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WORKING PAPER

News, Liquidity Dynamics and Intraday Jumps: Evidence from the HUF/EUR market

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News, Liquidity Dynamics and Intraday Jumps:

Evidence from the HUF/EUR market*

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Abstract

We study intraday jumps on a pure limit order FX market by linking them to news announcements and liquidity shocks. First, we show that jumps are frequent and contribute greatly to the return volatility. Nearly half of the jumps can be linked with scheduled and unscheduled news announcements. Furthermore, we show that jumps are information based, whether they are linked with news announcements or not. Prior to jumps, liquidity does not deviate from its normal level, nor do liquidity shocks offer any predictive power for jump occurrence. Jumps emerge not as a result of unusually low liquidity but rather as a result of an unusually high demand for immediacy concentrated on one side of the book. During and after the jump, a dynamic order placement process emerges: some participants endogenously become liquidity providers and absorb the increased demand for immediacy. We detect an interesting asymmetry and find the liquidity providers to be more reluctant to add liquidity when confronted with a news announcement around the jump. Further evidence shows that participants submit more limit orders relative to market orders after a jump. Consequently, the informational role of order flow becomes less pronounced in the thick order book after the jump.

JEL: F31, G15

Keywords: microstructure, foreign exchange, jumps, liquidity, Hungary, limit order book

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1. Introduction

Jumps, which are significant discontinuities in asset prices, have been an important topic in financial research over the last few decades. Empirical research shows that jumps in financial time series are common and contribute greatly to asset volatility. As an integral part of the underlying price process, they pose extreme price risk for traders and they are of vital importance for risk management purposes.

Our study investigates intraday jumps on the exchange market and their relation to macroeconomic news releases and the liquidity dynamics of the limit order book. We study the interbank HUF/ EUR exchange market over a two-year sample period (2003 and 2004). First, we detect jumps and document their prevalence and size on an emerging foreign exchange market, which is characterized by relatively low trading volumes. In previous research, jumps have been related with macroeconomic news of various sorts. We investigate to what extent this is actually the case. Besides scheduled macroeconomic announcements, we also incorporate real-time, unscheduled announcements in our dataset. Furthermore, it has been put forward by Lahaye *et al.* (2011) that jumps which cannot be related to news announcements can be caused by insufficient market liquidity.

However, the concept of liquidity is elusive as it has multiple dimensions (Amihud 2002; Pástor & Stambaugh 2003; Acharya & Pedersen 2005). For example, Liu (2006) defines liquidity as the ability to trade large quantities quickly at low cost and with little price impact. Four dimensions, namely trading quantity (depth), trading speed (immediacy), trading cost (tightness), and price impact (resiliency) emerges from this definition. As one of our motives is to pin down the cause of the jump, we map the different dimensions of liquidity that can be observed in the limit order book, and investigate whether there is any systematic pattern prior to the jump. We find that the jump itself influences the behavior of market participants, and we shed a new light on how traders formalize their "make or take" decision during and after a jump. We link our work with empirical regularities regarding traders' order placement strategy, and investigate to what extent they still hold under extreme market conditions.

By definition, jumps are latent as they are an integral part of the price process, which makes them difficult to estimate. In their seminal work, Barndorff-Nielsen and Shephard (2004) show that under maintained conditions the quadratic variation process could be decomposed into an integrated variation component and a jump component. Moreover, they provide two non-parametric measures of volatility designed for the discrete nature of empirical high-frequency data: realized variance and realized bipower variation. The former measures the quadratic variation while the latter measures the integrated variation. The difference between the two provides a consistent estimate of the jump component under maintained conditions. In their later work, Barndorff-Nielsen and Shephard (2006b) propose several finite sample jump detection statistics based on asymptotic distribution theory. Huang and Tauchen (2005) further provide extensive simulation evidence in support of the finite sample properties of these jump test statistics. The jump detection method has been applied in empirical researches of various settings. For example, Andersen *et al.* (2007a) confirm the existence of jumps in FX, equity and treasury markets and make important progress in the forecasting realized volatility by separating the jump component from its continuous sample path counterpart. Beine *et al.* (2007) find that coordinated interventions by central banks in FX markets cause fewer but more pronounced jumps after accounting for the announcement effect.

More recently, various attempts have been made to modify the jump identification method, so that it can pin down the exact timing of the jump at the intraday level. Andersen *et al.* (2007b) and Andersen *et al.* (2010) present a recursive jump detection method for identifying intraday jumps, thereby providing superior information on jumps. Alternative methods to detect intraday jumps have also been presented by Lee and Mykland (2008), Jiang *et al.* (2011) and Boudt and Petitjean (201x) among others.

The advances made in jump detection methods enjoy a burst of recent analysis on the link between macroeconomic fundamentals (news) and jumps on various financial markets. Huang (2007) confirms that jumps occur more frequently on news-days than on non-news days in US futures market. Focusing on US treasury market, Dungey *et al.* (2009) find that the majority of cojumps are associated with scheduled news releases, which is later confirmed by Jiang *et al.* (2011). Placing more emphasis on the general regularity of jump dynamics across different asset markets (US stock, Treasury and USD/EUR market), Evans (2011) documents that around one-third of the intraday jumps occur immediately after the release of news and that the informational shocks explain large proportions of the jump magnitude. In their seminal work, Lahaye *et al.* (2011) analyze the difference in size, frequency and timing of jumps across three US stock index futures, one treasury bond futures and four major currency pairs, and further link these dynamics to their likely sources (such as informational shocks). Several stylized facts emerge from their work: First, foreign exchange markets experience significantly more jumps while the average jump magnitude is smaller compared to other asset markets. Second, the link between macroeconomic news and jumps is weaker in foreign exchange markets than in other asset markets, which Lahaye *et al.* (2011) attribute to the restricted news dataset and other possible sources of jumps such as idiosyncratic liquidity shocks commonly observed in the currency markets during the slow trading process.

Related high frequency studies have also examined the relation between liquidity dynamics of the market and jumps. Bajgrowicz and Scaillet (2011) find that trading volume, as a rough gauge of market liquidity, explains independently a small portion of jumps in the US stock market, as trading volume reaches its highest value during the 5 minute interval prior to the jump. Using a probit model, Jiang *et al.* (2011) confirm that lagged liquidity shocks are able to predict the occurrence of jumps after accounting for the effect of informational shocks. Using an event study approach, Boudt and Petitjean (201x) document that jumps are largely driven by a sharp rise in the demand for immediacy, as the number of trades increases dramatically prior to jumps, while market depth at the best price does not decay as commonly expected. To sum up, potential economic sources of jumps in financial markets include scheduled macroeconomic news, unscheduled news releases, and market liquidity shocks.

An independent strand in the microstructure literature has focused on investors' order submission strategies in limit order book markets: the classical "make or take" decisions (see Bloomfield *et al.* 2005, among others). On the theory side, Cohen *et al.* (1981), Glosten (1994), Seppi (1997), Harris (1998), Parlour (1998), Foucault (1999), Sandås (2001), Hollifield *et al.* (2004), Foucault *et al.* (2005) and Roşu (2009) develop liquidity-based models of limit-order book. The main predictions of these models include that (1) the proportion of limit orders relative to market orders increases subsequent to a rise in asset volatility, (2) the proportion of limit orders relative to market orders increases subsequent to the widening of spreads, and (3) own side depth encourages the submission of market orders. On the empirical side, Biais *et al.* (1995), Griffiths *et al.* (2000), Ahn *et al.* (2001), Ranaldo (2004) and Cao *et al.* (2008) have provided consistent evidence with these predictions. More recently, experimental and empirical studies based on information-based models of the limit order book uniformly suggest that informed traders tend to use, under certain conditions, limit orders at the side where liquidity is needed (see Bloomfield *et al.* 2005; Kaniel & Liu 2006 , among others). Bloomfield *et al.* (2005) posit that, under certain conditions, informed traders change their order aggressiveness over the trading period by submitting limit orders at the side where liquidity is scarce as they are less subject to adverse selection costs.

Jumps are sudden price spikes that pose significant price risk to investors. Obviously, it is interesting to examine traders' "make or take" decisions under these extreme market conditions. Moreover, it is of great interest to test whether the predictions regarding traders' order placement strategy still hold conditioning on the occurrence of jumps with and without macroeconomic news. In spite of the relevance of the topic, there are few empirical works that investigate the order placement strategies around intraday jumps.

Our article contributes to the empirical studies on jumps in at least three ways:

First, we apply an established jump identification method to a small and less liquid exchange rate market in contrast to existing work which focuses on the most liquid major currency pairs such as USD/EUR and USD/GBP. Our aim is to examine to which extent the jump dynamics exhibited in these major currencies could be generalized to the other currencies, in particular the Hungarian Forint. One could expect jumps would be more prevalent in the HUF/EUR market than in major exchange rate markets due to its illiquidity, less market capitalization or even its distinctive trading characteristics as examined in Frömmel *et al.* (2011). Our results confirm that jumps are large and prevalent in a relatively illiquid market such as HUF/EUR market. Around 18.2% of our sample days are identified as containing at least one intraday jump with the jump component contributing nearly one-half of the realized volatility during these jump days.

Secondly, we extend the announcement effect literature by investigating the link between jumps and news releases of various sorts. Our enlarged news dataset covers not only the scheduled macroeconomic news announcements, but also the unscheduled news announcements which will change investors' expectation on future fundamentals. The enlarged news dataset also enables us to (informally) compare the relative importance of different news categories. Our results suggest that both scheduled and unscheduled news are related to jumps with the unscheduled news such as polls, surveys, forecasts and analysis on (future) fundamentals producing the most of the jumps (30.4%).

