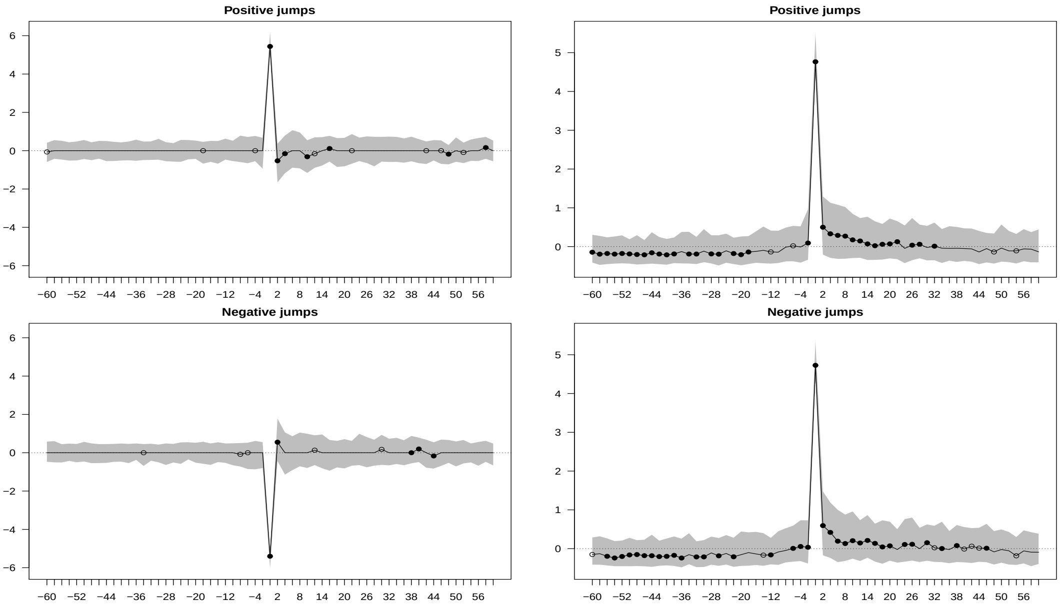
Third and seventh columns present summary statistics for all positive and negative jumps, respectively. Columns 4 (resp. 8), 5 (resp. 9) and 6 (resp. 10) are summary statistics for positive (resp. negative) jumps that coincide with the absence of news release, the release of macronews and the release of firm news in the 10 minutes around the jump interval, respectively. All statistics are computed over the 30 stocks included in the filtered sample of 839 jumps in the period July 2007-December 2009, used for the event study analysis. The hourly interval hh:30-(hh+1):30 is hh:30 included and (hh+1):30 excluded.

jumps in our sample of the 30 DJIA constituents between July 2007 and December 2009. We impose two additional conditions before including jumps to the event sample. First, jumps occurring in the first and last hour of the day are excluded since comparing incomplete event windows in a cross sectional framework would severely hinder our ability to infer the dynamics of liquidity measures throughout the event window. Second, when two jumps occur within the same day, they must be separated in time by at least half a trading day. This criterion prevents contamination of jump events. If two jumps were to occur close in time, then the after-effects of the first jump might affect observations near the second jump. After applying the first filter, the number of detected jumps shrinks from 1669 to 1096, while the second filter reduces further the event sample to 839 jumps.

Table 2 indicates that the timing of the jumps associated with news does not match the timing of those that are not. While the latter are relatively uniformly distributed over the day, most of the former are associated with macroeconomic news and occur in the 13:30-14:30 interval. The second panel of Table 2 evaluates the impact of news on the size of the jumps. The median magnitude of jumps coinciding with macroeconomic news arrivals tends to be almost twice as large as the median size of jumps that are not associated with news. The median size of jumps associated with firm news is also larger, albeit smaller than in the case of macroeconomic news.

Figure 2 reports the median of the (centered absolute) standardized returns $r_{t,i}/(\xi_t f_{t,i})$ for each event time. If jumps have no effect on the other returns in the window, the median

Figure 2: Standardized returns around jumps



(a) Standardized returns (b) Absolute standardized returns

Full black line is the median (absolute) standardized return. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (●) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from the same distribution as the ones on days without jumps) is rejected at the 99% confidence level. White bullets (○) indicate a rejection at a 95% only (i.e. $1\% < p - value \leq 5\%$).

(centered absolute) standardized return should be close to zero.[9] Interestingly, we find that the median return in the 2-minute interval after a positive price jump tends to be negative, while this median is positive after a negative jump. This would indicate that part of the price jump is due to some short-term market overreaction, although it remains small in size. In addition, overreaction to negative jumps (which are typically associated with bad news) seems to be more pronounced than overreaction to positive jumps. In the right plot, we also notice that volatility on days with jumps increases above its level on days without jumps around 6 minutes before the jump. Subsequently, volatility stays above both the pre-jump level and the level observed on days without jumps for more than 30 minutes after the jump.

Standardization. Liquidity measures need to be standardized to make them comparable across firms, days and intraday times. In contrast to most event studies on liquidity, we use the median (instead of the mean) for standardizing. This is motivated by the fact that

[9] The $|r_{t,i}|/(\xi_t f_{t,i})$ are centered around the median of the absolute value of a standard normal random variable, which is 0.674 (i.e. the 75% quantile of the standard normal distribution).

distributions of liquidity measures are heavily skewed to the right. Plerou et al. (2005) describe in much detail the distribution of liquidity measures. For a liquidity measure L, denote by L_t the median of the distribution of liquidity values on day t, and write the corresponding sample median as $\hat{L}_t$

For all liquidity variables except depth and order imbalance, we assume a multiplicative model that specifies the intraday liquidity value $L_{t,i}$ in the absence of jumps as the product between the daily factor L_t, a deterministic intraday factor L_i and an i.i.d. error term $\eta_{t,i}$ with median 1:

$$\text{Day without jumps:} \quad L_{t,i} = L_t L_i \eta_{t,i}. \tag{4.1}$$

This specification is related to the multiplicative error model in Engle (2002), applied to analyze volume by Manganelli (2005). The impact of jumps on the liquidity value is specified as the additive component $j_{t,i}$:

$$\text{Day with jumps:} \quad L_{t,i} = L_t L_i \eta_{t,i} + j_{t,i}. \tag{4.2}$$

If jumps have no impact on liquidity, then $j_{t,i} = 0$ for all i, t. Let ND be the collection of days without jumps. It follows that under the model assumptions above, the natural estimator for the intraday liquidity factor L_i is:

$$\hat{L}_i = \text{median}_{t \in ND} \frac{L_{t,i}}{\hat{L}_t}. \tag{4.3}$$

Based on these results, we analyze the percentage deviation of the deseasonalized liquidity measure from its daily level

$$\bar{L}_{t,i} = \frac{L_{t,i}}{\hat{L}_t \hat{L}_i} - 1. \tag{4.4}$$

If jumps have no impact on liquidity, then $\bar{L}_{t,i}$ should have a zero median and have the same distribution on jump days as on non jump days. We will test this using the Mann-Whitney test.

