Intraday liquidity dynamics of the DJIA stocks around price jumps

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Abstract

We study the intraday dynamics of liquidity around price jumps using trades and quotes data sampled at the 2-minute frequency for the 30 stocks in the Dow Jones Industrial Average (DJIA). Based on an original event-type methodology, we shed new light on the debate about the liquidity response by market participants to information arrivals. We show that the relationship between jumps and market liquidity depends on the respective dimensions of liquidity. First, the increase in ex-ante and ex-post trading costs is statistically significant but the economic impact remains limited. Second, jumps are driven by a sharp rise in the demand for immediacy, rather than by weak liquidity supply. As such, jumps do not seem to be due to an endogenous deficient provision of market liquidity. Third, there is rather strong evidence of resilience, whatever the liquidity measures under consideration.

Keywords: High-frequency data, jump, liquidity, volatility.

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1 Introduction

The occurrence of jumps is of particular interest in finance. First, their impact in periods of market stress can be very significant (Bates 2000; Duffie et al. 2000). Second, higher moments of asset return distributions and the related implied volatility smiles are better explained when jumps are considered (Bates 1996; Bakshi et al. 1997; Andersen et al. 2002; Carr and Wu 2007). Third, the presence of jumps makes markets incomplete, i.e. jump risk cannot typically be hedged away, which in turn may lead investors to demand a larger premium to carry these risks (Pan, 2002). Consequently, a risk averse investor is arguably expected to shun investments with sharp unforeseeable movements, all else being equal (Eraker et al. 2003). Finally, and perhaps more importantly, 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).

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 (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.

The research question of this paper is the following: How does liquidity behave around intraday price jumps? Since detecting arrival times of jumps is critical, we apply the Lee and Mykland (2008) jump detection test, modified by Boudt et al. (2010) who take intraday volatility patterns into account. In this paper, we carry out an event study based on the

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

median to analyze the impact of price jumps on liquidity measures. Although event studies were initially conceived to analyze the impact of events such as merger announcements on financial markets (see e.g. Fama et al. 1969 and MacKinlay 1997), the methodology has also been applied to study the response of market liquidity to a wide variety of events (see e.g. Lee et al. 1993, Krinsky and Lee 1996, and Kavajecz 1999).

To the best of our knowledge, such an event study has never been applied to study the link between intraday liquidity dynamics and properly identified intraday price jumps. In addition, previous research on liquidity dynamics has mainly focused on the effect of macro news. Fleming and Remolona (1997) find that the arrival of news on the bond market produces a quasi instantaneous price change with a corresponding reduction in volume. This is followed by an increase in volume and persistent volatility. Grossman and Miller (1988) examine liquidity during the crash of October 1987 and finds that a flood of sell orders caused a paralyzing liquidity dry-up. Jiang et al. (2010) study jumps in the U.S. Treasury market and find that macroeconomic news announcements are often preceded by a withdrawal of liquidity, which is positively related to the number and size of 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 behaviour of liquidity around price jumps since many jumps are not directly associated with macro news (Lahaye et al., 2010). 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. In this paper, we study the intraday dynamics of liquidity and market activity around all jumps, whatever the type of news and whether there is news announcement or not.

Our results shed new light on the debate about the liquidity response by market participants to information arrivals. While most studies show that prices react quickly to information arrivals, there is still no consensus on the liquidity response to such events. While studies like Lee et al. (1993) show that information arrivals tend to worsen market liquidity conditions, others find that liquidity remains more or less unaffected (Brooks 1994). The role of public information disclosures is also unresolved from a theoretical point of view. Kim and Verrecchia (1994) introduce a model in which anticipated public information increases informed judgements and trading because traders do their best to process such public disclosure into their own private views. A higher level of informed trading then translates into an increase in the bid-ask spread at announcement dates. However, Diamond and Verrecchia (1991) argue that public disclosure reduces adverse selection and thus improves market liquidity at the time of the announcement. This paper reconciles these opposing views by showing that they are both correct, depending upon the dimension of liquidity that is being looked at.

The remainder of the paper is organized as follows. In Section 2, we explain the procedure used to detect 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 Price jump detection

The event of interest is 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:

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

where $\mu(t)$ is the drift term with a continuous and locally finite variation sample path, $\sigma(t)$ is a strictly positive spot volatility process and $W(t)$ is a standard Brownian motion. The component $\kappa(t)dq(t)$ refers to the pure jump component, where $dq(t) = 1$ if there is a jump at time t and 0 otherwise, and $\kappa(t)$ represents 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 large 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 day t by $r_{t,i} \equiv p(t + i/M) - p(t + (i-1)/M)$, 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 the average daily volatility s_t together with an intraday volatility factor $f_{t,i}$:

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

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

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

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. (2010). 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 $\exp(-e^{-\beta^*}) = 1-\alpha$, i.e. $\beta^* = -\log(\log(1-\alpha))$. This conservative procedure should be expected to find only α spurious jumps in a given sample of n observations. In the empirical analysis, we set $\alpha = 0.1$.

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

[2] See Boudt et al. (2010) for further details about the periodicity filters.

provided by the NYSE for the period July 2007-December 2009.[3] Over these 2.5 years there are 628 trading days. 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 RTAQ (Cornelissen and Boudt 2010). The filtered trades and quotes data sets are then matched after correcting for an average 5-second delay in the time of trades. Similar to Chordia et al. 2000, the direction of each transaction is determined by the Lee and Ready (1991) widely-used algorithm.[4] Our data are sampled at a two-minute frequency. On a similar data set, Andersen et al. (2009) 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.[5] 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 ask (bid) quote in interval i (without necessarily corresponding to any trade).

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,

[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.

[4]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.