Thirdly, to the best of our knowledge, our work is the first to bridge the gap between jump-related literature and the order placement literature. Using event study methodology, we zoom in on the dynamics of various liquidity dimensions around jumps, providing a comprehensive picture on how the limit order book looks like before, during and after the jump. Furthermore, we test whether the predictions from limit order book models for order placement still hold under these extreme market conditions. We find only a very weak, if any, pattern in liquidity prior to jumps after controlling for the announcement effect. Consistent with Boudt and Petitjean (201x), we find that jumps do not emerge as a result of unusually low liquidity, but as a result of an unusually high demand for immediacy concentrated on one side of the limit order book, implying increased information asymmetry across traders during the jump period. Moreover, more limit orders are added to the ask (bid) side subsequent to a positive (negative) jump, confirming the existence of discretionary liquidity providers who supply liquidity at the side where it is needed the most. We also observe an interesting asymmetry in post-jump resiliency, which is clearly higher for negative jumps than for positive jumps. Finally, we perform an additional regression-type analysis to show that post-jump transaction order flow is less informative, as more limit orders relative to market orders are submitted to the order book subsequent to jumps. Overall, our results confirm the predictions from limit order book models: the submission of limit orders is encouraged by the widening of the spread and increased volatility caused by a jump.

To presage our results, the rest of the paper proceeds as follows. Section 2 describes a pure order-driven FX market in general and our unique dataset in particular. Section 3 explains our theoretical framework regarding the jump detection method. Section 4 presents our empirical findings regarding the jump dynamics and the announcement effect. Section 5 presents our event-study results on the liquidity dynamics around jumps. Section 6 provides further evidence on pre-jump and post-jump liquidity patterns. Section 7 concludes.

2. Data

The foreign exchange market

The foreign exchange market is a two-tier market. Trades on the foreign exchange market can be divided into customer trades, i.e. trades between a bank and customers (the ultimate end-users, for instance importing and exporting firms, mutual or hedge funds, governments and central banks) and interbank trades. In this work we focus on the interbank market, to which customers do not have access. It is here that the price formation takes place. The market is a pure order-driven market, without designated market maker. Participants can submit orders 24h a day. The majority of trades on this market are nowadays done via electronic broking systems. Since their introduction in 1992 their share in total transaction volume has steadily increased, depending on the country, from 4 to 6 per cent in 1995 to more than 55% of the interbank market in 2010 (BIS 1996, 2010).[1]

There are two main platforms competing in the foreign exchange market: Reuters D3000 and EBS (Electronic Broking System). In our analysis we rely on the Reuters D3000 system. As an electronic limit order book it contains buy and sell orders in a price-time priority. Euro sale and purchase offers are placed at limit prices. Besides these limit orders, consisting of the maximum respectively minimum price and the quantity offered to be traded, it is also possible to place a market order, i.e., an order without a specified price. They are immediately matched with the best corresponding limit order and thus more aggressive. While limit orders add liquidity to the limit order book, market orders take liquidity from the book. The following matches may lead to a trade: two limit orders that are matched up by the system, or a market order that is matched up with the best limit order on the opposite side.

The HUF/EUR market

Our dataset consists of all quotes, i.e., limit and market orders, on the HUF/EUR interbank market that have been placed during the years 2003 and 2004 via the Reuters D3000 broking system. Because at this time the competing system EBS did not offer services for the HUF/EUR market, the dataset covers the complete trading on electronic brokerage platforms, and thus the major part of the total market activity (which would also include OTC trades). The HUF trade accounted during or sample period for only 0.22% of the global turnover on the FX market (BIS 2005). This dataset was also described in Gereben and Kiss M. (2006).

The reconstruction of the limit order book

We observe the price, the quantity in Euro that was offered or asked, whether it was a market or a limit order and the exact time when the order was placed and when it disappeared. We observe whether the order was withdrawn or whether it was executed, i.e., matched with another limit or market order. We do not observe the identity of the traders.Our analysis requires information on the state of the limit order book at the intraday level. We therefore reconstruct the order book, and update it whenever a new event occurs (limit order submission, market order submission, limit order cancellation). When a new limit order is submitted, the order book is (re-)calculated by adding all activated limit orders to the relevant

[1] The share of electronic trading in interbank trading is by some authors even estimated at 85% of the total interbank activity (Sager & Taylor 2006).

side of the book.[2] When a new market order is submitted, it is verified whether the activated orders that leave the book upon submission of the order cover the market order. If not, the liquidity available for the activated limit orders at the opposite side of the book is adapted. A marketable limit order is treated in the same way as a market order, but if it has not been filled completely it will stay in the book with a reduced volume.[3] Cancelation of existing limit orders is also taken into account. It is verified whether orders leave the book before the next order is submitted to the trading platform. Each time this happens, a new event is identified and added to the time series of limit order book states. The event time will here be the removal time of the order. To obtain the new order book state the post-event orders are sorted according to price and time priority.

The output of the limit order book reconstruction process is a series of observations in event-time, with for each event a timestamp at 10 ms. precision and all orders at the bid and ask side (with their respective quotes, quantities, record numbers, entering and removal times). For very short periods zero or negative spreads can be observed. Their presence can be explained by the absence of clearing agreements between certain banks (in this case, the two banks who have posted the best orders at the respective sides of the book do not have such an agreement). As other banks, which do have clearing agreements with the issuers of the best orders from both sides, can take advantage of this situation, these zero or negative spreads are short-lived.

Legally recognized holidays in Hungary and weekends are left out.[4] Figure 1 shows graphically the evolution of the HUF/EUR quote and the volume traded via the electronic limit order book. Furthermore, we only use data from 7am till 7pm CET. Figure 2 shows the bimodal intraday distribution of ticks (with ,for example, the quantity of ticks displayed at 5 containing all ticks between 5am till 6am). After the time filter, we still cover almost the complete market activity. Table 1 shows key characteristics of the orders submitted to the market over the sample period, split up per half-year. The type of orders is shown to be very stable over time: 15-16% of the orders are market orders, 54-60% of the orders are limit orders which are cancelled without execution and 25-30% of the orders are limit orders which

[2] Activated orders are the orders which have been entered before the event time, and which have not left the book at the event time. Activated orders should not be confused with active orders (i.e. orders which initiate a trade).
[3] A marketable limit order is a limit order that can be immediately executed, because its price or equal to or better than the best quote from the opposite side of the book.
[4] For 2003 these were: 1/01, 15/03, 21/04, 1/05, 9/06, 20/08, 23/10, 1/11, 25/12 and 26/12. For 2004 these were: 1/01, 15/03, 12/04, 1/05, 31/05, 20/08, 23/10, 1/11, 25/12 and 26/12.

are partly matched with market orders or with marketable limit orders. Major part (71-79%) of the orders have a size of 1 mill., which is the minimum size. Table 2 presents basic descriptives of the limit order book. The quoted spread increases in the second half of 2003 (from 0.31 to 0.39 HUF/EUR), but decreases in 2004 (till 0.24 HUF/EUR). The average breadth (the quantity available at the best quote) is, interestingly, always bigger on the buy side. The same accounts for the average depth over the whole order book. In the second half of 2003 and the second half of 2004 we observe a sudden and large increase in depth at the buy side. This unusually high depth is caused by positive outliers: in the periods 24/9/2003-9/10/2003 and 10/11/2004-31/12/2004 there are unusually high orders added to the buy side (however, away from the best quote). The number of price levels at the buy side is on average 6-7, at the ask side there seems to be a slight increase in the average number of levels (from 5.64 in the first half of 2003 till 7.35 in the second half of 2004).

The advantage of our dataset for the analysis of jumps and their link with liquidity is threefold. First, on the foreign exchange market orders can be submitted on a continuous basis. There are, in contrast to for example equity markets, no opening or closing sessions that can affect the data. As the observed price and liquidity can never be driven by these artificial operations, the dynamics between announcements and liquidity should become clear more easily. Secondly, we are able to observe the complete liquidity as there are no orders which display only part of their total volume (iceberg orders). By consequence we have a clear view on the supply and demand on the market. Thirdly, we cover the lion's share of the market activity on the HUF/EUR market (most of the trading activity on the HUF/EUR market takes place via electronic limit order books, and we completely cover this form of trading). Compared to other studies, our dataset is unusually rich. This is to our knowledge the only study in which a complete tick-by-tick database and a full order book over a timespan as long as two years is used for the foreign exchange market. Still, we have to keep in mind that the data, although covering our market to a very large extent, can display different trading characteristics then other, major foreign exchange markets.

3. Methodology

3.1. Jump Detection

Realized variance and Bipower variation

We assume that the log-price $p(t)$ of the underlying asset follows a continuous-time jump-diffusion process (i.e. a Brownian semimartingale with finite jump process), as is traditionally used in asset pricing (Andersen et al. 2007b; Lee & Mykland 2008; Evans 2011):

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + k(t)dq(t) \quad [3.1]$$

where $\mu(t)$ is the continuous and bounded drift term, $\sigma(t)$ a strictly positive stochastic volatility process with a sample path that is right continuous and has well defined limits, $W(t)$ a standard Brownian motion, $q(t)$ is a counting process with possible time-varying intensity $\lambda(t)$ (which implies $P[dp(t) = 1] = \lambda(t)\ dt$), and $k(t) \equiv p(t) - p(t\text{-})$ is the size of the corresponding discontinuous jump in the underlying log-price movement, provided the jump exists.

Given the above theoretical setup, the quadratic variation (QV) for the cumulative return process over a fixed time interval T, consists of both, the continuous volatility component and the contribution of jumps to volatility. It is defined as:

$$[r,r]_T = \int_0^T \sigma^2(t)dt + \sum_{0<s<T} k^2(t) \quad [3.2]$$

According to Barndorff-Nielsen and Shephard (2004), a non-parametric measure of the daily return variation, realized variance (RV), is defined as the summation of the M high frequency intra-daily squared returns within day i:

$$RV_i = \sum_{j=1}^{M} r_{i,j}^2 \quad [3.3]$$

where r_{ij} is the return in the interval j out of M intervals on day i.[5] Based on the theory of quadratic variation (Barndorff-Nielsen & Shephard 2004, 2006a), realized variance converges to its probability limit, the increment of the quadratic variation process as the sampling frequency M tends to infinity:

[5] We refer to r_i as the return on day i, and to r_{ij} as the return in interval j on day i. Therefore daily and intradaily returns are linked by $r_i = \sum_{j=1}^{M} r_{i,j}$, with a total of M subintervals for each day.

$$RV_i \rightarrow \int_{i-1}^{i} \sigma^2(t)dt + \sum_{i-1<t\leq i} k^2(t) \qquad [3.4]$$

Therefore, the realized variance is a consistent estimator of the total return variation regardless of the existence of within-day jumps.