Because depth and order imbalance can take both positive and negative values, they are more naturally modeled as additive processes:

$$L_{t,i} = L_t + L_i + \varepsilon_{t,i} + j_{t,i}, \tag{4.5}$$

with $\varepsilon_{i,t}$ an i.i.d. error term with median zero. Similarly as above, this leads to the intraday periodicity estimator

$$\hat{L}_i = \text{median}_{t \in ND}(L_{t,i} - \hat{L}_t) \tag{4.6}$$

and the standardization

$$\bar{L}_{t,i} = L_{t,i} - \hat{L}_t - \hat{L}_i. \tag{4.7}$$

Aggregation. To make a general statement about the effect of jumps on liquidity, we have to aggregate all events into a single one. For each event period $\tau \in [-60, 60]$, we summarize observed standardized liquidity measures by taking the median of the standardized liquidity values in (4.4)-(4.7) across individual events. We again prefer the median over the mean on two grounds. First, the distributions of $\bar{L}_{t,i}$ remain heavily skewed, which calls for the use of a robust measure of central tendency. Second, by construction, the median value of $\bar{L}_{t,i}$ in the control sample of non-jump days will be equal to 0. Therefore, we retain the ability to directly interpret the aggregated values of $\bar{L}_{t,i}$ as percentage deviations from typical levels. We aggregate over all firms and years in the sample, but distinguish between event windows with positive and negative jump returns. Finally, in order to visualize the spread of the distribution of standardized liquidity measures, we also compute the 2.5% and 97.5% empirical quantiles.

Hypothesis testing. For each time interval of the aggregate event window, we use the Mann-Whitney test to evaluate the null hypothesis that the distribution of the standardized liquidity values on jump days is the same as on days without jumps.

5 Empirical analysis

The unique feature of the following empirical event study is to analyze the dynamics of liquidity around all jumps by identifying their exact intraday timing. We study the dynamics of spreads, trading volume, number of trades, average trade size, order imbalance and depth and relate them to the four dimensions of liquidity identified by Liu (2006): trading cost (width), trading quantity (depth), trading speed (immediacy) and price impact (resiliency). We subsequently carry out a parametric analysis to assess the role of liquidity shocks in both jumps and price discovery. We also control for the arrivals of news and do not exclusively focus on macroeconomic news announcements. Although macro news are associated with jumps more often than firm-specific news, the latter typically dominate the former when it comes to estimating the magnitude of the price impact (at the individual stock level, of course).

5.1 Spreads around jumps

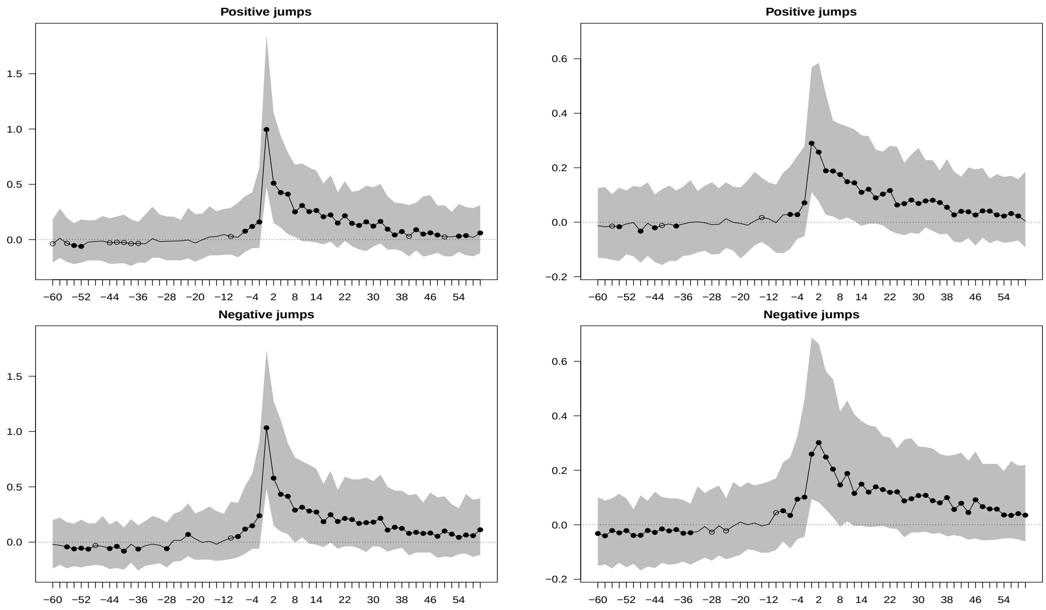
Figure 3 shows a significant shock in spreads at the time of a price jump, indicating a rise in at least one of the three typical cost components of the spread: order processing costs, inventory holding costs, and/or asymmetric information risk.

Jumps lead to a 100% deviation from the 'typical' time of day value in ex-post liquidity, as measured by the size-weighted proportional effective spread (ESPRD). This negative impact of jumps on ex-post liquidity must nevertheless be put into perspective. The ESPRD shows strong resilience since its level on days with jumps is back to its level on day without jumps after around half an hour. In addition, there is no evidence of leakage since no rise in ex-post liquidity occurs before the jump: Spreads in the minutes preceding a jump are similar to those on days without jumps. The classical explanation would be that market participants could not adjust their behavior in advance of the release of important news. It may be the case that most of these jumps occur at unpredictable time schedules. They may also come from unexpected revisions in market expectations following scheduled news announcements.

The impact of jumps on ex-ante liquidity (as measured by the QSPRD, i.e. the size-weighted proportional quoted spread) is less pronounced since the incremental effect of jumps is around 27% (versus 100% for ex-post liquidity). Ex-post liquidity is thus more severely affected than ex-ante liquidity, confirming that liquidity providers respond to the occurrence of jumps by being reluctant to improving their displayed quoted prices rather than by posting wider bid-ask spreads. Finally, quoted spreads show strong resiliency as well. After less than 15 minutes after the jump, they exceed the normal level by less than 10%.

Trading costs are therefore affected by the occurrence of jumps. With respect to the first dimension of liquidity (as measured by width), market liquidity is worsened by the occurrence of jumps, which are typically triggered by events with large information contents. These findings support the view of Lee et al. (1993) and Handa et al. (2003) who show that well-defined price adjustments, higher volatility, and larger spreads are observed around important events, such as earnings announcements. Lee et al. (1993) document a sharp rise in spreads in the half hour containing an earnings announcement, especially those that result in high returns. They also find that effective spreads rise more than quoted spreads.

Figure 3: Size Weighted Proportional Effective and Quoted Spreads



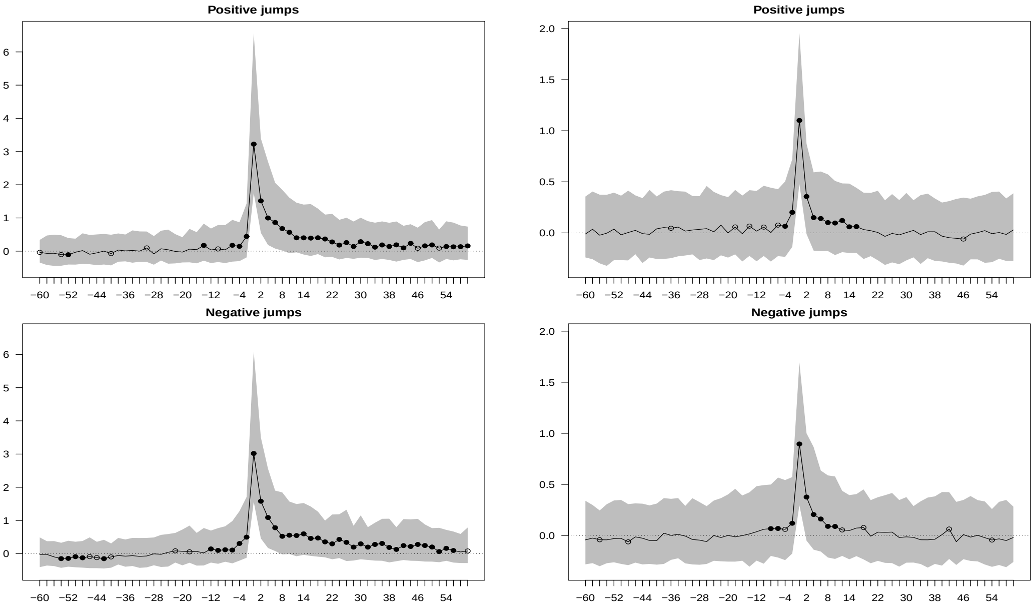
(a) Effective Spreads (ESPRD) (b) Quoted Spreads (QSPRD)

Full black line is the median standardized liquidity measure. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (●) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from the same distribution as the ones on days without jumps) is rejected at the 99% confidence level. White bullets (○) indicate a rejection at a 95% only (i.e. $1\% < p - value \leq 5\%$).