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

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

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 types of spread we obtain two-minute observations by calculating the size-weighted average over the interval. Size-weighted proportional quoted spreads are weighted by the depth available at the prevailing quotes while size-weighted proportional effective spreads are weighted by the number of shares traded:

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

and

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

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 (BBO). 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.

$$MeanDepth_i = MeanBidDepth_i + MeanAskDepth_i, \tag{3.5}$$

with

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

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

$$DI_i = \frac{(MeanAskDepth_i - MeanBidDepth_i)}{MeanDepth_i} \tag{3.7}$$

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

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

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 $MeanSize_i = \frac{1}{NT_i} SumSize_i$. Finally, we also take order imbalance (OI) into account, which is estimated as the number of shares of buyer-initiated trades less the number of shares of seller-initiated trades (scaled by total trading volume):

$$OI_i = \frac{SSSizeT_i}{SumSize_i} \tag{3.9}$$

where

$$SSSizeT_i = \sum_{k=1}^{NT_i} D_{i,k} Size_{i,k} \tag{3.10}$$

and $D_{i,k}$ 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. For days with jumps, we distinguish between large and small jumps, with large jumps leading to an absolute price return greater than 1%.

The number of observations (nobs) relates to the number of 2-minute intervals. For example, there are close to 1.7 million 2-minute recorded returns in the sample of days without jumps. As there are 195 2-minute intervals within a day and 30 stocks included in our study, we have an average of 293 days without jumps. Out of 628 days, it implies that jumps would occur every two days on average across time and stock. Days with large (resp. small) jumps represent around 8% (resp. 34%) of the whole sample of days.

At first sight, liquidity on days without jumps does not look fundamentally different than liquidity on days with small jumps, in spite of the fact that the absolute 2-minute returns can be much higher on days without jumps. In fact, the maximum 2-minute return on days with small jumps is limited to 1% (by construction) while it is equal to 8.59% on days with no jumps. It is indeed possible to observe a very high 2-minute return without any jump occurring because of a high continuous volatility, as measured by the average daily RBV in (2.2). Spreads are slightly lower on days with small jumps than on days with no jump, while it is the opposite for the other measures of liquidity, such as the trading volume, the number

Table 1: Summary statistics

	Returns (in%)	SWPQS (in%)	SWPES (in%)	SumSize	MeanSize	NT	AOI (in %)	MeanDepth	MeanAskDepth	MeanBidDepth	ADI (in%)
Days without jumps											
nobs	1716390	1710812	1710812	1710812	1710812	1710812	1710812	1715695	1715695	1715695	1715693
min	-6.83	0.76	0.00	100	100	1	0.00	0.00	0.00	0.00	0.00
med	0.00	3.94	4.43	7800	450	17	35.48	89.45	42.91	43.13	16.61
mean	-0.00	4.96	5.79	19193	748	21	40.44	823.78	410.15	413.62	20.90
max	8.59	853.62	1094.30	18189800	337655	120	100.00	1301633.89	1279274.21	885346.78	98.92
Days with small jumps											
nobs	997620	992890	992890	992890	992890	992890	992890	997017	997017	997017	997017
min	-1.00	0.76	0.00	100	100	1	0.00	2.50	1.00	1.17	0.00
med	0.00	3.27	3.59	7300	437	16	36.79	82.03	38.97	39.40	17.59
mean	0.00	3.76	4.31	16702	688	20	41.65	589.53	295.86	293.68	21.90
max	1.00	159.75	182.41	14391592	2733800	120	100.00	2269018.61	732736.89	1855903.13	99.51
Days with big jumps											
nobs	250770	249951	249951	249951	249951	249951	249951	250544	250544	250544	250544
min	-8.25	0.87	0.00	100.00	100.00	1.00	0.00	2.00	1.00	1.00	0.00
med	0.00	6.51	7.43	9200.00	505.26	18.00	35.11	103.08	49.81	49.52	16.42
mean	0.00	7.82	9.62	28230.00	977.99	22.68	39.88	1249.55	619.34	630.21	20.89
max	9.28	399.14	1482.72	5321388.00	1282100.00	120.00	100.00	334766.77	248763.33	254322.13	99.65

Returns are 2-minute log returns. $SWPQS$ is the 2-minute size-weighted proportional quoted spread. $SWPES$ is the 2-minute size-weighted proportional effective spread. *SumSize* measures trading volume, i.d. the total value of all the shares traded over 2 minutes. NT is the total number of transactions over 2 minutes. *MeanSize* is the mean size of a transaction (i.e. $SumSize/NT$) over a 2-minute interval. AOI is the absolute order imbalance computed over 2 minutes. $MeanAskDepth$ (resp. $MeanBidDepth$) is the average depth at the ask (i.e. bid) observed over 2 minutes. $MeanDepth$ is the sum of $MeanBidDepth$ and $MeanAskDepth$. ADI is the absolute depth imbalance. All statistics are cross-sectionally computed, i.e. computed over the 30 stocks included in the sample covering the July 2007-December 2009 time period.

of trades, the mean trade size, and the different measures of depth. Absolute order and depth imbalances are very similar.

When comparing days with no jumps and days with big jumps, a different picture emerges. The range of absolute returns on days without jumps are very close to those recorded on days with large jumps. Nevertheless, the minimum and maximum 2-minute returns across all days are still observed during days where a big jump occurred. Median and average spreads are two thirds wider on days with big jumps. This negative impact on liquidity is nevertheless attenuated by higher trading volume, mean trade size, number of trades, and depth on days with big jumps. As before, there is no difference in order or depth imbalance between the two sub-samples of days.