To decompose the continuous sample path component from the *QV* process, Barndorff-Nielsen and Shephard (2006a) introduce the scaled realized bipower variation (*BPV*), defined as the summation of the product of adjacent absolute high frequency returns standardized by a constant:

$$BPV_i = \mu_1^{-2} \sum_{j=2}^{M} |r_{i,j}| \cdot |r_{i,j-1}| \qquad [3.5]$$

where $\mu_1 = E(|u|) = \sqrt{2/\pi}$ and $u \sim N(0,1)$. Under some further assumptions[6] regarding the underlying log-price dynamics in equation [3.1], the (scaled) realized bipower variation converges uniformly in probability to the integrated volatility as *M* tends to infinity (for a proof see Theorem 2 in Barndorff-Nielsen and Shephard (2004)):

$$BPV_i \rightarrow \int_{i-1}^{i} \sigma^2(t)dt \qquad [3.6]$$

Therefore, the difference between the realized variance and the (scaled) realized bipower varition provides a consistent estimation of the pure jump contribution to the quadratic variation process within the day, as *M* tends to infinity:

$$RV_i - BPV_i \rightarrow \sum_{i-1<t\leq i} k^2(t) \qquad [3.7]$$

Based on the relation between realized variance and bipower variation it is then possible to construct tests for the occurrence of jumps, see Huang and Tauchen (2005) for a survey. We rely on the ratio test statistics (*Z*) to identify statistically significant jumps (See Huang and Tauchen 2005):

[6] As is further demonstrated in Barndorff-Nielsen and Shephard (2006a), the only additional assumption required is that the stochastic volatility $\sigma(t)$ is independent of the standardized Brownian motion $W(t)$ in equation [3.1]

$$Z_i = M^{\frac{1}{2}} \frac{[RV_i - BPV_i]RV_i^{-1}}{[(\mu_1^{-4} + 2\mu_1^{-2} - 5) \cdot max\{1, TQ_i \cdot BPV_i^{-2}\}]^{\frac{1}{2}}} \sim N(0,1) \quad [3.8]$$

with the tripower quarticity (TQ) defined as

$$TQ_i = M\mu_{4/3}^{-3} \sum_{j=3}^{M} |r_{i,j}|^{\frac{4}{3}} \cdot |r_{i,j-1}|^{\frac{4}{3}} \cdot |r_{i,j-2}|^{\frac{4}{3}} \quad [3.9]$$

Where $\mu_{4/3} = E\left(|u|^{\frac{4}{3}}\right) = 2^{\frac{2}{3}}\Gamma(\frac{7}{6})/\Gamma(\frac{1}{2}) \approx 0.8309$. Under maintained assumptions, equation [3.8] implies that the ratio statistic follows standard normal distribution. Following the literature we set the significant level to α = 0.0001 and therefore the critical value is $\Phi_{1-\alpha} = 3.719$.

Microstructure noise and jump measurements

In practice, the assumed regularity of the log-price movement is contaminated by market microstructure frictions such as discrete price tick, bid-ask spread bounce and etc. On the one hand, the existence of microstructure noise in the underlying log-price process renders realized variance an inconsistent estimator of its probability limit (the quadratic variation) (Andersen et al. 2007b). On the other hand, both the realized bipower variation and tripower quarticity are biased against the finding of significant jumps due to the noise-induced first-order autocorrelation revealed in the high frequency return series. To alleviate the adverse effect of microstructure noise on jump detection scheme, we tackle the problem in two ways: First, we choose a ten-minute sampling frequency at which the microstructure frictions no longer present a distorting influence on realized variance (Andersen et al. 2010)[7]. Second, we modify the calculation of realized bipower variation and tripower quarticity by replacing the adjacent absolute returns in equation [3.5] and [3.9] with their staggered counterparts to break up the spurious autocorrelation pattern observed in the high frequency return series (similar to Andersen et al. (2007a); Beine et al. (2007); Evans (2011); among others):

$$BPV_i = \mu_1^{-2}\left(\frac{M}{M-2}\right)\sum_{j=3}^{M} |r_{i,j}| \cdot |r_{i,j-2}| \quad [3.10]$$

[7] The volatility signature plots in Andersen *et al.* (2010) suggests that there's a systematic declining pattern in the realized variance measure as the sampling frequency increases in the range of 5 to 300 seconds, which destabilizes our measurement of *RV* (and hence the difference between *RV* and *BPV*), therefore, a 10-minute sampling scheme seems an appropriate, albeit somewhat conservative, method to control microstructure noise.

$$TQ_i = M\mu_{4/3}^{-3}\left(\frac{M}{M-4}\right)\sum_{j=3}^{M}|r_{i,j}|^{\frac{4}{3}}\cdot|r_{i,j-2}|^{\frac{4}{3}}\cdot|r_{i,j-4}|^{\frac{4}{3}} \quad [3.11]$$

The staggered version of realized bipower variation and tripower quarticity is then used in equation [3.8] to compute the new ratio test statistic for jump detection. Huang and Tauchen (2005) show that the ratio Z-statistic with staggering offers improved size and power properties in finite sample simulation and is quite robust to the size of microstructure noise.

Since the test statistic only indicates the days when at least one significant jump occurred, but neither the exact time nor the number of jumps, we apply the sequential intraday jump detection scheme proposed by Andersen et al. (2010)[8] to identify all the intraday jumps.

3.2. Event study methodology

In this section, we investigate the intraday liquidity dynamics around jumps using the intraday event study methodology (see Boudt & Petitjean 201x; Gomber *et al.* 2013; Mazza 2013 , for similar application). We employ a variety of liquidity measures commonly used in the empirical literature to capture the different dimensions of the market liquidity (eg. Boudt & Petitjean 201x; Mazza 2013). Appendix I gives a full-fledged definition of all the liquidity measures used in the study.

The event study approach proceeds as follows: First, we construct a centered jump event window which includes the six 10-minute intervals before and after the jump event. Second, we exclude intraday jumps which are clustered in time in order to avoid contagion effect. That is, when two jumps occur within the same day, they must be separated in time by at least two hours. Otherwise, both of the jumps are excluded from our sample. For similar concerns, days with three or more jumps are also excluded from the final sample. Third, all liquidity measures are standardized to make them comparable across days and intraday periods. Given the fact that liquidity measures are highly skewed at the intraday level and have strong seasonal patterns, we opt for the novel standardization procedure highlighted in Boudt and Petitjean (201x). Appendix II provides a detailed description on the standardization procedure. Fourth, we aggregate across individual jump events for a single point estimate. We

[8] Jiang and Oomen (2008) and Jiang *et al.* (2011) employ similar sequential jump identification scheme with the slight difference that they use the median of the remaining intraday returns to calculate the revised ratio statistics.

favor the median value, rather than the mean value, of the standardized liquidity measure across individual events as our point estimator. The rationale behind our preference is well-grounded. First, liquidity measures such as number of trades, trading volume, and depth (per ten minutes) have a lower bound of zero, while in theory they do not have an upper bound. Therefore, the distribution of their standardized value remains highly skewed, which is also confirmed in our sample. Second, as argued by Boudt *et al.* (2011), the median of the standardized liquidity measures on non-jump days will be 1 for depth and volume measures and 0 for order and depth imbalance measures by construction. In that case, the interpretation of the median of the standardized liquidity measure is quite straightforward: It shows the (percentage) deviation from the typical levels during the same time of the day. Fifth, a Wilcoxon rank sum test on the median is performed to evaluate the null hypothesis that price jumps do not have any effect on liquidity. In order words, liquidity measures tend to stay at their normal level around jumps (median value of the standardized liquidity measures is zero). The alternative hypothesis is that liquidity measures are either abnormally lower or higher than their normal level around jumps.

It is important to mention that we explicitly distinguish between positive jumps events and negative jumps events, as positive jumps are mostly linked with large market buy orders combined with the paucity of liquidity at the ask side while negative jumps are linked with large market sell orders combined with the paucity at the bid side. In other words, we expect the liquidity dynamics around positive jumps and negative jumps will mirror each other. Therefore, our final event study samples are distinguished between positive jump events and negative jump events. For each category, we further divide them into positive (negative) jumps events associated with news announcements and positive (negative) jumps events without news announcements.

4. Jumps and news announcements

Prevalence and size of jumps

In this subsection, we investigate the jump intensity and magnitude for the HUF/EUR rates, which is a relatively illiquid market compared to major currencies such as USD/EUR. The results are summarized in Table 3. We detect 90 realized jump days with at least one intraday jump. There are 125 intraday jumps in total (see Table 4). The jump intensity—defined as the ratio of realized jump days to total trading days—is 18.2% for our sample period, which is quite similar to the jump frequency found in prior literature on the major currency markets: Beine *et al.* (2007) report a jump intensity of 10%–13% for the USD/EUR and JPY/USD markets between 1987 and 2004. Andersen *et al.* (2007a) document a 14% jump frequency for the DEM/ USD rates between 1986 and 1999. Lahaye *et al.* (2011) report that the jump frequency lies within the range of 22%–25% for the USD/EUR, USD/GBP, USD/JPY and USD/CHF markets between 1987 and 2004. We further find that the average jump duration—defined as the mean time length (measured in days) between two neighbouring jump days—is 6.6 days for our sample. We also calculate to what extent the jump component contributes to the realized variance on realized jump days. On average, 42.59% of the price variation on jump days can be attributed to jumps. This is also in line with previous work on major currencies. For example, Evans (2011) report a jump contribution of 35.80% on the the USD/ EUR market.

When comparing positive and negative jumps (see Table 4), we find that the differences both in terms of frequency and magnitude are small and not statistically significant. Therefore, we can conclude that jumps are symmetric in terms of both frequency and size. This is consistent with previous research on major currency markets (Lahaye *et al.* 2011).

We find that intraday jumps are concentrated on two periods, one in the morning (between 8:00 and 8:20 (CET)) and one in the afternoon (between 15:50 and 16:50 (CET)). We see that 66.67% of the jumps takes place during these timespans.