5.2 Trading volume and depth around jumps

The demand for immediate execution increases around jumps. We observe this evidence in terms of trading volume, number of trades, and average trade size. Figure 4 shows a very significant surge in trading volume at the time of a price jump. In the 2-minute jump interval, the abnormal median trade volume is three times the time-of-day median value across days with no jumps. We also note that trading volume starts increasing significantly more than 10 minutes before the occurrence of the jump and it remains significantly higher than its median level in the 60 minutes following the price jump. According to Easley and O'Hara (1992) and Glosten and Milgrom (1986), this unusually large trading volume puts pressure on the specialists' inventory and may signal informed trading. Thus, high demand for immediacy around information disclosures is often accompanied by higher spreads: When the specialist notices unusually high volumes of trade, she is more likely to increase spreads to compensate for inventory holding costs or/and higher adverse selection risk.

Figure 4: Trading Volume and mean depth



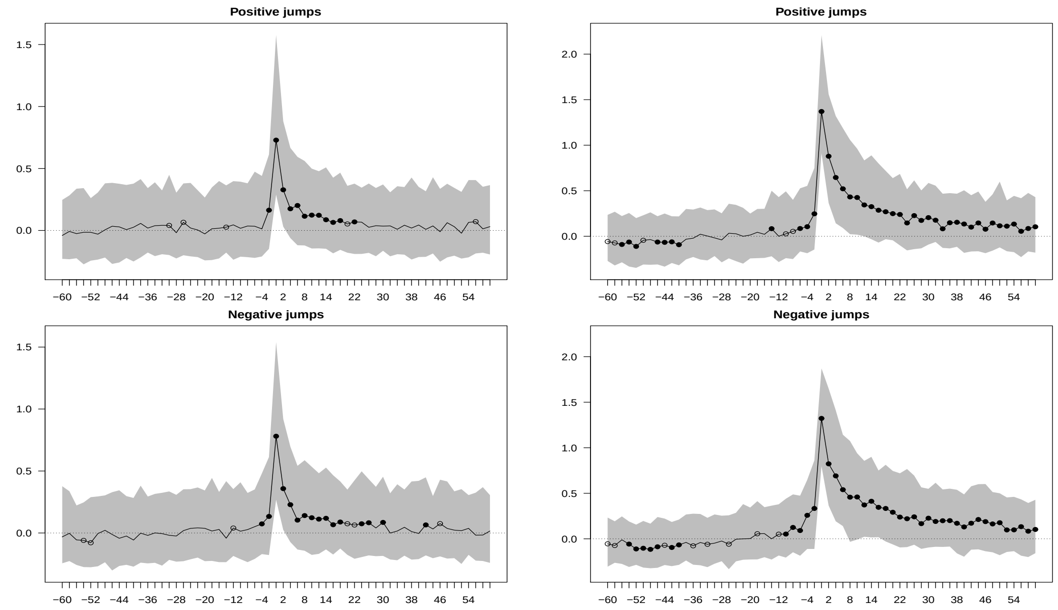
(a) Volume (VOLU) (b) Depth (DPTH)

Full black line is the median standardized liquidity measure. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (●) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from the same distribution as the ones on days without jumps) is rejected at the 99% confidence level. White bullets (○) indicate a rejection at a 95% only (i.e. $1\% < p - value \leq 5\%$).

Let us zoom in on the drivers behind this volume surge: Is it due to a higher number of trades or to a larger trade size? Figure 5 shows that both the number of trades and average trade size jump up. These findings confirm that jumps are driven by variations in the demand for immediacy. Jumps are due to the market inability to absorb new orders without moving the price significantly up or down.

In general, the median incremental effect of jumps on average trade size is around 75% across stocks and days. Kim and Verrecchia (1994) link the size of trades to the quality of information possessed by traders. Easley and O'Hara (1987) point out that informed traders prefer to trade in larger sizes. These propositions fit well into the information scenario: when the source of information is public, the traders' information advantage is fleeting rapidly. Immediacy becomes of essential and traders therefore prefer larger trade sizes. Of course, to minimize price impact, large orders may be split into smaller ones, either by the investors themselves or by the floor brokers. Such splitting of orders may explain the rise in the number

Figure 5: Average Trade Size and Number of Trades



(a) Average Trade Size (ATS)

(b) Number of trades (NT)

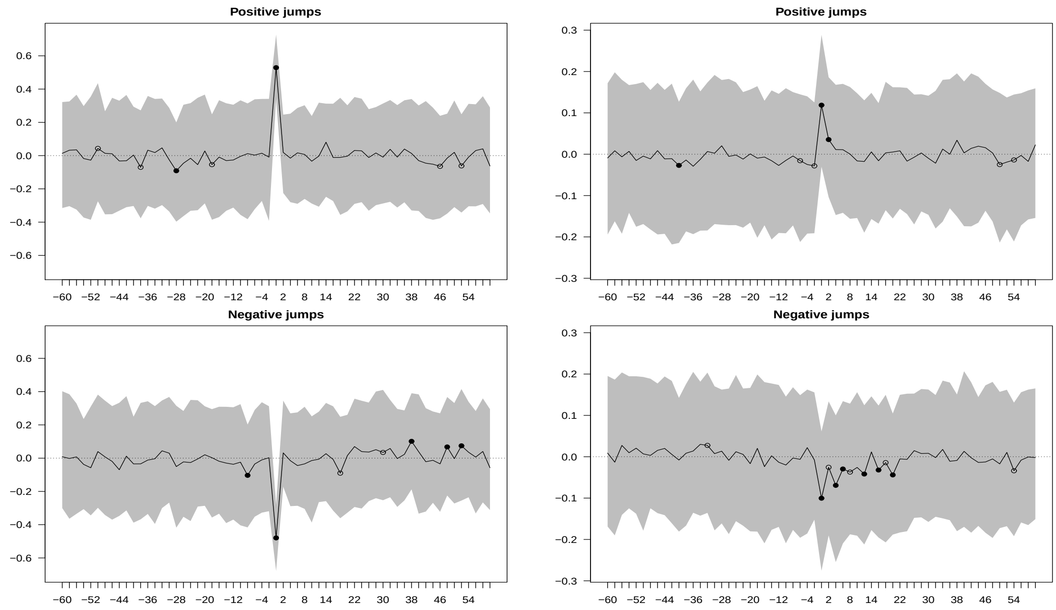
Full black line is the median standardized liquidity measure. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (●) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from the same distribution as the ones on days without jumps) is rejected at the 99% confidence level. White bullets (○) indicate a rejection at a 95% only (i.e. $1\% < p - value \leq 5\%$).

of transactions. However, the rise in average trade size is marked and undeniable, suggesting that the demand of immediacy is particularly strong.

The effect of jumps on the number of transactions is even higher: When a jump occurs, the number of trades is 2.5 times its time-of-day median value across days with no jump. We also note that the persistence in trading volume on days with large jumps is due to the persistence in the number of trades, not in the average trade size. This level of persistent and intense trading around jumps suggests that market participants need some time to rebalance their portfolio, satisfy their pent-up demand or even adjust their hedging positions.