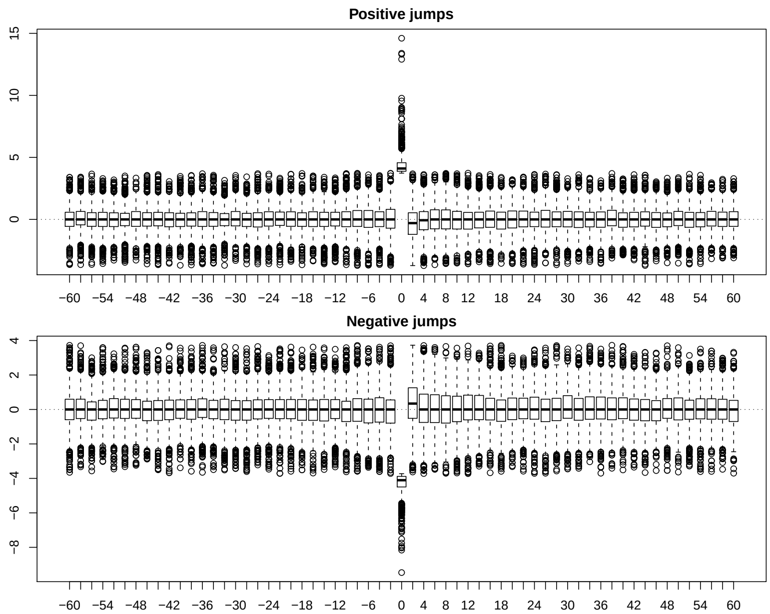
Although Table 1 sheds some light on the general features of liquidity on days with and without jump, it does not give us any information on the dynamics of intraday liquidity around properly identified intraday price jumps. To make such an analysis, we use an event study methodology that is defined in the next Section.

4 Methodology

To study the impact of price jumps on liquidity, we perform intraday event studies on different measures of liquidity. The null hypothesis of the event study is that: *Price 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 observations relative to the jump. Defining $\tau = 0$ as the intraday time of the jumps, $i + \tau$ indicates the τ-th observation counting from i. The full event window is represented by all even integer $\tau \in [-60, 60]$. The length of this window provides a

Figure 1: Standardized returns around price jumps



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.[6]

Event occurrences. The Lee and Mykland jump test presented in Section 2 detects 9437 price 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. Jumps on days with three or more jumps are excluded. This criterion prevents contamination of jump events. If two jumps were to occur close in time, then the after-effects of the first jump would likely distort observations near the second jump. This overlapping of events is called clustering. Clusters of jumps introduce covariance among jump effects which could distort our event window based analysis. After applying these filters the event sample shrinks to 2183 jumps.

Figure 1 reports the boxplot of standardized returns $r_{t,i}/(s_t f_{t,i})$ for each event time. We see

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

that, also after standardization by the spot volatility, the magnitude of the positive jumps is on average higher than the size of the negative jumps in our sample. Interestingly, we find that the median return in the 2-minute interval after a positive price jumps tends to be negative, while this median is positive after a negative jumps. 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. For all other event times, the boxplots are centered around zero. There is no evidence of abnormal dynamics in volatility before or after the jump.

Standardization. Liquidity measures need to be standardized to make them comparable across firms. Following Lee et al. (1993), we divide depth and volume measures of each company by their time of day median computed over the sample of days without jumps. This serves two purposes. First, these standardized measures allow comparisons across firms. Second, by calculating a different median for each time interval of the day, we filter out the effect of intraday patterns of liquidity. 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 distributions of liquidity measures are heavily skewed to the right. Plerou et al. (2005) describe in much detail the distribution of liquidity measures.

The standardized liquidity measure $\bar{L}_{t,i}$ on day t at time of day i is given by:

$$\bar{L}_{t,i} = \frac{L_{t,i}}{median_{t \in ND}(L_{t,i})} - 1, \tag{4.1}$$

where ND is the collection of days without jumps. Note that $\bar{L}_{t,i}$ can be interpreted as the percentage deviation from the 'typical' time of day value. These values are comparable across firms, which makes aggregation possible. We use a slightly different standardization method for spreads, order and depth imbalances, which are already proportional measures. We standardize by subtracting the non-jump median value for the time of day. Again, it is possible to interpret these values as the percentage difference from the 'normal' level.

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 (4.1) 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 1 for depth and volume measures, and 0 for order and depth imbalances as well as spreads. Therefore, we retain the ability to directly interpret the aggregated values of $\bar{L}_{t,i}$ as percentage deviations from typical levels (after subtracting 1 for depth and volume indicators). We aggregate over all firms and years in the sample, but distinguish between event windows with positive and negative jump returns. We also create a subsample of large jumps with an absolute price return exceeding 1%. For every $\tau \in [-60, 60]$ of the event window, we thus obtain four aggregated point estimates from four different samples: the full sample of positive jumps, the full sample of negative jumps, exclusively large positive jumps and exclusively large negative jumps. 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

Our empirical event study is unique in the sense that we study the dynamics of liquidity around all jumps by identifying their exact intraday timing, without exclusively focusing on news announcements. We subsequently study the dynamics of spreads, trading volume, number of trades, mean 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).