Jumps and public news announcements[9]

By theory, price tends to jump to the new equilibrium level immediately after new information (shocks) has been revealed to the market. Therefore, one obvious source of jumps is prescheduled macroeconomic news. These announcements represent potential shocks to the market if the statistics released do not match the market expectations.[10] Previous research in this field suggests that nonfarm payroll, central bank announcements, and trade balance shocks are the major news items that are most closely linked with foreign exchange jumps (Neely 2011). In this work, we also adopt a variety of macro news items such as the releases of GDP, PPI and trade balance information in Hungary and the European Union. To account for possible cross-currency pressure such as cojumps and global liquidity shocks (see Banti *et*

[9] The data on news announcements is collected from the very comprehensive Dow Jones Factiva News database, which contains data from newswires such as Reuters and Dow Jones.
[10] Unfortunately, we cannot observe the surprise component of the announcement.

al. 2012), we also include the macroeconomic announcements from the United States, leading EU countries such as Germany and France, and neighbouring CEEC countries such as Poland.[11] Following Lahaye *et al.* (2011), we attribute the jump occurrence to a news event using a 60-minute matching window centered around the jump. That is, if a news event takes place between the 30 minutes before and 30 minutes after the jump, we assume that the jump is directly linked with it. Table 5 summarizes our findings. We can link 16% of the detected jumps with scheduled news announcements. The conditional probability of observing a jump given a particular sort of news item is the highest for GDP releases for Hungary (25%), followed by inflation releases for Germany (8.33%) and inflation releases for Poland (8.33%). Given a jump, there is no clear pattern as which type of news has a high probability of having caused the jump (not a single type of news has a higher conditional probability than 1.60%).

In addition to linking jumps with prescheduled macroeconomic announcements, we also investigate the potential link with unscheduled, real-time news announcements that can potentially influence the HUF/ EUR quote. As this news influences the expectations on fundamentals, it can, according to standard models of exchange rate determination, influence the quote directly (Evans & Lyons 2005). We include central bank interventions, polls, surveys, forecasts, analyses by financial institutions and leading economists, political changes and natural disasters, following Copeland (2005). Table 6 presents our results in detail. We can link a significant part of the jumps (30.4%) with unscheduled news announcements. Amongst the 15 largest jumps, 4 jumps can be explained by this type of news (as much as the number of jumps that can be explained by scheduled macroeconomic news announcements). Overall, our results show that unscheduled, real-time news is another important source of jumps. Still, nearly half of the jumps remain unexplained, which is possibly due to the prevalence of private information in the FX market. Informed traders capitalize on their private information by taking up the liquidity of the order book, forcing the price to jump to a new level. Section 5 and 6 provide more in-depth evidence on our conjectures of informed trading by examing the liquidity dynamics around the jump.

[11] The motivation for incorporating macroeconomic announcements for other economies is double. First, market participants form their expectations on macroeconomic statistics for the European Union based on the release of national statistics, which takes place earlier than the release of the aggregated statistics. Secondly, recent empirical evidence on cojumps on foreign exchange markets showed that fundamental shocks to one currency pair can put substantial risk on linked markets (Lahaye *et al.* 2011; Neely 2011).

5. Jumps and liquidity dynamics

In addition to investigating the link between public news and jumps, a proper understanding of jumps and where they come from requires an in-depth analysis of the interaction that takes place in the book around jumps. Conventional wisdom suggests that a jump reflects the inability of the limit order book to absorb relatively large market orders quickly. Therefore, large market orders have to walk up or down the book for execution. However, this mechanical view neglects the role of limit order flows when a jump occurs. In fact, the limit order book is a platform where interaction, among informed traders, market makers (liquidity providers) and noise traders, takes place via market and limit orders. The sudden increase of volatility impacts the liquidity of the market as traders (dynamically) revise their order placement strategy (such as order aggressiveness and order size). Therefore, built on theoretical models of the limit order book developed in previous research (Glosten 1994; Foucault 1999), we further develop hypotheses on the dynamic relation between price jumps and the different dimensions of liquidity.[12]

In this section we describe the liquidity dynamics prior to, during and after jumps, incorporating both the mechanical and dynamical view (as they both can matter). The findings in this section shed a new light on what the cause is of jumps, whether there is a stylized liquidity pattern that preceeds jumps and how the jump affects the interaction that takes place. We apply here the event study approach (cf. supra). For clarification purpose, we present here mainly the liquidity dynamics around positive jumps as the liquidity dynamics around positive jumps and negative jumps mirror each other.[13] The detailed results can be found in Table 7 (positive jumps) and Table 8 (negative jumps). Figure 5 till Figure 13 present boxplots for various indicators on the state of the limit order book (and this for each 10 minute interval from 1 hour prior to the jump till 1 hour after the jump). The central mark is the median, and the edges of the box are the 25th and 75th percentiles. The whiskers point at the most extreme observation which is still no outlier.[14]

[12] Here we use a broader definition of news, which includes now also private news such as the customer order flow observed by the market participant. The assumption that jumps are information-based is supported by the fact that we observe an increased imbalance of the order flow during jumps, which is a common proxy for information. Additional evidence can be found in the price reversal pattern after the jump (See Figure 4)

[13] And where this is not the case, we mention it explicitly.

[14] Observations are considered to be outliers if they are larger than $q_3 + 1.5*(q_3-q_1)$ or smaller than $q_1-1.5*(q_3-q_1)$ with q_1 is the 25th percentile and q_3 is the 75th percentile.

5.1 Liquidity dynamics prior to the jumps

Hypotheses: origin of jumps

Previous literature suggests that lagged liquidity shocks in the order book such as a widened spread, decreased market depth and levered number of trades indicate the occurrence of jumps (Boudt & Petitjean 201x; Jiang *et al.* 2011). Our event study setting provides a straightforward way to validate the above predictions. In case there are pre-jump liquidity shocks, we should observe the median value of some liquidity variable during the pre-jump periods to be significantly different from zero. We distinguish three potential relations between preceding liquidity in the book and the occurrence of jumps:

H1: A price jump will occur when the liquidity in the limit order book is unusually low, and cannot absorb a normal market order flow.

H2: A price jump will occur when the liquidity in the limit order book is normal, and the market order flow is unusually high.

H3: A price jump will occur when a high level of liquidity triggers an even higher flow of market orders which cannot be absorbed by the liquidity in the limit order book.

Results

Prior to a positive jump, there is no significant change in the size-weighted proportional quoted spread (tightness). Nor do we observe any strong trend in trading activies during the 60 minutes prior to the jump, as trading volume stays at its normal level and transactionorder flow is balanced (immediacy). Furthermore, the volume of outstanding limit orders (both overall and at the best quote) on the side that has to absorb the jump shows no universal pattern in the 60 minutes prior to the jump (depth and breadth). Our findings have implications for the predictability of jumps based on the liquidity in the book, a topic that we explore further (See p. 23, Predictability of jumps using probit analysis).

5.2 Liquidity dynamics during and after the jump

Hypotheses: interaction during jumps

In order to interpret our observations during and after the jump, we introduce here three types of participants, who follow each different order placement strategies (if any). Participants can at each point of time be classified according to the strategy they are following. Especially on this type of interbank market, the same agent can apply different strategies depending on his specific sitation at that time.[15] We formulate ex ante predictions on the overall outcome of a dynamic order placement strategy by these heterogenous agents.

We distinguish respectively:

- *Informed traders:* Participants who act on private information on the future evolution of an asset, like they are introduced in Kyle (1985). On the foreign exchange market, their information can be based on the customer order flow (Rime 2000). Informed traders can be patient (and submit aggresive limit orders) or impatient (and submit market orders). The motivation for informed traders to be patient includes lower price impact.[16] They will, however, be impatient when their information is short-lived, or, following Bloomfield *et al.* (2005), when their private valuation lies outside the range of the inside quotes. Both patient and impatient informed traders can be present at the same time on the market, because they can have heterogenous private beliefs.

  H4: The presence of patient informed traders will, upon arrival of positive (negative) information, lead to increased submission of limit orders at the buy (sell) side, against competitive quotes.

  H5: The presence of impatient informed traders will, upon arrival of positive (negative) information, lead to increased submission of market buy (sell) orders.

- *Market makers:* Participants who primarily provide liquidity to the market. Although there are no designated market makers on the interbank foreign exchange market, participants can be attracted by the profit market making offers. The idea that a market making role emerges from the trading process is also referred to as endogenous

[15] In that sense, trader identities would here not be very informative.

[16] Evidence for the existence of patient informed traders can be found in, amongst others, Eisler *et al.* (2011) and Hautsch and Huang (2012). In these works it is shown that limit orders contain information, as they have a permanent price impact.

liquidity provision.[17] Market makers set a spread between the best buy and best sell. This is the source of their revenues. When setting the spread, they take the following costs into account: order processing costs (representing per unit administration costs and fixed costs such as wages, floor space rent,…), inventory holding costs (the cost of holding an unwanted inventory) and adverse selection costs (a compensation for the risk of trading with a better informed counterparty).[18] They will typically submit competitive limit orders. After a jump, which we found to be trade induced in the previous paragraph, the spread rises in a limit order book because the market orders are highly imbalanced and one side of the market gets depleted. Market makers are attracted by this high spread and post limit orders.[19] This increase in supply of liquidity will improve the best prices, and will bring the spread back to its equilibrium value (eg. Goettler *et al.* 2005).

H6: The presence of market makers will, upon arrival of information, lead to an increased provision of liquidity at the market.

- *Noise traders:* Participants who do not trade based on information, but trade based on their liquidity needs. Their part of the flow is balanced over time. We do not observe noise traders in our results, as we only measure unexpected trading flows and unexpected liquidity.

Results: tightness

As jumps appear to be trade-induced, the trading volume increases during a jump interval. The higher number of transactions consumes the liquidity available in the market, and the spread will consequencly in a mechanical way go up. Moreover, liquidity providers tend to place limit order further away from the midquote, to avoid being picked off due to the increased price risk. However, the widening of the spread in combination with the paucity of liquidity at one side of book makes it more rewarding to provide liquidity. Discretionary liquidity providers see which side of book requires liquidity and will submit more limit orders

[17] For a recent work dealing with the behaviour of endogenous liquidity providers in comparison to designated market makers, see Anand and Venkataraman (2013).
[18] For an analysis of the importance of these components on this market, see Frömmel and Van Gysegem (2012).
[19] As a consequence of this increased liquidity provision, the market enters then again a phase of high liquidity (which will afterwards again be taken away). This sequence of high liquidity – low liquidity is also referred to as a liquidity cycle (See e.g. Foucault *et al.* 2013) .

to this side. These limit orders are designed to benefit from the increased demand for immediacy.