Interestingly, we provide weak evidence of a run-up in volume and spreads before jumps. In Figures 3-4, the curve remains pretty flat until right before the jump. This suggests that the information content of news leading to jumps is essentially unexpected. The occasional small run-up is more likely to be due to a reflection of a climate of uncertainty than an anticipation

Figure 6: Order Imbalance and Depth Imbalance



(a) Order Imbalance (OI) (b) Depth Imbalance (DI)

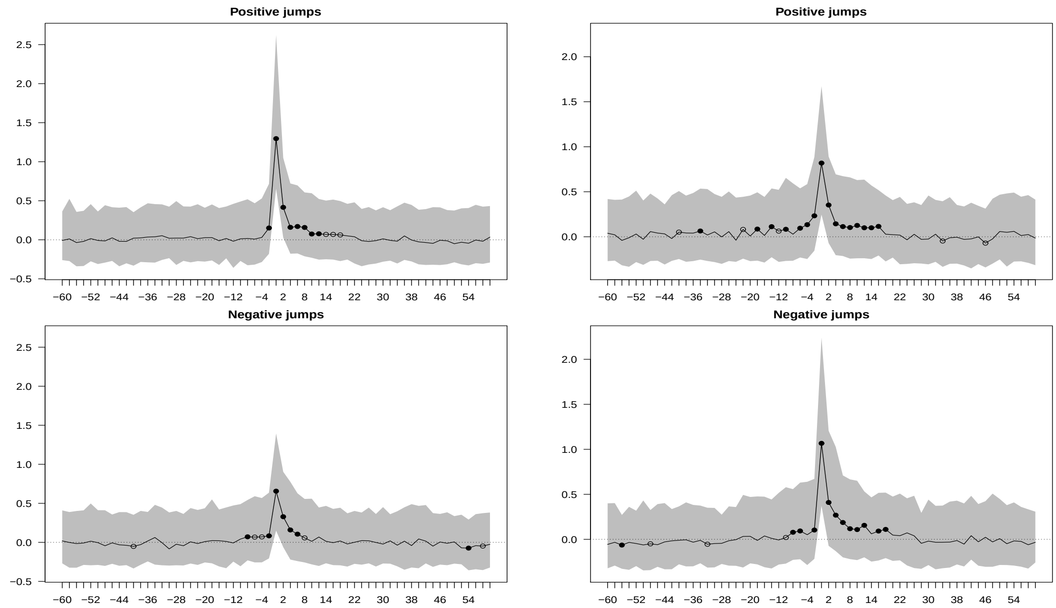
Full black line is the median standardized liquidity measure. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (•) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from the same distribution as the ones on days without jumps) is rejected at the 99% confidence level. White bullets (◦) indicate a rejection at a 95% only (i.e. $1\% < p - value \leq 5\%$).

by astute market players. This argument is reinforced by the complete absence of drift in order imbalance before the jumps, as shown in Figure 6.

Figure 4 illustrates how quoted market depth (at the best-bid offer) increases around jumps. Despite higher spreads and trading volume, depth does not withdraw from the market. Liquidity provision even improves when a jump occurs. It is noteworthy that a greater demand for liquidity, rather than a weak liquidity supply, is associated with extreme price changes. Simply put: an increased demand for immediacy does not translate into weak liquidity supply. Jumps do not seem to be due to a deficient provision of market liquidity, suggesting that they cannot be considered endogenous. On the one hand, a larger number of trades is executed and a higher volume is traded. On the other hand, market depth on both sides of the market helps meeting this higher demand of liquidity (Figure 7).

Total mean depth hides movements of depth at the bid and the ask. Figure 7 shows that during a positive (negative) jump, the ask (bid) quote increases (decreases) more than bid (ask)

Figure 7: Mean Ask and Bid Depth



(a) Ask depth (ADPTH) (b) Bid depth (BDPTH)

Full black line is the median standardized liquidity measure. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (•) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from the same distribution as the ones on days without jumps) is rejected at the 99% confidence level. White bullets (◦) indicate a rejection at a 95% only (i.e. $1\% < p - value \leq 5\%$).

quote. Such findings suggest that jumps depend mainly on the elevated trading aggressiveness of one side of the market, and not on the traders' reluctance to provide liquidity on the opposite side of the book. Indeed, positive (negative) jumps are associated with even thicker sell side (buy side). This evidence is consistent with Parlour (1998) who shows that in a competitive environment, liquidity supply provides higher market depth to the most aggressive side of the market. In addition, the increase in liquidity provision on both sides of the market is accompanied by a modest and short-lived depth imbalance (Figure 6). Jumps lead to a 10% deviation in depth imbalance from the 'no jump' time-of-day median value and the imbalance disappears around 10 minutes after the occurrence of a jump.

The combination of spread and depth changes suggest that, on average, quoted liquidity does not deteriorate significantly in response to volume shocks around jumps. Although the first dimension of liquidity (i.e. trading costs) is negatively affected by the occurrence of jumps, the second dimension (i.e. trading quantity) benefits substantially. While the spread widening effect is consistent with Easley and O'Hara (1992)'s model in which specialists use trading volume to infer the presence of informed traders, the increase in liquidity provision is consistent with Harris and Raviv (1993) in which increased volume primarily reflects increased liquidity trading and, therefore, higher overall market liquidity.

Figure 6 shows that trading activity at the time of a jump is very unbalanced. Positive (negative) jumps are characterized by a large buying (selling) pressure of about 60% above the 'non-jump' time-of-day median value. According to Chordia et al. (2002), the degree of order imbalance is an indication about the relevance of the information release to the market. Since a high number of trades may be considered as a large sample of independent observers of the same signal, a high disequilibrium between buy and sell transactions suggests that market participants widely agree on the positive or negative effect of the news being released. Our results also show that order imbalance drops back quickly to its pre-jump level after the jump, in contrast to trading volume which is more persistent. Although market participants may initially agree on the direction of the prices, heterogenous beliefs about the revised fundamental value of the asset appear afterwards, leading to high trading volume and a more balanced fight between bulls and bears.

5.3 Impact of news on the liquidity dynamics around jumps

The next question that we study in Table 3 is how the occurrence of news affects the impact of jumps on liquidity. In Table 3 the median abnormal liquidity observed 10 minutes before the jump, at the jump and 30 and 60 minutes after the jump are reported when aggregated over 8 sets: all positive (negative) jumps, all positive (negative) jumps that are not associated with news, and all positive (negative) jumps that are associated with macroeconomics news and those associated with firm-specific news. The median abnormal liquidity of all positive (negative) jumps corresponds with the Figures 3-7.

In terms of trading costs, the increase in both ex-ante and ex-post spreads within the 2-minute jump interval is found to be substantially higher when jumps coincide with news releases. The increase in trading costs after a news release is also persistent, especially when jumps are associated with macroeconomic news: the shock in spreads seems to persist for 60 minutes after the occurrence of a jump. The most persistent shocks occur on ex-post trading costs (i.e. effective spread) when there is a negative jump accompanied by the release of a (bad) macroeconomic news announcement.

If we look at volume, average trade size, and number of trades, the increase and the persistence in the demand for immediacy are also found to be typically higher when a jump coincides with a macroeconomic or firm news release (than when it does not). The increase in each of these liquidity proxies at the time of the jump tends to be the highest when the jump is associated with firm news.

In contrast to the other liquidity proxies, shocks in depth, order imbalance, and depth imbalance are especially short-lived and rather unaffected by the release of news.

Overall, the release of news around jumps amplifies the rise in both trading costs and demand for immediacy. However, the arrival of news does not really affect neither order imbalance nor liquidity provision: liquidity providers do not respond to the increase in trading costs and demand for immediacy by providing less liquidity, keeping order imbalance relatively unchanged.