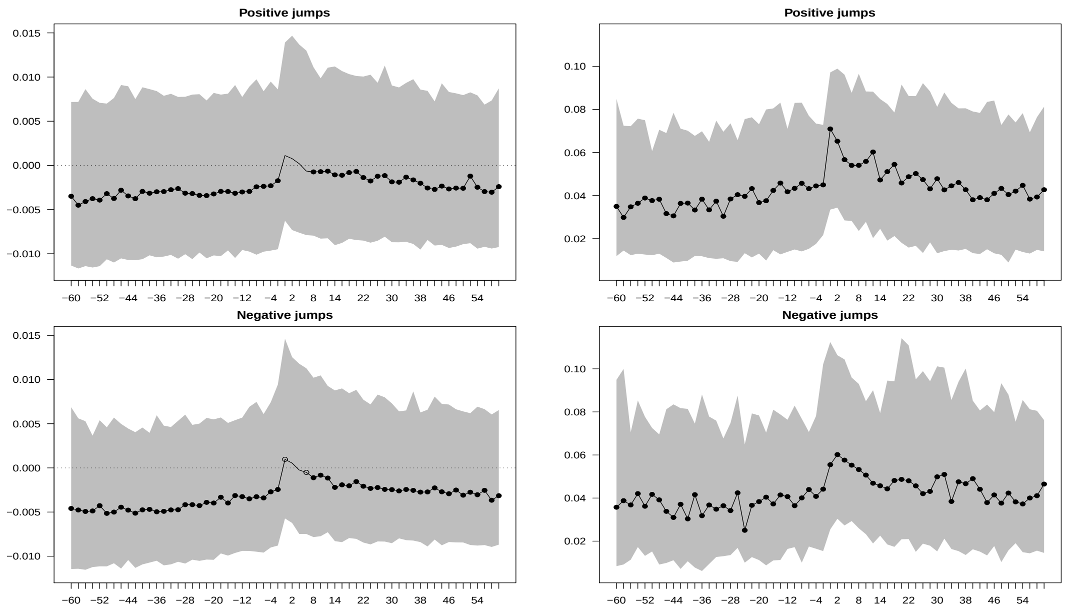
5.1 Spreads

Figures 2 and 3 show a significant shock in spreads at the time of a big 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. For example, big jumps lead to a 15% deviation from the 'typical' time of day value in ex-post liquidity, as measured by the size-weighted proportional effective spread (SWPES). This negative impact of big jumps on liquidity must nevertheless be put into perspective: Spreads are generally wider on days during which large jumps occur. The classical explanation would be that market participants adjust their behavior when they expect stressful market conditions all day long due to the release of important news or/and a high level of heterogeneity of beliefs in the market. This is probably the case for macroeconomic news or earnings announcements schedules which are known in advance and may cause large price jumps when they go against market expectations. Our results show that the SWPES is approximately 5% wider one hour before (as well as after) the occurrence of a large jump. Consequently, the net effect of big jumps on ex-post liquidity would be close to 10% on average across stocks and days. As expected, market participants are less keen on improving the displayed quoted prices to get the transaction done when price changes are severe. In addition, the impact of big jumps on ex-ante liquidity (as measured by the SWPQS, i.e. the size-weighted proportional quoted spread) is less pronounced since the incremental effect of big jumps are between 2 and 3%. Big jumps lead to wider quoted prices at which a large number of transactions occur. Finally, spreads show some resiliency since they are back to pre-jump levels, even though they remain at higher levels than when no jump occurs at the same time of the day.

Based on the sub-sample of small jumps, the picture is rather different. Small jumps occur on days during which liquidity as measured by the spreads seems particularly good. Both the SWPQS and SWPES are significantly lower before and after small jumps (in comparison to their levels at the same time of day when no jump occurs). Interestingly, the impact of small jumps on ex-ante liquidity is not even statistically significant: it just increases the SWPQS by around 0.5%, back to his 'typical' time-of-day value. This does not hold true for ex-post liquidity which significantly deteriorates when a small jump occurs (at the 95% confidence level), although the economic impact remains limited: There is indeed an incremental increase in the SWPES by around 2%, much lower than the 10% increase in the case of large jumps. Again, liquidity providers respond to the occurrence of jumps to a greater extent by being more reluctant to improving their displayed quoted prices, than by posting wider bid-ask spreads.

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 big 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 2: Size Weighted Proportional Quoted Spreads

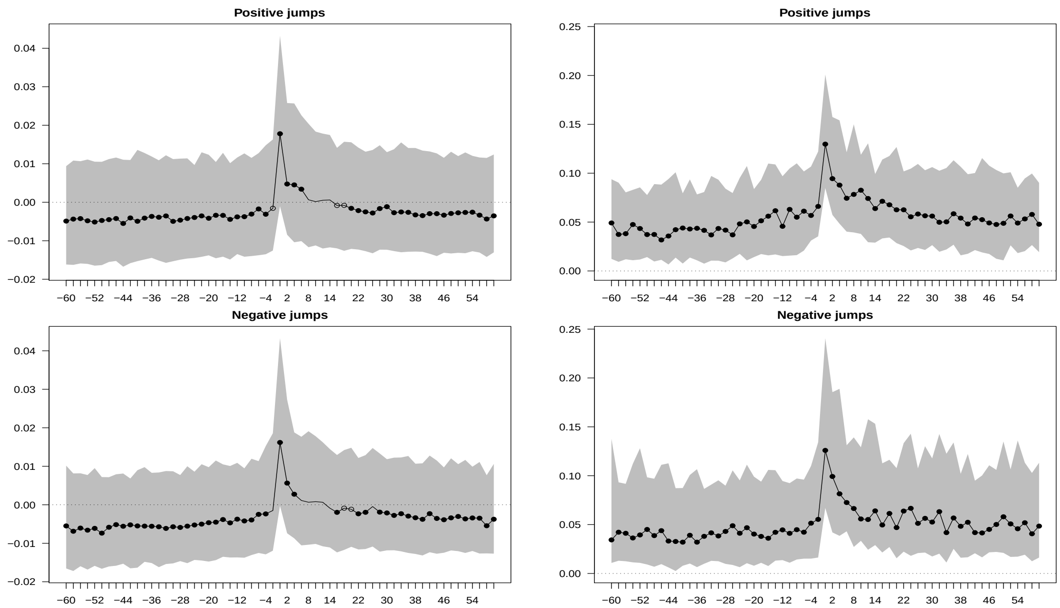


(a) Small jumps (b) Large jumps

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. $1\% < p - value \leq 5\%$).