This is also what we observe. During the jump, the spread increases with 25.09%. We see that liquidity providers are attracted by this spread, and bring it back to its normal level 20 minutes after the jump (H6). The spread returns slightly quicker to its normal level after negative jumps.

Results: immediacy

Previous theoretical work predicts that order submissions tend to be clustered over time (amongst others, Kyle 1985; Admati & Pfleiderer 1988; Wang 1994). These findings were empirically confirmed by amongst others Campbell *et al.* (1993) and Covrig and Ng (2004). One could expect that by consequence an increase in volume traded will persist for some time after the jump. However, as spreads remain high after a jump, transactions are more costly. This high spread will impact traders submitting less aggressive limit orders.

During a jump, market order submissions in the direction of the information increase drastically. As a result, the order flow gets more asymmetrical (with an increase of the imbalance with 57.89% towards more buy orders), and the trading volume increases by 180%. (H2, H5)

The increased trading activity continues up till 20 minutes after the jump, but there is no sign of order flow imbalance ex post positive jumps. Thus, it seems like the increased trading after the jump is more balanced. The increase in trading activity is smaller after negative jumps, and the activity also returns faster to its normal level.

Results: depth and breadth

Mechanically, one would expect that the depth and breadth become unusually low at one side of the book during a jump, because informed traders are using the liquidity in one side of the book. Within the framework of a dynamic limit order market, like it was developed by Foucault (1999) and Foucault *et al.* (2005), the increase of price risk caused by increased volatility is due to an increase in the information asymmetry across traders. Consequently, we expect an increase in the placement of limit orders relative to market orders (and thus an increase in depth) immediately after the jump. Patient traders would then make the book thicker at the opposite side. At the same time, the liquidity provision by market makers could restore the liquidity after the jump.

This is also what we see in the data. At the ask side we find that the depth decreases with 23.04%, due to the increased arrival of one-sided market orders (H5). At the same time, the total depth at the buy side is found to be 10.76% higher than expected. The liquidity at the best buy (breadth) is 14.82% higher than expected. This confirms the presence of patient informed traders (H4).[20] The breadth at the ask side is unusually high during the jump (8.07% higher), which is consistent with the prediction that market makers become active and start providing liquidity (H6).

Results resiliency

Using evidence from experimental asset markets, it was shown that a market making role emerges endogenously on a financial market (Bloomfield *et al.* 2005). This is in line with empirical evidence by Ahn *et al.* (2001), who highlight the importance of distinguishing between increased volatility arising from the bid side or from the ask side. Attracted by the increasing reward, traders will start to submit limit orders (and thus provide liquidity) at the side where liquidity is needed the most.

We do find in our results that the liquidity is restored after a jump, consistent with the emergence of market makers who add liquidity to the book. We see that the overall volume of limit sell orders entered after a positive jump is 127.27% higher than expected (See Table 11).[21] This is only partly the result of a quote updating process (as the cancellations at this side are only 86.87% higher than expected, unreported). While during the jump interval, the increased activity of patient informed traders dominates over the increase in limit orders posted by market makers, this reverts in the interval immediately after the jump. After the jump, market makers continue to provide unusually high liquidity up till 30 minutes after the jump. They bring the spread back to its normal level, and also restore the depth (from 20

[20] For negative jumps, these patient informed traders seem to be active already before the jump. They post limit orders at the ask side in the 60 minutes before the jump and make the book unusually imbalanced. Their impact on the book is also bigger (respectively 22.46% and 24.11% more liquidity during and immediately after the jump compared to 10.76% and 16.50% after positive jumps).
[21] Later in this paper, we provide further evidence on order submission strategies (See p. 25, Post-jump order submission strategy).

minutes after the jump onwards).[22] Our findings illustrate the effectiveness of endogenous liquidity providers, even in a relative illiquid market and after a large price discontinuity.

Results: asymmetries between public and private news induced jumps

We find that for most liquidity dimensions, the dynamics of liquidity are very similar for jumps that are caused by public news announcements, and jumps for which this is not the case. A reason for this surprising symmetry could be that they are both linked with information, like we have argued above, and that they are in this sense also more similar than what one would expect. This hypothesis is supported by the price reversal pattern (See Figure 4).

We find however one interesting and strong asymmetry in tightness: for jumps that can be linked with public news, the spread rises with 49.90% during a positive jump interval and 35.15% during a negative jump interval. For jumps that cannot be linked with public news, the spread rises only with respectively 18.52% and 17.75%. This may seem counterintuitive at first sight, because public information is symmetric and private information is not. We think this can be explained by the behavior of the liquidity providers, who are more reluctant to provide liquidity when a jump is caused by a public news announcement. It might be that they want to wait till consensus is reached on the interpretation of the news, and that they hesitate to provide liquidity when they know for sure that the movements are caused by information (even when this information is public). We find support for this in the price reversal pattern: the initial jump at both sides is reverted after public news announcements, while this is only to a much lesser extent the case for jumps that are not linked with a public news announcement. This also points at an insufficient liquidity provision in an early stage after the jump.

6. Further Analysis

The prior section provides a comprehensive view on how market liquidity evolves around the jump. However, several important issues remain unsolved: Is it possible to forecast the jump occurrence using information available prior to the jump? Does the speed of price discovery remain unchanged after the jump? What kind of order placement strategy do traders adopt

[22] After positive jumps, the depth an breadth become even unusually high till 40 minutes after the jump. This overshooting cannot be found back after negative jumps.

after experiencing the extreme price risk due to jumps? In this section we provide further evidence on these issues.

6.1 Predictability of jumps using probit analysis

Despite the fact that there are very weak, if any, pre-jump liquidity patterns in the event study section, it is still possible that a certain dimension of the liquidity shocks is indicative of subsequent jumps or liquidity shocks jointly contribute to the occurrence of jumps. Therefore, we further assess the predictive power of liquidity shocks of multiple dimensions prior to the jump via a probit model.[23] Our explanatory variables are selected in an attempt to cover all dimensions of liquidity and are in line with Boudt and Petitjean (201x). To avoid the contagion effect from consecutive jumps, we focus only on sample days with a single intraday jump. We estimate the jump probability with the following model specification:

$$P(JUMP_t = 1|\boldsymbol{Z}) = \Phi\begin{pmatrix}\alpha + \beta_1 SWPQS_{t-1} + \beta_2 Volume_{t-1} + \beta_3 |OI|_{t-1} + \beta_4 MD_{t-1} \\ +\beta_5 |DI|_{t-1} + \gamma INFO_t\end{pmatrix} \qquad [6.1]$$

where $P(JUMP_t = 1|\boldsymbol{Z})$ denotes the probability that a jump occurs conditional on a set of explanatory variables, $\boldsymbol{Z}$. In equation [6.1], the set of explanatory variables includes lagged values of spread ($SWPQS$), trading volume ($Volume$), absolute order flow imbalance ($|OI|$), mean depth at the best price (MD) and absolute depth imbalance ($|DI|$) at the best price. In addition, a contemporaneous informational dummy ($INFO$) is also added to control for the possible announcement effect. All the liquidity variables used in [6.1] can be inferred from the Reuters screen, which is available to all market participants.

The estimation results are reported in Table 9. Consistent with our findings in the event study section, conventional liquidity measures offer weak, if any, predictive power in forecasting the occurrence of jumps after controlling the effect of informational shocks. First, none of the liquidity variables in equation [6.1] are statistically significant. Second, the null hypothesis that the coefficients of all liquidity variables are jointly zero is not rejected at the 10% significance level.

[23] Our results remain unchanged when we use a logit regression. These results are available upon request.

6.2 Post-jump price discovery

In this subsection, we further examine the price discovery process after a jump in the FX market. Prior evidence suggest that the informational role of transaction order flow weakens subsequent to price jumps in the US bond and equity market (Boudt & Petitjean 201x; Jiang *et al.* 2011). We extend the work on post-jump price discovery to the FX market by examining all the single-jump days and non-jump days via the following model:

$$R_{t+1} = \alpha_0 + \alpha_1 D_{JUMP} + \beta_0 OF_t + \beta_1 OF_{t+1} + \beta_2 OF_{t+1} \times D_{JUMP} + \varepsilon_{t+1} \qquad [6.2]$$

where R_{t+1} denotes 100 times the change of the logarithmic mid-quote during the 10-minute interval *t+1*, OF_t (OF_{t+1}) is the signed volume of transaction order flow over the interval *t* (*t+1*) measured in millions of euros. D_{JUMP} is the post-jump dummy, which takes the value of one for the six 10-minute intervals immediately after the jump and zero otherwise. We differ from previous studies such as Jiang *et al.* (2011) by including the lagged order flow (OF_t) in the model specification to account for the possible price reversal in the next period as suggested by Pástor and Stambaugh (2003). That is, we expect that both the lagged and current order flow would impact price discovery process, but in the opposite direction. Therefore, the coefficient β_0 captures the liquidity effect of lagged order flow, β_1 captures the normal price impact of order flow, and β_2 captures the additional price impact of contemporaneous order flow immediately after the jump, which is robust to subsequent price reversals.

The results of the regression are presented in Table 10. The coefficient on contemporaneous order flow is significantly positive, confirming the role of order flow in the price discovery process (see Evans & Lyons 2002). As expected, the coefficient on the lagged order flow is significantly negative but much less in magnitude than that on the current order flow, suggesting the existence of subsequent price reversal due to illiquidity. Finally, the coefficient on the interaction term between the post-jump dummy and the current order flow is significantly negative at the 5% level. This is consistent with prior literature that the informational role of post-jump order flow is less pronounced than during normal trading periods.

While we confirm the stylized fact regarding post-jump price discovery, it remains interesting to investigate why order flow becomes less informative immediately after jumps. Jiang *et al.* (2011) attribute it to the possibly lowered dispersion of investor belief immediately following the occurrence of jumps. Motivated by our findings in the event study, we, however, perceive it differently: The reduced informational role of (transaction) order flow may as well be explained by the altered order submission strategy immediately after the price jump, which we investigate in the next subsection.