5.4 Contribution of liquidity shocks to jumps

The empirical findings documented in the previous subsections suggest that liquidity shocks around jumps are substantial but do not necessarily worsen market quality across the board. In this subsection, we examine how shocks in effective spread (ESPRD), mean depth (DPTH), number of trades (NT), absolute order (flow) imbalance (OI*) and absolute depth imbalance (DI*) explain the probability that a jump will occur.[10]

In Table 4, we run three binary dependent variable models to test whether any liquidity variable contributes to the occurrence of stock jumps with a 2-minute time lag. The logit, probit, and gombit models lead to the same conclusions: shocks in the effective spread and the number of trades are the key liquidity drivers behind the occurrence of a jump. The number of stocks with positive and significant coefficients for the number of trades varies between 26 and 29 stocks across the three models. This number is between 24 and 29 for the effective spread. All other liquidity variables have negligible impact. In particular, imbalances do not increase the explanatory power of the regressions beyond trade frequency and market width, confirming our nonparametric event study. Jumps do not seem to be related to the one-sided withdrawal or disequilibrium in displayed depth. Market practitioners do not significantly withdraw their orders (on one side of the market, at least) to avoid being picked off in the

[10] The abnormal levels of liquidity are constructed similarly as in (4.4) and (4.7), but using the lagged daily liquidity $\hat{L}_{t-1}$ rather than $\hat{L}_t$. More precisely, for spreads, depth and number of trades, the liquidity shock in the forecast equations are computed as $L_{t,i}/(\hat{L}_i\hat{L}_{t-1})$ and for the depth and order imbalance, we use $L_{t,i}-\hat{L}_{t-1}-\hat{L}_i$.

Table 3: Impact of news on the liquidity dynamics around jumps

		Positive jumps				*Negative jumps*			
			No News	Macro News	Firm News		No news	Macro News	Firm News
ESPRD	-10	*0.029*	0.015	**0.080**	-0.023	*0.037*	0.050	*0.048*	-0.097
	0	**0.995**	**0.846**	**1.601**	**1.723**	**1.034**	**0.795**	**1.572**	**1.322**
	30	**0.122**	**0.097**	**0.231**	**0.154**	**0.181**	**0.106**	**0.427**	*0.163*
	60	**0.060**	0.036	**0.125**	0.075	**0.112**	0.054	**0.217**	*0.261*
QSPRD	-10	-0.002	-0.001	-0.004	0.001	*0.044*	0.020	**0.093**	0.043
	0	**0.290**	**0.250**	**0.628**	**0.616**	**0.259**	**0.199**	**1.010**	**0.354**
	30	**0.069**	**0.050**	**0.133**	**0.114**	**0.107**	**0.089**	**0.178**	*0.118*
	60	*0.005*	-0.003	**0.069**	0.031	**0.035**	*0.005*	**0.125**	0.026
VOLU	-10	*0.067*	*0.119*	0.005	-0.228	**0.100**	0.083	*0.143*	-0.055
	0	**3.223**	**2.854**	**4.677**	**12.040**	**3.018**	**3.000**	**2.727**	**4.429**
	30	0**0.284**	**0.189**	**0.719**	**1.018**	**0.297**	**0.174**	**0.633**	**0.626**
	60	**0.158**	*0.061*	**0.413**	*0.260*	*0.081*	0.073	0.084	*0.921*
ATS	-10	0.018	0.017	0.025	0.013	0.014	0.004	0.061	-0.224
	0	**0.729**	**0.625**	**0.847**	**2.474**	**0.781**	**0.780**	**0.656**	**0.962**
	30	0.035	0.012	0.121	*0.139*	**0.085**	0.067	**0.156**	*0.238*
	60	0.031	0.022	**0.120**	-0.061	0.016	0.021	-0.029	0.096
NT	-10	*0.027*	*0.038*	0.023	0.041	*0.052*	0.026	**0.151**	0.207
	0	**1.370**	**1.219**	**1.651**	**2.358**	**1.322**	**1.222**	**1.462**	**1.481**
	30	**0.205**	**0.138**	**0.500**	**0.543**	**0.226**	**0.162**	**0.435**	*0.367*
	60	**0.104**	0.019	**0.457**	*0.306*	**0.103**	*0.061*	**0.227**	*0.543*
DPTH	-10	*0.057*	*0.067*	0.035	0.137	0.060	0.065	-0.002	-0.004
	0	**1.101**	**1.079**	**1.060**	2.575	**0.895**	**1.044**	**0.463**	**1.209**
	30	0.003	-0.027	0.063	0.253	-0.014	-0.012	-0.023	0.452
	60	0.029	-0.037	0.112	0.109	-0.020	-0.023	-0.107	0.274
OI	-10	-0.004	0.006	-0.045	0.192	-0.024	0.015	-0.225	-0.228
	0	**0.529**	**0.561**	**0.465**	**0.529**	**-0.480**	**-0.510**	**-0.417**	**-0.282**
	30	-0.009	-0.017	0.010	0.126	*0.034*	0.025	0.082	-0.123
	60	-0.062	-0.049	*-0.183*	0.365	-0.058	0.015	*-0.124*	-0.107
DI	-10	-0.015	-0.041	0.013	0.019	-0.02	-0.008	-0.023	-0.287
	0	**0.119**	**0.119**	**0.115**	0.073	**-0.100**	**-0.100**	**-0.097**	*-0.154*
	30	-0.010	-0.005	-0.016	-0.009	0.008	-0.007	0.055	-0.011
	60	0.023	0.034	0.017	-0.095	-0.002	-0.005	0.015	-0.074

Abnormal liquidity is measured as the median standardized liquidity measure. Third and seventh columns present the abnormal liquidity for all positive and negative jumps, respectively. Columns 4 (resp. 8), 5 (resp. 9) and 6 (resp. 10) are summary statistics for positive (resp. negative) jumps that coincide with the absence of news release, the release of macronews and the release of firm news in the 10 minutes around the jump interval, respectively. All statistics are computed over the 30 stocks included in the filtered sample of 839 jumps in the period July 2007-December 2009, used for the event study analysis. Numbers in bold indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from the same distribution as the ones on days without jumps) is rejected at the 99% confidence level. Numbers in italics indicate a rejection at a 95% only (i.e. $1\% < p-value \leq 5\%$).

Table 4: Contribution of liquidity shocks to the probability of price jump. Stock by stock binary discrete choice models, using a 2-minute time lag.

	DPTH	ESPRD	NT	OI*	DI*	VOLA
LOGITModel						
$\overline{\beta}$	-0.029	0.302	0.562	-0.007	-0.384	-0.817
$\overline{\sigma_\beta}$	0.107	0.069	0.121	0.702	1.232	0.720
# + significant at 5%	5	28	29	0	0	0
# + significant at 10%	9	28	29	1	0	0
# − significant at 5%	0	0	0	1	1	3
# − significant at 10%	0	0	0	1	2	6
% McFadden R^2	4.037					
PROBITModel						
$\overline{\beta}$	-0.008	0.175	0.112	0.011	-0.080	-0.240
$\overline{\sigma_\beta}$	0.031	0.046	0.031	0.189	0.329	0.191
# + significant at 5%	5	29	26	0	0	0
# + significant at 10%	6	29	27	1	0	2
# − significant at 5%	0	0	0	0	1	6
# − significant at 10%	0	0	0	1	2	7
% McFadden R^2	4.412					
GOMBITModel						
$\overline{\beta}$	-0.004	0.065	0.085	0.008	-0.028	-0.117
$\overline{\sigma_\beta}$	0.015	0.021	0.025	0.085	0.148	0.086
# + significant at 5%	4	24	29	0	0	0
# + significant at 10%	5	26	29	1	0	0
# − significant at 5%	0	0	0	0	1	7
# − significant at 10%	0	0	0	2	1	8
% McFadden R^2	4.674					

$$P(JUMP_{(i)t} = 1|\mathbf{X}) = G(\alpha_i + \beta_{1,i}DPTH_{(i)t-1} + \beta_{2,i}ESPRD_{(i)t-1} \\ +\beta_{3,i}NT_{(i)t-1} + \beta_{4,i}OI^*_{(i)t-1} + \beta_{5,i}DI^*_{(i)t-1} + \beta_{6,i}VOLA_{(i)t-1})$$