The picture is nevertheless not bleak. First, the economic impact of these big jumps remains limited since the median (97.5% largest) increase in transaction costs, as measured by the quoted and effective spreads, is in all cases less than a 15% (25%) deviation from the 'no jump' time-of-day value. Second, small jumps which are typically due to the release of less significant information disclosures do not make a statistical difference on the level of the spreads. Third, both the quoted and effective spreads seem to be reasonably resilient, in contrast to the persistence found by Lee et al. (1993) around earnings announcements. Although width does not improve around jumps, liquidity providers manage to keep it at a relatively tight level, which can be due to a high level of competition among them. For example, Goettler et al. (2005) argue that volatility (on the true asset value) promotes competition among limit order submitters, regardless of whether they risk being picked off by informed traders, leading to lower transaction costs. Finally, in Foucault et al. (2003), limit-order traders are showed to keep quoted bid-ask spreads tight and to update their quote more quickly when they anticipate information disclosures and face high competitive pressure.

Figure 3: Size Weighted Proportional Effective Spreads



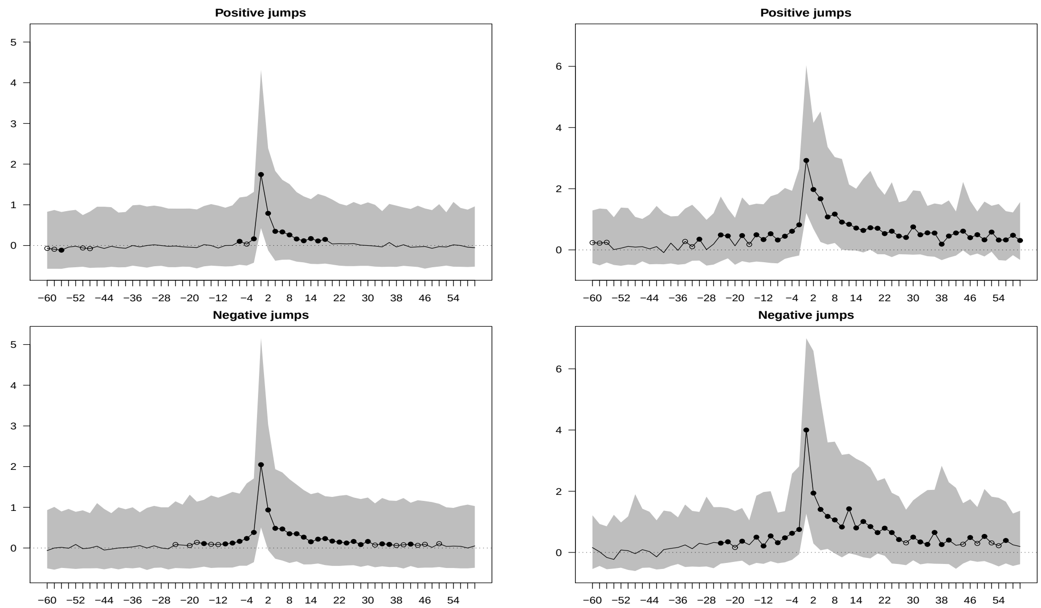
(a) Small jumps (b) Large jumps

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, number of trades, and mean trade size

The demand for immediate execution increases around jumps. We observe this evidence in terms of trading volume, number of trades, and mean trade size. Figure 4 shows a very significant surge in trading volume at the time of a price jump. Small jumps have a median trade volume that is three times the time-of-day median value across days with no jumps. Large jumps are characterized by even higher trading volumes. Big negative jumps even lead to a 400% deviation in trading volume, i.e. five times the 'benchmark' time-of-day median value. We also note that trading volume starts increasing significantly more than 20 minutes before the occurrence of big jumps. For big jumps, it falls back to its pre-jump level 20 to 30 minutes after the jump, displaying some persistency in the process. 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

Figure 4: Trading Volume



(a) Small jumps (b) Large jumps

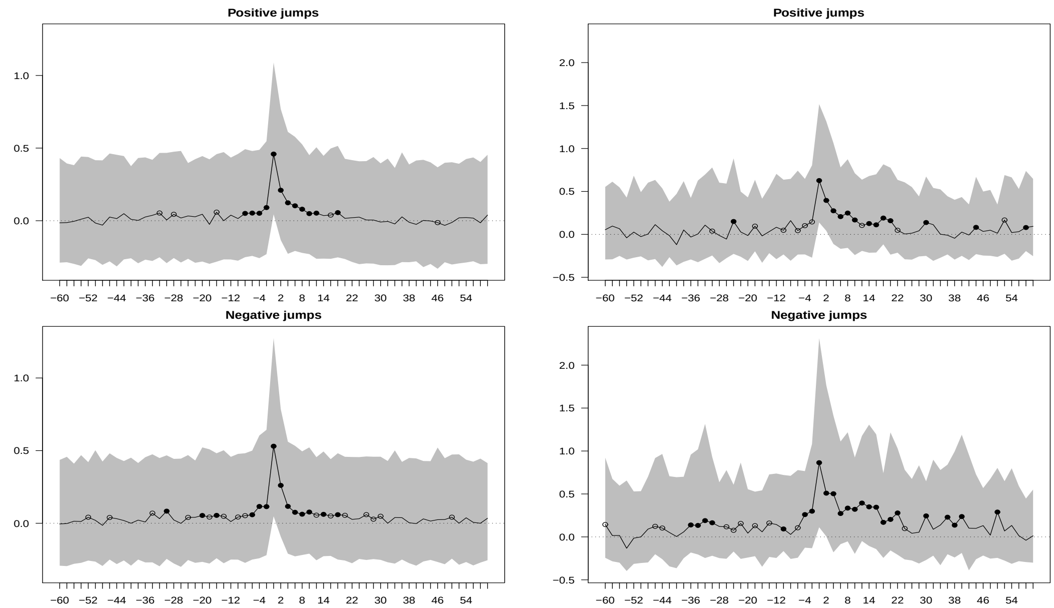
Full black line is the median standardized liquidity measure. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (•) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from 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. $1\% < p-value \leq 5\%$).