6.3 Post-jump order submission strategy

In this subsection, we investigate in depth the impact of jumps on the subsequent order placement strategy using regression analysis. Prior studies suggest that a higher proportion of limit orders relative to market orders emerges immediately after enlarged asset volatility or a widened spread (Biais *et al.* 1995; Griffiths *et al.* 2000; Ahn *et al.* 2001; Cao *et al.* 2008). Motivated by our findings in the event study section, we extend the order placement literature by focusing on the impact of intraday jumps, rather than volatility, on the subsequent order-flow composition. In particular, we estimate whether the occurrence of jumps leads investors to submit more limit orders relative to market orders, or the other way around.

To address these questions, we use the change of market depth available at the best price from interval t to $t+1$ ($\Delta Depth_{t+1}$) as a proxy of the order-flow composition. As it is argued by Ahn *et al.* (2001), $\Delta Depth_{t+1}$ captures the difference between the net volume of newly placed limit orders and the volume of market orders executed during the time interval $t+1$. Therefore, we estimate the following empirical model which is similar to Equation 6 in Ahn *et al.* (2001).

$$\Delta Depth_{t+1} = \alpha_0 + \alpha_1 D_{JUMP} + \rho_1 \Delta Depth_t + \beta_0 Risk_t + \beta_1 Risk_t D_{JUMP} + \sum_k \gamma_k TIME_{k,t+1} + \varepsilon_{t+1} \quad [6.3]$$

where $\Delta Depth_{t+1}$ ($\Delta Depth_t$) is the change of mean depth available at the best price from interval t (t-1) to $t+1$ (t), D_{JUMP} is the post-jump dummy, which takes the value of one for the six 10-minute intervals immediately after the jump and zero otherwise, $Risk_t$ is the volatility risk during the interval t, $TIME_{k,t+1}$ is an intraday dummy variable that takes the value of one if interval $t+1$ belongs to the time interval k and zero otherwise, and ε_{t+1} is the error term. Apparently, the coefficient ρ_1 measures the autocorrelation pattern of the change of market depth, while γ_k controls for the typical intraday variation in liquidity variables ("time of day" effect). The coefficient β_0 measures the effect of increased volatility on the subsequent order-flow mix and β_1 captures the additional post-jump impact on order-flow composition, which is of our interest.

The result of the regression is presented in Table 12. For the purpose of brevity, we only report the coefficients on the lagged changes of market depth, lagged volatility risk, the post-jump dummy and the interaction term. Consistent with prior literature (see Ahn *et al.* 2001, among others), the coefficient on the lagged change of mean depth is significantly negative, supporting the self-adjusting mechanism of the order flow. That is, there will be an influx of more limit orders than market orders when limit orders were relatively scarce in the prior period, which is consistent with the conventional wisdom that market depth tends to get replenished to its normal shape (resiliency). Similar to the results reported in Table III of Ahn *et al.* (2001), there is no strong evidence that increased transitory volatility would lead investors to submit more limit orders than market orders as β_0 is insignificantly different from zero (the sign of the coefficient is in fact slightly negative).[24] Finally, the coefficient estimate on the interaction term between post-jump dummy and lagged volatility risk remains strongly positive at the 5% level, confirming our expectation that investors prefer to submit more limit orders instead of market orders subsequent to the occurrence of jumps. It should be noted that two forces contribute to the increased use of limit orders after a jump. On the one hand, the sudden increase of transitory volatility due to jumps makes it attractive for participants to adopt market making strategies, as the expected gain of supplying liquidity outweighs the expected loss of trading against an informed trader and holding an unwanted inventory for a short time span. On the other hand, even informed traders will opt for limit orders instead of market orders, because the cost of submitting a market order increases dramatically due to the rise in transitory volatility associated with the jump. As we do not have the identity of the traders, we cannot distinguish between these two forces.

Overall, our evidence on traders' post-jump order submission strategy is consistent with the results in the event study section: the "make or take" decision is altered following price jumps as more liquidity (depth) is built up in the book with newly submitted limit orders. The reason for a weakened post-jump price discovery process become clear: transaction order flow become less informative with a thick order book.

[24] One possible explanation for the insignificance of β_0 is that the relation between transitory volatility and the change of market depth does not need to be monotonically increasing, nor linear. In an unreported regression we find that the coefficient on the quadratic risk is highly significant and positive, indicating the relation might not be linear.

7. Conclusion

Using a unique dataset (including the complete limit order book) over a two year timespan, we investigated the relation between intraday jumps, news announcements and liquidity dynamics in the HUF/EUR interdealer market.

First, our results conform to the general finding that jumps are frequent on financial markets. In a relatively illiquid FX market, such as our HUF/EUR market, we find that around 18.2% of the sample days contain at least one intraday jump with the jump component contributing to nearly one-half of the realized volatility during the jump day.

Secondly, we investigate the relation between jumps and news releases of various sorts. In particular, we employ a much broader dataset of news announcements which includes not only scheduled news releases, but also unscheduled news announcements such as polls, surveys, forecasts and analyses on future fundamentals. We find that scheduled news explains 16% of the jumps, while unscheduled news explains 30.4% of the jumps, confirming that both news on fundamentals (scheduled news), and news which will change the market expectations on future fundamentals (unscheduled news) are both important sources of large exchange rate movements. Still nearly half of the jumps remain unexplained by (public) news announcements. However, we show that jumps are information-based, independent whether they are linked with public news or not, as they have a similarly large permanent price impact and are both accompanied by highly imbalanced order flows.

Thirdly, we test the predictions from limit order book models under extreme market conditions by zooming in on the various dimensions of liquidity dynamics around jumps. Using an event-study approach, we find that prior to jumps the liquidity pattern does not deviate from that in normal trading periods. During the jump period, our results suggest that jumps do not emerge because of unusually low liquidity supply, but because of an unusually high demand for immediacy concentrated on one side of the order book. Moreover, a dynamic order placement process emerges after the jump: More limit sell (buy) orders are added to the book subsequent to a positive (negative) jump, which is consistent with the presence of endogeneous liquidity providers on the market. Attracted by the higher reward for providing liquidity, they submit limit orders at the side where it is needed the most. In addition, we detect a high level of resilience in the market, but this resilience is on average more pronounced for negative jumps than for positive jumps. Another interesting asymmetry is that the liquidity providers tend to be more reluctant to add liquidity when confronted with a news announcement around the jump. By consequence the spreads increase more dramatically in cases of jumps with news announcements than that of jumps without news events.

Finally, our further analyses offer more insights. First, the probit analysis shows that none of the liquidity variables offer predictive power for jump occurrence, which is consistent with the normal liquidity pattern prior to jumps documented in the event study section. Second, we find that post-jump order flow is in general less informative than in normal trading periods. This is in line with the additional evidence from the third analysis on order submission strategy: more limit orders relative to market orders are submitted to the book after the jump. Therefore, the informational role of order flow becomes less pronounced in the thick order book after the jump.

One direction for future research is to investigate the liquidity dynamics around jumps under different market microstructures (e.g. market with designated market makers, the customer FX market). This would be highly relevant for the purpose of optimal market design.

Tables

	2003 Jan-Jun	2003 Jul-Dec	2004 Jan-Jun	2004 Jul-Dec
Number of orders	89339	94151	114891	115416
Market orders (%)				
Buy side	8.12%	7.96%	7.52%	7.96%
Ask side	7.58%	7.58%	7.55%	7.97%
Limit orders (not exec., %)				
Buy side	29.92%	30.16%	31.23%	28.37%
Ask side	27.09%	27.95%	28.21%	26.11%
Limit orders (at least partly exec., %)				
Buy side	13.27%	12.96%	12.81%	14.71%
Ask side	14.01%	13.40%	12.67%	14.88%
Size				
Small size (1 Mill., %)	71.16%	76.03%	78.25%	75.99%
Medium size (2 Mill., %)	16.52%	14.38%	13.46%	14.24%
Large (+2 Mill., %)	12.32%	9.59%	8.29%	9.77%

Table 1: Order descriptives.

	2003 Jan-Jun	2003 Jul-Dec	2004 Jan-Jun	2004 Jul-Dec
Average spread (HUF/EUR)	0.31	0.39	0.35	0.24
Average breadth				
Buy side	1.97	1.73	1.66	2.06
Ask side	1.84	1.67	1.54	1.63
Average depth				
Buy side	12.89	28.36	11.96	43.52
Ask side	11.38	9.67	9.70	12.66
Average number of levels				
Buy side	6.22	6.12	6.02	6.99
Ask side	5.64	5.27	5.83	7.35

Table 2: Book descriptives.

Panel A: Descriptives of the price process

	Realized Volatility	All Continuous Components	All Jump Components	Significant Jump Components
Observations	494	494	494	90
Mean ($*10^{-3}$)	0.33	0.30	0.03	0.17
Median ($*10^{-3}$)	0.12	0.11	0.00	0.06
Standard Deviation ($*10^{-3}$)	1.40	1.39	0.16	0.35
Minimum ($*10^{-3}$)	0.01	0.01	0.00	0.01
Maximum ($*10^{-3}$)	28.30	28.30	2.07	2.07
Skewness	17.02	17.37	8.61	3.57
Kurtosis	329.76	339.07	87.36	16.27

Panel B: Jump characteristics

	Mean	Min.	Med.	Max.	Standard Deviation
Jump duration (in days)	6.6	1.0	6.0	28.0	5.5
Contribution to volatility (on jump day)	42.59%	11.52%	38.67%	94.08%	22.27%

Table 3: Prevalence and size of jumps.

	Positive Jumps		Negative Jumps	
Observations	65		60	
Number of Jump Days	56		52	
	Size	Variance	Size	Variance
Mean ($*10^{-3}$)	3.08	0.016	-2.54	0.010
Median ($*10^{-3}$)	2.23	0.005	-1.97	0.004
Standard Deviation ($*10^{-3}$)	2.50	0. 030	0.184	0.016
Minimum ($*10^{-3}$)	0.59	0	-8.95	0
Maximum ($*10^{-3}$)	14.42	0.208	-0.61	0.080
Skewness	2.08	4.59	-1.73	3.04
Kurtosis	5.90	26.39	3.15	9.78

Table 4: Positive vs. negative jumps.