The above regression is run for each of the 30 constituents of the DJIA index over the period July 2007-December 2009 at the 2-minute frequency level. $P(JUMP_{(i)t} = 1|\mathbf{X})$ is the response probability that a jump occurs for stock i at intraday time t given a set of explanatory variables $\mathbf{X}$ which includes shocks in mean depth (DPTH), effective spread (ESPRD), number of trades (NT), absolute order (flow) imbalance (OI*), absolute depth imbalance (DI*), as well as realized volatility (VOLA). All explanatory variables are included with a time lag of 2 minutes, except volatility which is computed over the 20-minute interval before the jump. G is the CDF of the logistic, standard normal, and Type-I extreme value (skewed) distribution, respectively. The logit, probit, and gombit models are estimated by maximum likelihood using the Quadratic Hill Climbing optimization algorithm. Huber-White standard errors are computed. For brevity, we only report the equally-weighted cross-sectional mean beta coefficients, with corresponding statistics and cross-sectional mean McFadden R-squared. We also report the number of positive and negative beta coefficients which are statistically different from zero at the 5% and 10% levels.

upcoming jump event. We also confirm the weak role played by the imbalance in order flow, as pointed out by the complete absence of drift before the jumps in Figure 6. Because the power of the Lee-Mykland jump test increases when volatility is lower, the level of volatility is negatively related to the likelihood to detect jumps.

In Table 5, we study the contribution of liquidity shocks to jumps at longer time lags.[11] There is again strong evidence that the occurrence of jumps is significantly increased by pre-jump shocks in the number of trades and in the effective spread. The explanatory power of these two liquidity shock variables remains strong even at the 20-minute time lag. Shocks in the effective spread and the number of trades lose their significance at longer lags.

In Table 6, the logistic regression includes two additional explanatory variables. The objective is to capture the contribution of both macro and firm-specific news to the occurrence of jumps. The explanatory power is found to be higher at each time lag. The increase in the goodness-of-fit of the logistic model is due to the significance of both the firm-specific and macro news dummies. Nevertheless, the effect of firm-specific news seems more pervasive. While the number of stocks with positive and significant coefficients for the macro dummy is always between 10 and 15, it varies between 12 and 19 stocks for the firm-specific dummy. Most importantly, the marginal effects of firm-specific news are always more than twice those of macro news. As in Bollerslev et al. (2008), when it comes to characterizing the occurrence of jumps on large US caps, we confirm that firm-specific news are the dominant factor in terms of their impact on the occurrence of jumps at the individual stock level.[12]

5.5 Contribution of liquidity shocks to price discovery

To study the information content of liquidity variables with respect to price discovery, we regress returns computed at different time intervals on the key liquidity variables described above. We also control for the release of news and the occurrence of jumps by adding two

[11] We only report the results for the logit model because the probit and gombit models lead to very similar results. They are available upon request.

[12] As indicated before, the joint probability of observing a jump and a firm-specific news release is around 5%, while it is close to a third for the joint probability of observing a jump and a macro news release. The lower joint probability of the former (in spite of the higher probability of a jump conditional on a firm specific news) can be explained by the fact that the unconditional probability of a macroeconomic news release is much larger than the unconditional probability of firm news. In fact, over the complete sample, we have 5128 macro news items, while the number of firm news releases ranges between 215 and 6391 per ticker with median value of 1213.

Table 5: Contribution of liquidity shocks to the probability of jumps. Stock by stock logit models. Beyond 2-minute time lag.

	DPTH	ESPRD	NT	OI*	DI*	VOLA
$4-minute\ lag$						
$\overline{\beta}$	-0.022	0.320	0.234	-0.024	-0.159	-0.982
$\overline{\sigma_\beta}$	0.074	0.069	0.055	0.444	0.779	0.737
# + significant at 5%	5	27	29	0	0	0
# + significant at 10%	5	29	29	2	0	0
# − significant at 5%	0	0	0	0	0	6
# − significant at 10%	0	0	0	1	0	10
% McFadden R^2	4.218					
$10-minute\ lag$						
$\overline{\beta}$	-0.004	0.124	0.150	0.035	-0.052	-1.155
$\overline{\sigma_\beta}$	0.030	0.038	0.052	0.225	0.425	0.806
# + significant at 5%	8	25	27	3	1	0
# + significant at 10%	10	27	27	4	1	0
# − significant at 5%	1	0	0	1	0	7
# − significant at 10%	1	0	0	1	0	10
% McFadden R^2	3.760					
$20-minute\ lag$						
$\overline{\beta}$	-0.004	0.055	0.084	0.029	0.013	-0.953
$\overline{\sigma_\beta}$	0.018	0.026	0.045	0.138	0.238	0.814
# + significant at 5%	7	17	24	3	3	0
# + significant at 10%	7	22	25	3	5	0
# − significant at 5%	1	0	0	0	1	3
# − significant at 10%	2	0	1	0	1	8
% McFadden R^2	3.061					
$60-minute\ lag$						
$\overline{\beta}$	-0.002	0.014	0.018	0.018	0.027	-0.745
$\overline{\sigma_\beta}$	0.010	0.013	0.026	0.060	0.105	0.573
# + significant at 5%	6	9	10	2	3	0
# + significant at 10%	6	10	14	6	3	0
# − significant at 5%	0	0	0	0	1	3
# − significant at 10%	1	0	1	2	1	9
% McFadden R^2	2.196					

$$P(JUMP_{(i)s}=1|\mathbf{X}) = G(\alpha_i + \beta_{1,i}DPTH_{(i)s-\Delta} + \beta_{2,i}ESPRD_{(i)s-\Delta}$$
$$+\beta_{3,i}NT_{(i)s-\Delta} + \beta_{4,i}OI^*_{(i)s-\Delta} + \beta_{5,i}DI^*_{(i)s-\Delta} + \beta_{6,i}VOLA_{(i)s-\Delta})$$

The above regression is run for each of the 30 constituents of the DJIA index over the period July 2007-December 2009 at the 2-minute frequency level. $P(JUMP_{(i)s}=1|\mathbf{X})$ is the response probability that a jump occurs for stock i at intraday time s given a set of explanatory variables $\mathbf{X}$ which includes shocks in mean depth (DPTH), effective spread (ESPRD), number of trades (NT), absolute order (flow) imbalance (OI*), absolute depth imbalance (DI*), as well as realized volatility (VOLA). All explanatory variables are included with a time lag of $\Delta = 4/10/20/60$ minutes, except volatility which is computed with a time lag of $\Delta = 20/20/20/60$-minute interval before the jump. G is the CDF of the logistic distribution. The logit model is estimated by maximum likelihood using the Quadratic Hill Climbing optimization algorithm. Huber-White standard errors are computed. For brevity, we only report the cross-sectional mean McFadden R-square as well as the number of positive and negative beta coefficients which are statistically different from zero at the 5% and 10% level.

Table 6: Contribution of news to the probability of jumps. Stock by stock logit models. 2-minute time lag and beyond.