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.

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? Figures 5 and 6 show that both the number of trades and mean 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 mean trade size is around 50% across stocks and days (although mean trade size nearly doubles around big negative jumps). 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,

Figure 5: Mean Trade Size



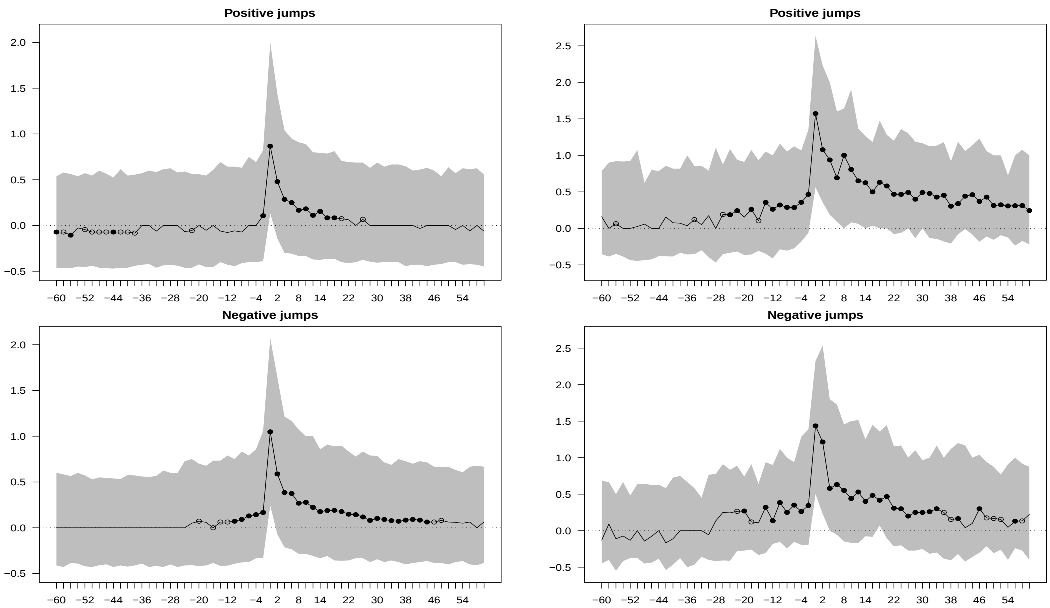
(a) Small jumps (b) Large jumps

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. $1\% < p-value \leq 5\%$).

the traders' information advantage is fleeting rapidly. Immediacy becomes of the essence 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 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 big 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 mean trade size. This level of persistent and intense trading around big jumps suggests that market participants need some time to rebalance their portfolio, satisfy their pent-up demand or even adjust their hedging positions.

Figure 6: Number of Trades



(a) Small jumps (b) Large jumps

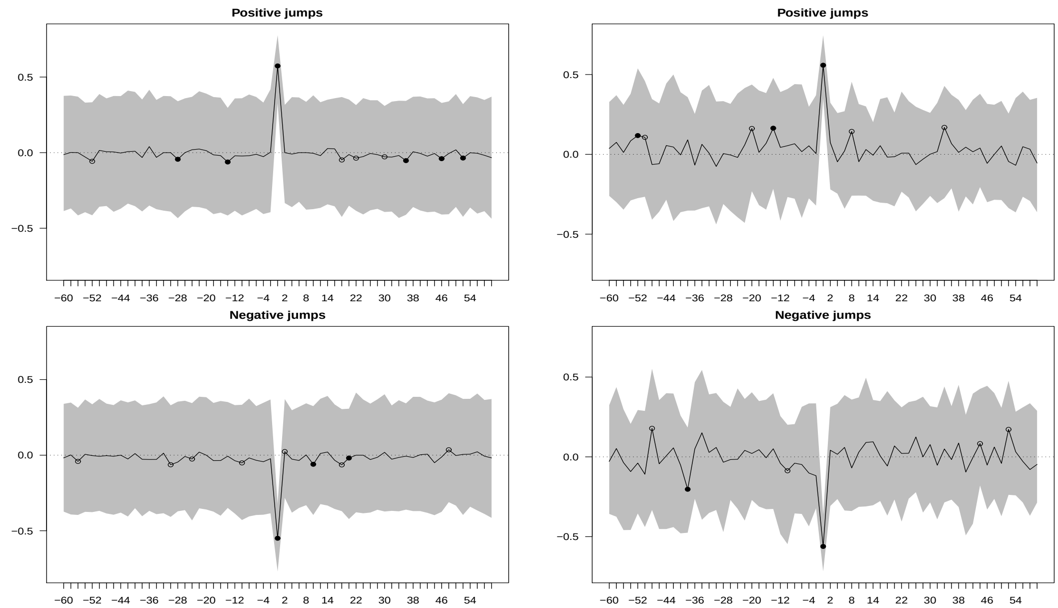
Full black line is the median standardized liquidity measure. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (•) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from 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. $1\% < p - value \leq 5\%$).

5.3 Order Imbalance

Interestingly, we provide weak evidence of a run-up in volume and spreads before jumps. In Figures 3 to 7, 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 by astute market players. This argument is reinforced by the complete absence of drift in order imbalance before the jumps, as shown on Figure 7.