	Time of Announcement	Number of Observations	Number of observations that match jumps	P(Jump|News)	P(News|Jump)
All categories			20	< 1%	16.00%
News on Hungary					
GDP	9 am	8	2	25.00%	1.60%
Public Sector Balance	10 am/ 5 pm	24	1	4.17%	0.80%
Current Account Balance	8:30 am	24	1	4.17%	0.80%
Retail Sales	9:00 am	24	1	4.17%	0.80%
News on Germany					
CPI	8 am	24	1	4.17%	0.80%
Wholesale Price	8 am	24	1	4.17%	0.80%
Import Price	8 am	24	1	4.17%	0.80%
News on the United States					
PPI	2:30 pm	24	2	8.33%	1.60%
CPI	2:30 pm	24	1	4.17%	0.80%
Real GDP	2:30 pm	8	1	12.50%	0.80%
Tradebalance	2:30 pm	24	1	4.17%	0.80%
Consumer Confidence	4 pm	24	1	4.17%	0.80%
New Home Sales	4 pm	24	1	4.17%	0.80%
Construction Spending	4 pm	24	1	4.17%	0.80%
ISM Index	4 pm	24	1	4.17%	0.80%
News on CEEC's: Poland					
PPI	4 pm	24	2	8.33%	1.60%
Industrial Output	4 pm	24	1	4.17%	0.80%

Table 5: Jumps and scheduled macroeconomic announcements.

	Explained by News	Explained by Scheduled Announcements	Explained by Unscheduled, Real-Time News
All jumps	58 (46.40%)	20 (16.00%)	38 (30.40%)
Ranked by size of the Jump			
Top 15	8 (53.30%)	4 (26.70%)	4 (26.70%)
Top 16 to 30	7 (46.70%)	2 (13.33%)	5 (33.33%)
Top 31 to 50	11 (55.00%)	4 (20.00%)	7 (35.00%)
Rest of the Jumps	32 (42.70%)	10 (13.33%)	22 (29.33%)

Table 6: Share of jumps explained by news announcements.

	-60	-50	-40	-30	-20	-10	0	10	20	30	40	50	60
Tightness													
SWPQS	-5,25%	-4,36%	1,31%	0,60%	-4,72%	-1,56%	25,09%	18,03%	-3,00%	-3,06%	6,95%	6,14%	8,76%
Immediacy													
VOL	16,67%	-4,35%	0,00%	0,00%	-11,27%	0,00%	180,00%	87,50%	25,00%	0,00%	0,00%	0,00%	0,00%
OI	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	57,89%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
Depth													
$DPTH_B$	0,12%	-0,63%	-4,47%	5,11%	-3,54%	-5,46%	10,76%	16,50%	5,75%	1,41%	0,11%	-3,11%	-6,27%
$DPTH_A$	-9,55%	-3,77%	-8,74%	-3,72%	0,14%	-6,94%	-23,04%	-12,91%	19,01%	18,85%	16,99%	19,15%	4,74%
DI	-3,52%	-2,62%	0,94%	-4,16%	0,30%	0,14%	-15,81%	-8,52%	0,44%	6,93%	9,15%	6,73%	3,15%
Breadth													
$BRDTH_B$	5,59%	-1,63%	-3,45%	0,62%	2,74%	2,33%	14,82%	1,28%	-0,36%	3,18%	2,71%	7,67%	-1,49%
$BRDTH_A$	-2,39%	12,23%	-1,70%	-0,82%	2,22%	-4,57%	8,07%	8,76%	11,82%	8,76%	8,79%	0,93%	7,07%
BI	0,00%	7,00%	1,22%	0,00%	-4,23%	-0,98%	-4,50%	5,76%	3,01%	0,00%	0,00%	-3,28%	0,00%

Table 7: Liquidity dynamics around positive jumps (Light gray: significant at 10% level, medium gray: significant at 5% level, dark gray: significant at 1% level).*

* SWPQS: Size-weighted proportional quoted spread, VOL: Volume traded, OI: Order flow imbalance, $DPTH_B$: Mean depth at the bid side, $DPTH_A$: Mean depth at the ask side, DI: Mean depth imbalance, $BRDTH_B$: Mean depth at the best bid, $BRDTH_A$: Mean depth at the best ask, BI: Mean imbalance of depth at the best quotes.

	-60	-50	-40	-30	-20	-10	0	10	20	30	40	50	60
Tightness													
SWPQS	1,69%	3,89%	2,79%	7,74%	-0,83%	-0,90%	23,88%	6,02%	2,24%	8,71%	6,77%	-3,75%	7,94%
Immediacy													
VOL	0,00%	0,00%	42,86%	6,67%	0,00%	0,00%	125,00%	50,00%	0,00%	18,92%	0,00%	20,00%	0,00%
OI	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%	-33,33%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%
Depth													
$DPTH_B$	-10,65%	-12,63%	-16,24%	-11,08%	-4,30%	-11,83%	-37,07%	-18,77%	-12,69%	3,33%	-4,98%	-15,35%	-2,97%
$DPTH_A$	18,30%	16,36%	20,77%	25,60%	27,18%	7,56%	22,46%	24,11%	19,30%	-0,07%	11,40%	4,91%	2,49%
DI	10,56%	8,93%	14,83%	16,30%	10,15%	5,27%	20,08%	19,02%	14,84%	9,69%	4,93%	10,07%	2,31%
Breadth													
$BRDTH_B$	-2,70%	-5,92%	3,76%	1,25%	-6,65%	2,14%	9,59%	-0,63%	0,00%	4,26%	-0,02%	0,00%	1,46%
$BRDTH_A$	18,48%	17,19%	22,57%	-1,57%	6,60%	-5,71%	13,98%	2,54%	-3,53%	-4,64%	-1,88%	-3,46%	3,69%
BI	2,03%	7,69%	0,00%	1,21%	9,58%	-1,59%	-1,04%	5,00%	0,00%	0,00%	0,00%	0,00%	0,00%

Table 8: Liquidity dynamics around negative jumps (Light gray: significant at 10% level, medium gray: significant at 5% level, dark gray: significant at 1% level).*

* SWPQS: Size-weighted proportional quoted spread, VOL: Volume traded, OI: Order flow imbalance, $DPTH_B$: Mean depth at the bid side, $DPTH_A$: Mean depth at the ask side, DI: Mean depth imbalance, $BRDTH_B$: Mean depth at the best bid, $BRDTH_A$: Mean depth at the best ask, BI: Mean imbalance of depth at the best quotes.

	A	β_1	β_2	β_3	β_4	β_5	γ	Adj. R^2	L	Joint test
Specification 1										
Coeff.	-1.953	-18.319	-0.013	-0.300	-0.067	-0.576	2.028	6.70%	-288.11	7.45
NW s.e.	0.093	20.138	0.033	0.220	0.163	0.441	0.316			
Test stat.	-21.090	-0.910	-0.410	-1.360	-0.410	-1.310	6.42			
p-value	0.000	0.363	0.685	0.172	0.683	0.192	0.000			0.19

Table 9: Probit regression of jump probability.

	α_0	α_1	β_0	β_1	β_2	Adj. R^2
Specification 1						
Coeff.	-0.000	-0.006		0.008	-0.003	22.19%
NW s.e.	0.000	0.004		0.001	0.001	
Test stat.	-0.640	-1.470		9.730	-2.500	
p-value	0.525	0.142		0.000	0.012	
Specification 2						
Coeff.	-0.000	-0.006	-0.001	0.008	-0.003	22.70%
NW s.e.	0.000	0.004	0.000	0.001	0.001	
Test stat.	-0.530	-1.370	-3.650	9.790	-2.380	
p-value	0.597	0.170	0.000	0.000	0.018	

Table 10: Regression of price change on order flow.

Resiliency after positive jumps

	0	10	20	30	40	50	60
LO_B	188,89%	112,89%	26,87%	14,64%	0,00%	-22,22%	-23,02%
LO_S	127,27%	220,00%	42,86%	70,73%	14,29%	22,61%	0,00%
LOI	13,58%	-8,33%	-0,37%	-5,26%	0,00%	0,00%	0,00%
LO_{BB}	233,33%	100,00%	0,00%	-11,11%	0,00%	0,00%	-25,00%
LO_{SB}	108,33%	185,71%	33,33%	13,95%	1,96%	1,96%	-16,67%
LOI_B	14,29%	-11,58%	0,00%	0,00%	0,00%	0,00%	0,00%

Resiliency after negative jumps

	0	10	20	30	40	50	60
LO_B	126,67%	122,22%	25,00%	-12,50%	0,00%	40,63%	11,24%
LO_S	220,00%	82,11%	-18,37%	23,60%	23,60%	33,33%	33,33%
LOI	-15,00%	6,89%	0,00%	0,00%	0,00%	0,00%	0,00%
LO_{BB}	122,22%	80,00%	0,00%	0,00%	11,11%	12,50%	23,08%
LO_{SB}	250,00%	55,56%	0,00%	0,00%	20,00%	33,33%	25,00%
LOI_B	-27,87%	0,00%	0,00%	0,00%	0,00%	0,00%	0,00%

Table 11: Resiliency after jumps (Light gray: significant at 10% level, medium gray: significant at 5% level, dark gray: significant at 1% level).*

* LO_B: Volume of limit buy orders submitted, LO_S: Volume of limit sell orders submitted, LOI: Imbalance of the volume of limit orders submitted, LO_{BB}: Volume of limit orders entered at the best buy, LO_{SB}: Volume of limit orders entered at the best sell, LOI_B: Imbalance of the limit orders entered at the best quote.

	α_0	α_1	β_0	β_1	ρ_1	Adj. R^2
Specification 1						
Coeff.	-0.007		-0.083		-0.271	6.20%
NW s.e.	0.051		0.116		0.024	
Test stat.	-0.130		-0.720		-11.270	
p-value	0.895		0.475		0.000	
Specification 2						
Coeff.	-0.006	-0.078	-0.139	0.988	-0.271	6.21%
NW s.e.	0.051	0.066	0.121	0.412	0.024	
Test stat.	-0.110	-1.190	-1.150	2.400	-11.270	
p-value	0.910	0.234	0.252	0.017	0.000	

Table 12: Regression of depth change on lagged transitory volatility.