	DPTH	ESPRD	NT	OI*	DI*	VOLA	MACRO	FIRM
$2-minute\ lag$								
$\overline{\beta}$	-0.029	0.319	0.578	0.062	-0.301	-0.646	1.165	2.420
$\overline{\sigma_\beta}$	0.107	0.076	0.128	0.645	1.111	0.597	1.044	1.386
# + significant at 5%	5	29	29	0	0	1	10	14
# + significant at 10%	9	30	29	3	0	2	14	17
# − significant at 5%	0	0	0	1	0	5	0	0
# − significant at 10%	0	0	0	1	1	9	0	0
% McFadden R^2	6.733							
$4-minute\ lag$								
$\overline{\beta}$	-0.024	0.246	0.323	0.025	-0.122	-0.817	1.134	2.360
$\overline{\sigma_\beta}$	0.053	0.056	0.076	0.422	0.693	0.614	1.063	1.402
# + significant at 5%	4	29	29	1	0	0	10	13
# + significant at 10%	8	30	29	3	0	0	14	17
# − significant at 5%	0	0	0	0	0	7	0	0
# − significant at 10%	0	0	0	1	0	9	0	0
% McFadden R^2	6.869							
$10-minute\ lag$								
$\overline{\beta}$	-0.005	0.170	0.125	0.060	-0.026	-1.006	1.126	2.361
$\overline{\sigma_\beta}$	0.020	0.041	0.042	0.226	0.366	0.664	1.041	1.386
# + significant at 5%	5	29	24	3	0	0	10	14
# + significant at 10%	5	30	26	4	1	0	14	17
# − significant at 5%	0	0	0	1	0	9	0	0
# − significant at 10%	1	0	0	1	3	14	0	0
% McFadden R^2	6.126							
$20-minute\ lag$								
$\overline{\beta}$	-0.006	0.092	0.058	0.047	0.030	-0.768	1.130	2.433
$\overline{\sigma_\beta}$	0.011	0.040	0.028	0.138	0.224	0.662	1.039	1.361
# + significant at 5%	3	26	17	3	2	0	11	12
# + significant at 10%	4	27	22	3	5	0	15	18
# − significant at 5%	0	0	0	1	1	3	0	0
# − significant at 10%	1	0	0	2	1	7	0	0
% McFadden R^2	5.234							
$60-minute\ lag$								
$\overline{\beta}$	-0.005	0.026	0.014	0.024	0.036	-0.598	1.174	2.625
$\overline{\sigma_\beta}$	0.005	0.024	0.014	0.060	0.102	0.486	1.077	1.332
# + significant at 5%	3	12	8	3	3	0	11	17
# + significant at 10%	3	17	10	6	3	0	13	19
# − significant at 5%	0	0	0	1	0	4	0	0
# − significant at 10%	1	0	0	1	1	11	0	0
% McFadden R^2	3.850							

$$P(JUMP_{(i)s} = 1|\mathbf{X}) = G(\alpha_i + \beta_{1,i}DPTH_{(i)s-\Delta} + \beta_{2,i}ESPRD_{(i)s-\Delta}$$
$$+\beta_{3,i}NT_{(i)s-\Delta} + \beta_{4,i}OI^*_{(i)s-\Delta} + \beta_{5,i}DI^*_{(i)s-\Delta} + \beta_{6,i}VOLA_{(i)s-\Delta})$$

The above regression is run for each of the 30 constituents of the DJIA index over the period July 2007-December 2009 at the 2-minute frequency level. $P(JUMP_{(i)s} = 1|\mathbf{X})$ is the response probability that a jump occurs for stock i at intraday time s given a set of explanatory variables $\mathbf{X}$ which includes a dummy for macro news (MACRO) and firm-specific news (FIRM), shocks in mean depth (DPTH), effective spread (ESPRD), number of trades (NT), absolute order (flow) imbalance (OI*), absolute depth imbalance (DI*), as well as realized volatility (VOLA). All explanatory variables are included with a time lag of $\Delta = 2/4/10/20/60$ minutes, except volatility which is computed with a time lag of $\Delta = 20/20/20/20/60$-minute interval before the jump. G is the CDF of the logistic distribution. The logit model is estimated by maximum likelihood using the Quadratic Hill Climbing optimization algorithm. Huber-White standard errors are computed. For brevity, we only report the cross-sectional mean McFadden R-square as well as the number of positive and negative beta coefficients which are statistically different from zero at the 5% and 10% level.

dummies. The model is described in Table 7.[13] The dummy J is equal to 1 when there is a jump and 0 otherwise, while the dummy N is equal to 1 when there are news and 0 otherwise. On the one hand, we look the contribution of liquidity shocks to 'post-jump' price discovery , i.e. price discovery after the occurrence of a jump. On the other hand, we look the contribution of liquidity shocks to 'post-news' price discovery , i.e. price discovery after the release of news. We therefore include two intercept dummies and two interaction terms between each liquidity variable and each dummy.

Results indicate that liquidity shocks affect price discovery irrespective of the occurrence of a jump. Price discovery is undoubtedly affected by liquidity, in particular by order and depth imbalances. With respect to post-jump price discovery, there is almost no significant effect. Interaction terms are significant in a few cases only, indicating that no liquidity variable is more informative with respect to price discovery after the occurrence of a jump. At the 10-minute time interval, the coefficient for the interaction term is significant at the 10% level for a maximum of 4 stocks (with respect to order imbalance, again). In every case, there is a higher number of stocks with significant coefficients for the liquidity variable itself than for its interaction term. This holds true at each time interval and at every level of significance considered. We also see that the contribution of each liquidity variable to post-jump price discovery seems to decrease across time lags. All in all, the price discovery process seems rather unaffected by the occurrence of jumps.

Regarding the post-news price discovery process, results are more informative. Liquidity shocks in order imbalance affect price discovery are sensitive to the release of news. At the 10-minute and 20-minute time intervals, 16 stocks display a statistically significant coefficient at the 5% level for the interaction dummy between shocks in order imbalance and the news dummy. We also see that the contribution of shocks in effective spread to price discovery is also higher when news are released.

[13] To save space, only the results for the least squares estimator are reported, but the results using a robust regression estimator are similar. They are available upon request.

Table 7: Contribution of liquidity shocks to price discovery. Stock by stock least squares regression models.

	DPTH	DPTH*J	DPTH*N	ESPRD	ESPRD*J	ESPRD*N	NT	NT*J	NT*N	OI*	OI*J	OI*N	DI	DI*J	DI*N
10-minute post-jump															
# + significant at 5%	3	2	1	6	3	0	10	1	2	21	3	12	20	0	1
# + significant at 10%	3	3	2	6	3	0	12	2	3	21	4	16	20	0	3
# − significant at 5%	7	1	0	12	2	7	3	2	1	0	0	0	0	2	0
# − significant at 10%	7	2	0	13	2	7	4	3	2	0	1	0	0	2	1
Adj. R^2	8.77														
20-minute post-jump															
# + significant at 5%	5	0	0	6	2	0	11	0	2	21	1	12	21	0	1
# + significant at 10%	6	0	1	6	2	0	11	0	2	21	1	14	21	1	2
# − significant at 5%	7	1	0	15	1	6	3	1	2	0	0	0	0	1	2
# − significant at 10%	8	1	0	15	1	10	3	1	2	0	1	0	0	1	2
Adj. R^2	7.01														
40-minute post-jump															
# + significant at 5%	7	0	1	5	4	0	11	1	6	21	0	7	21	0	2
# + significant at 10%	8	0	2	5	4	0	11	1	9	21	0	8	21	0	2
# − significant at 5%	6	0	1	14	0	2	4	0	0	0	0	0	0	0	1
# − significant at 10%	7	1	2	14	0	3	4	0	0	0	1	0	0	2	1
Adj. R^2	5.42														
60-minute post-jump															
# + significant at 5%	8	0	1	5	1	0	13	0	8	21	0	7	21	1	1
# + significant at 10%	9	0	2	6	2	1	13	1	8	21	1	10	21	1	2
# − significant at 5%	7	0	1	13	0	4	6	1	1	0	0	0	0	0	1
# − significant at 10%	7	0	2	14	0	5	6	1	1	0	0	0	0	1	2
Adj. R^2	4.73														