Figure 7 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

Figure 7: Order Imbalance



(a) Small jumps (b) Large jumps

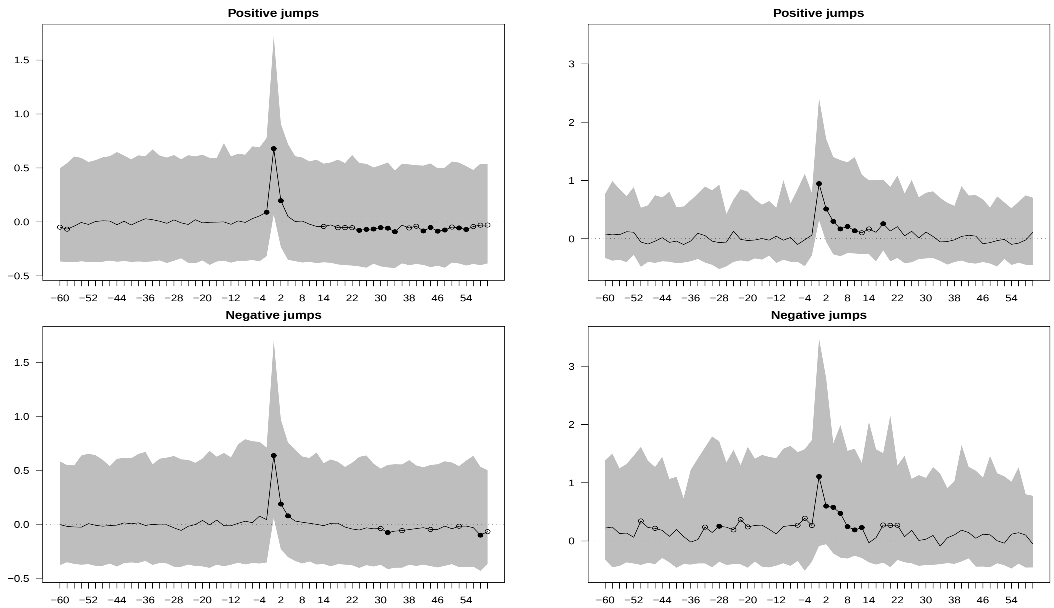
Full black line is the median standardized liquidity measure. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (•) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from 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. $1\% < p - value \leq 5\%$).

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.

5.4 Depth

Figure 8 illustrates how quoted market depth (at the best-bid offer) increases around price jumps. Despite higher spreads and trading volume, depth 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

Figure 8: Depth



(a) Small jumps (b) Large jumps

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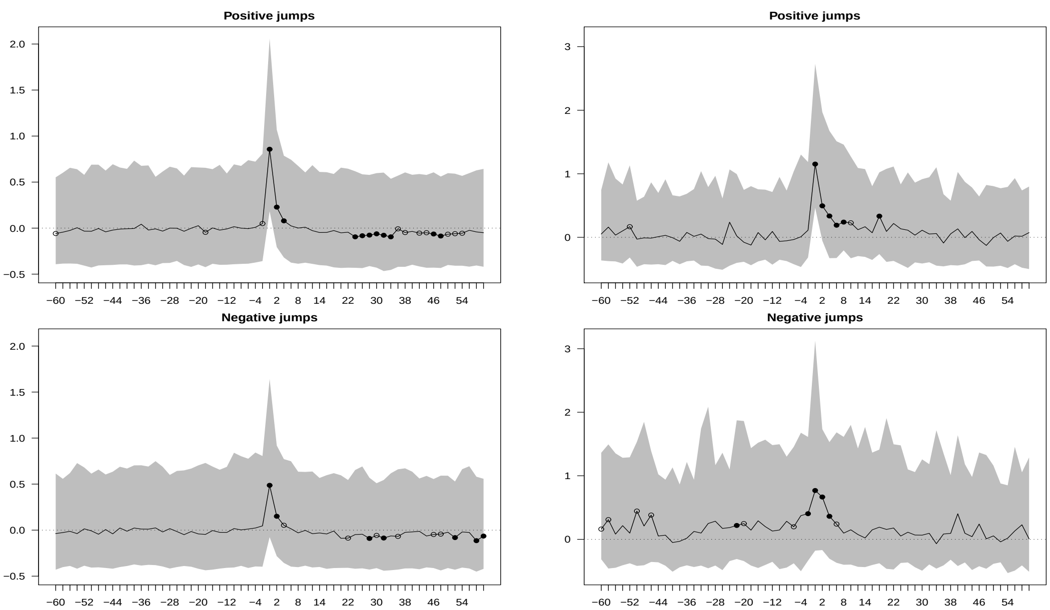
improves when a jump occurs. It is noteworthy that a greater demand for liquidity, rather than a weak liquidity supply, is associated with extreme price changes. Simply put: an increased demand for immediacy does no translate into weak liquidity supply. Jumps do not seem to be due to a deficient provision 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 (Figures 9 and 10).

Total mean depth hides movements of depth at the bid and the ask. Figures 9 and 10 show that during a positive (negative) jump, the ask (bid) quote increases (decreases) more than bid (ask) 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