$$
\begin{gathered}
\log(p_{(i)s+\Delta}/p_{(i)s}) = \alpha_i + \beta_{1,i}J_{(i)s} + \beta_{2,i}N_{(i)s} + \beta_{3,i}DPTH_{(i)s+\Delta} + \beta_{4,i}DPTH_{(i)s+\Delta}J_{(i)s} + \beta_{5,i}DPTH_{(i)s+\Delta}N_{(i)s} \\
+\beta_{6,i}ESPRD_{(i)s+\Delta} + \beta_{7,i}ESPRD_{(i)s+\Delta}J_{(i)s} + \beta_{8,i}ESPRD_{(i)s+\Delta}N_{(i)s} + \beta_{9,i}NT_{(i)s+\Delta} + \beta_{10,i}NT_{(i)s+\Delta}J_{(i)s} + \beta_{11,i}NT_{(i)s+\Delta}N_{(i)s} \\
+\beta_{12,i}OI^*_{(i)s+\Delta} + \beta_{13,i}OI^*_{(i)s+\Delta}J_{(i)s} + \beta_{14,i}OI^*_{(i)s+\Delta}N_{(i)s} + \beta_{15,i}DI^*_{(i)s+\Delta} + \beta_{16,i}DI^*_{(i)s+\Delta}J_{(i)s} + \beta_{17,i}DI^*_{(i)s+\Delta}N_{(i)s} + \epsilon_{(i)s+\Delta}
\end{gathered}
$$

The above regression is run for each of the 30 constituents of the DJIA index over the period July 2007-December 2009 at the 2-minute frequency level. $\log(p_{(i)s+\Delta}/p_{(i)s})$ is the log mid-quote returns observed for stock i over the next Δ time interval after time s, with $\Delta = 10, 20, 40$ and 60 minutes. The explanatory variables are shocks in mean depth (DPTH), effective spread (ESPRD), number of trades (NT), order (flow) imbalance (OI), and depth imbalance (DI). The dummy variable $J_{(i)s}$ ($N_{(i)s}$) is equal to 1 when there is a jump (firm-specific or macroeconomic news release) at time s for stock i and 0 otherwise. The regression is estimated using ordinary least squares with Newey-West standard errors. For brevity, we only report the cross-sectional mean adjusted R-squared as well as the number of positive and negative beta coefficients which are statistically different from zero at the 5% and 10% level.

Clearly, the most informative liquidity variable with respect to price discovery is the order imbalance. We also note that the contribution of liquidity shocks to price discovery is higher after the release of news than after the occurrence of jumps, although the effect is limited to a few liquidity variables.

6 Conclusion

How does stock market liquidity behave around intraday jumps? How informative are liquidity shocks when it comes to explaining the occurrence of jumps? Which liquidity shocks contribute the most to price discovery when jumps occur? How sensitive are these results to the release of news? To answer these questions, we study the dynamics of liquidity around jumps for the 30 constituents of the Dow Jones Industrial Average (DJIA) index. To the best of our knowledge, no event study has been carried out on the U.S. stock market to analyze the link between intraday liquidity dynamics and properly identified intraday jumps, whatever the type of information arrivals. To complement the nonparametric event study that we carry out in the first part of the paper, we implement a parametric analysis to assess the contribution of both liquidity shocks and news to the occurrence of jumps. We also estimate the contribution of liquidity shocks to the price discovery process, controlling for news arrivals and jump occurrences. Not only we analyze the dynamics of liquidity around all jumps by identifying their exact intraday timing, but we also retrieve all macroeconomic news announcements (prescheduled or not) as well as all firm-specific news provided by the Dow Jones and Reuters News Services.

If we characterize liquidity by market width, we do find a deterioration in liquidity around jumps for the DJIA constituents. The increase in transaction costs, as measured by the quoted and effective spreads, is statistically significant (at 1%). The incremental effect of jumps on ex-ante liquidity is around 27% while its is about 100% for ex-post liquidity. Besides trading cost (market width), Liu (2006) highlights three other dimensions of liquidity, namely, trading quantity (depth), trading speed (immediacy), and price impact (resilience). In terms of trading quantity and immediacy, we show that the demand for immediate execution increases sharply around jumps. For example, jumps coincide with a 300% increases in dollar trading volume, i.e. four times the benchmark 'no jump' time-of-day median value.

Zooming in on the drivers behind this volume surge, we find that both the number of trades and the average trade size jump up. In general, the incremental effect of jumps on average trade size is around 75% on average across stocks and days. The effect of jumps on the number of transactions is even higher: When a big jump occurs, the number of trades is 2.5 times its time-of-day median value across days with no jump. These findings confirm that jumps are driven by variations in the demand for immediacy. Jumps are due to the market inability to absorb a sharp increase in the demand for immediacy without moving the price significantly up or down.

However, depth (at the best bid-offer) does not withdraw from the market. The absence of withdrawal of depth at the best quote contribute to smaller jumps since market orders erode depth more slowly once the information is released. Liquidity provision even improves when a jump occurs. We show that positive (negative) jumps are associated with even thicker sell side (buy side). Such findings suggest that jumps depend mainly on the elevated trading aggressiveness of one side of the market, and not on the traders' reluctance to provide liquidity on the opposite side of the book. In fact, a greater demand for liquidity, rather than a weak liquidity supply, is associated with extreme price changes. As such, jumps do not seem to be due to an endogenous deficient provision of market liquidity. We also present evidence of significant resilience after the occurrence of a jump, whatever the liquidity measures under consideration.

Evidence of resilience after the occurrence of a jump is undeniable, whatever the liquidity measures under consideration. For example, although jumps lead to higher spreads, the effect is rather short-lived since spreads are back to pre-jump levels after around 10 minutes in the worst cases. In addition, imbalances in orders and depth drop back quickly to their pre-jump levels after the occurrence of a jump. The most persistent measure of liquidity is the number of trades, indicating that heterogenous beliefs about the revised fundamental value of the asset may persist after the jump, leading to high but more balanced trading volume.

When estimating the sensitivity of the liquidity proxies to the release of macro and firm news around jumps, we do find that the release of news around jumps amplifies the rise in both trading costs and demand for immediacy. However, the arrival of news does not really affect neither order imbalance nor liquidity provision: liquidity providers do not respond to the increase in trading costs and demand for immediacy by providing less liquidity, keeping order imbalance relatively unchanged.

In the parametric analysis, we show that liquidity shocks in the effective spread and the number of trades are the key liquidity drivers behind the occurrence of a jump. Compared with macroeconomic news, the arrival of firm-specific news is also identified as a stronger news driver behind the occurrence of jumps. As in Bollerslev et al. (2008), we confirm that firm-specific news events are the dominant factor in terms of their impact on the occurrence of jumps at the individual stock level. Finally, we find that several liquidity variables contribute to price discovery on DJIA stocks. This contribution is nevertheless not much affected by the occurrence of jumps. The post-news price discovery process is more informative, but mainly limited to order imbalance. Overall, order imbalance appears to be the most informative liquidity variable with respect to price discovery, especially after the arrival of news.

An avenue for further research (that we are currently exploring) is to study the information content of order books to better understand how liquidity within the book reacts around jumps and the release of news. This will certainly help refine studies about the impact of jumps and news on financial markets, including ours.

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