Figure 9: Mean Ask Depth



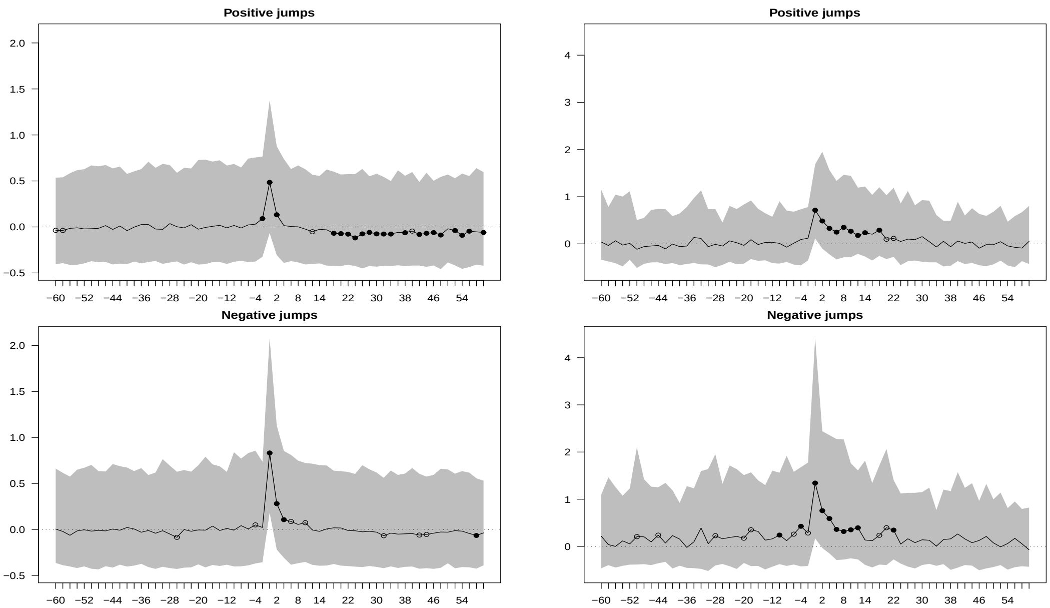
(a) Small jumps (b) Large jumps

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. $1\% < p - value \leq 5\%$).

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 11). 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 10: Mean bid depth



(a) Small jumps (b) Large jumps

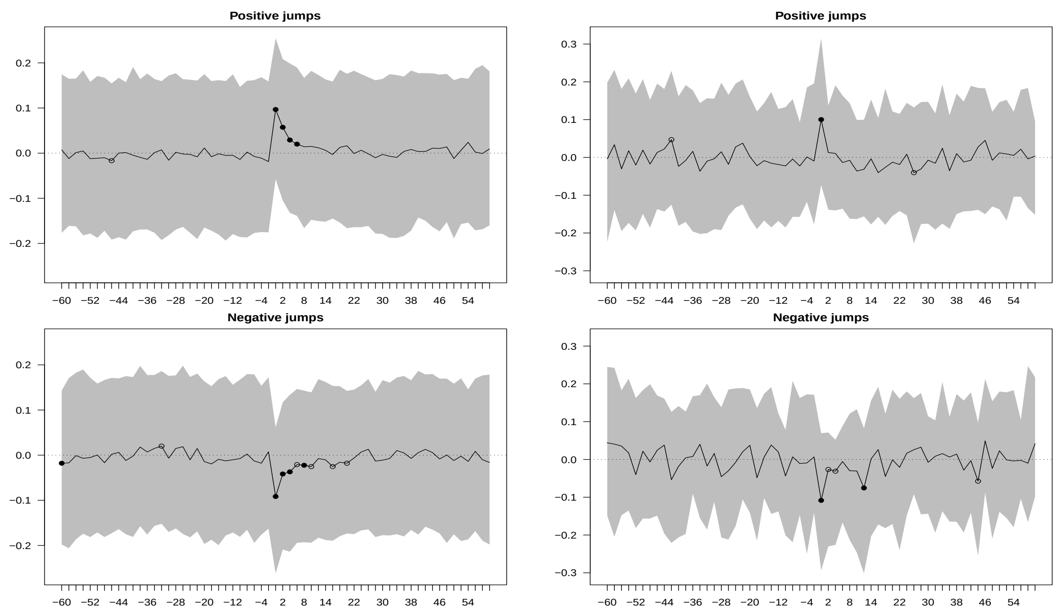
Full black line is the median standardized liquidity measure. The shaded region is the range between the 2.5% and 97.5% quantiles. Black dots (•) indicate that the null hypothesis of the Mann-Whitney test (according to which the standardized liquidity measures in the event window around jumps come from 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. $1\% < p-value \leq 5\%$).

6 Conclusion

How does liquidity behave around intraday price jumps? To answer this question, we study the dynamics of liquidity around properly identified jumps by identifying their exact intraday timing, without exclusively focusing on news announcements. This approach is motivated by Lee and Mykland (2008) who find that for individual equities, the majority of jumps occur with unscheduled news.

Our results shed new light on the debate about the liquidity response by market participants to information arrivals. While most studies show that prices react quickly to information arrivals, there is still no consensus on the liquidity response to such events. While studies such as Easley and O'Hara (1992), Lee et al. (1993), Kim and Verrecchia (1994) point to worsening market liquidity conditions, Diamond and Verrecchia (1991), Brooks (1994), Parlour (1998), Foucault et al. (2003), or Goettler et al. (2005) imply that information disclosures can improve

Figure 11: Depth imbalance



(a) Small jumps (b) Large jumps

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. $1\% < p - value \leq 5\%$).

market liquidity. This paper reconciles these views by showing that they are both correct, depending upon the dimension of liquidity that is being looked at.

Liu (2006) highlight four dimensions to liquidity, namely, trading cost (width), trading quantity (depth), trading speed (immediacy), and price impact (resilience). If liquidity is characterized by market width, there is no doubt: liquidity deteriorates around jumps. The increase in transaction costs, as measured by the quoted and effective spreads, is statistically significant (at 1%), but the economic impact remains nevertheless limited, with a maximum 15% deviation from the 'no jump' time-of-day value in ex-post liquidity.

If the second and third dimensions of liquidity (i.e. trading quantity and immediacy) are considered, the picture is different. The demand for immediate execution increases sharply around jumps. For example, big negative jumps (below -1% over a 2-minute interval) lead to a 400% increases in dollar trading volume, i.e. five times the benchmark 'no jump' time-of-day median value.

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. In general, the incremental effect of jumps on mean trade size is around 50% on average across stocks and days (although mean trade size nearly doubles around big negative jumps). 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. An increased demand for immediacy does no translate into weak liquidity supply: A greater demand for liquidity, rather than a weak liquidity supply, is associated with extreme price changes. Jumps do not seem to be due to an endogenous deficient provision of market liquidity.

Finally, 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.

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 price jumps. This will certainly help refine studies about the impact of news and economic events on financial markets.

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