Figures

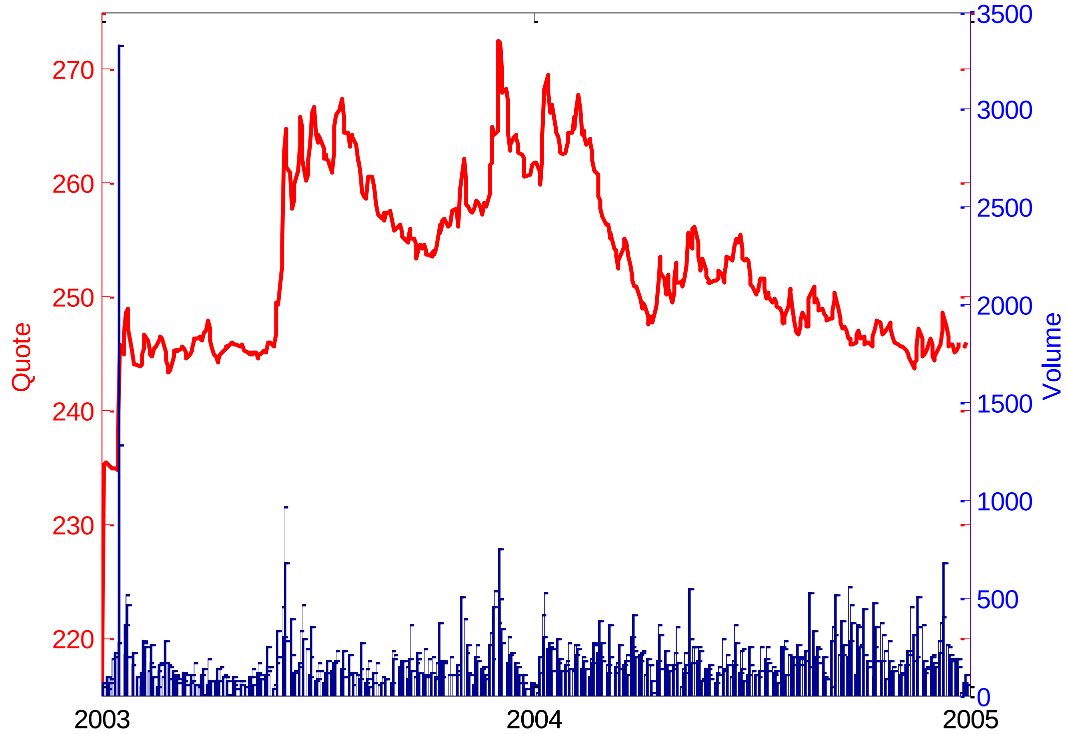

Figure 1: Average daily quote and total volume traded over the sample period.

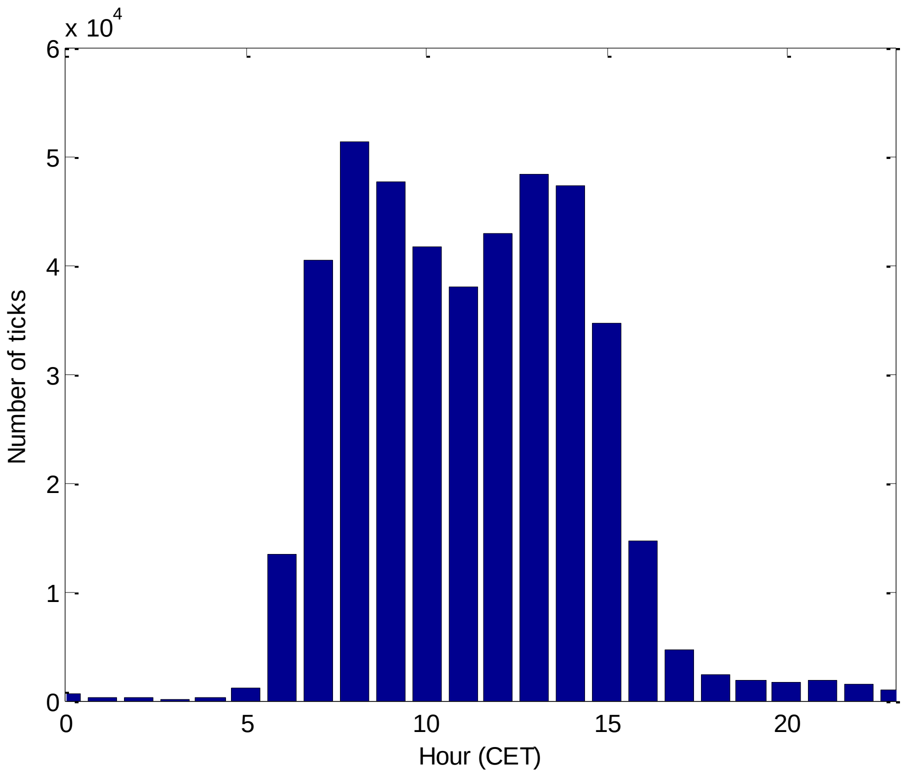

Figure 2: Intraday distribution of ticks (CET).

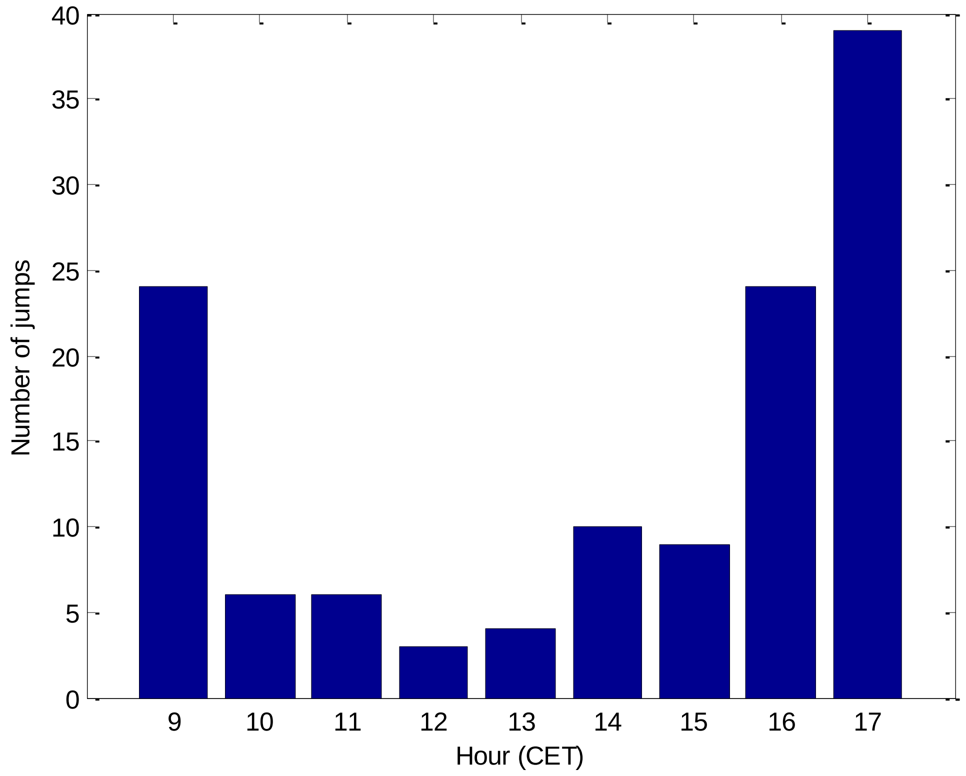

Figure 3: Intraday distribution of jumps.

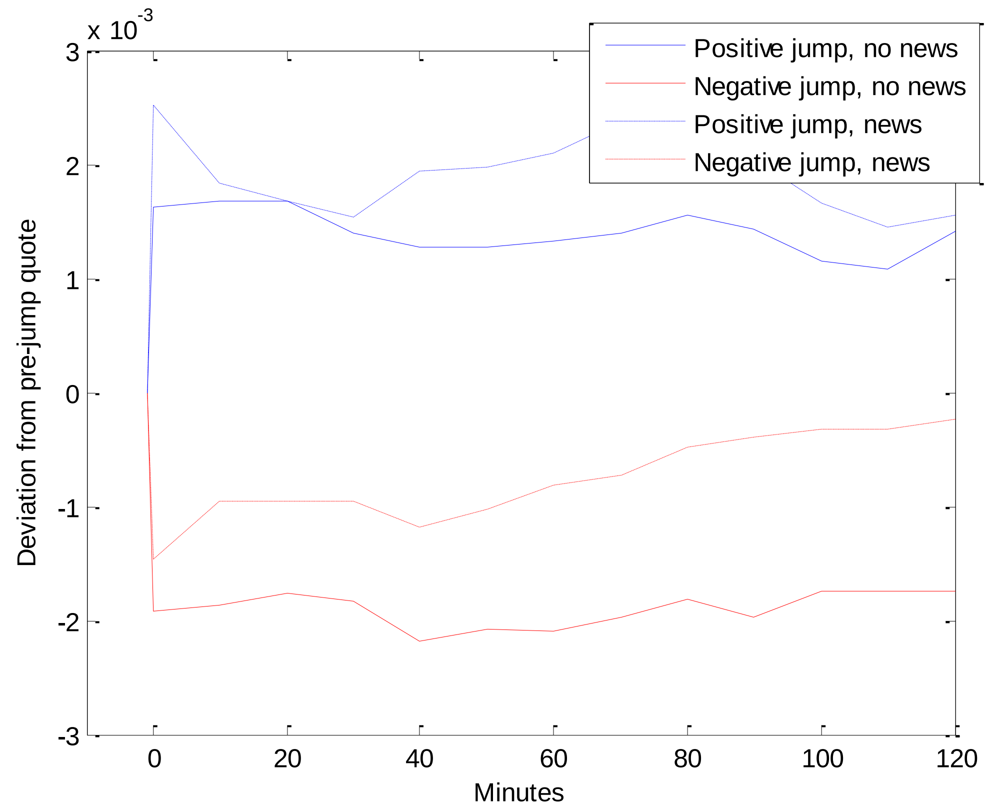

Figure 4: Price reversal after a jump.

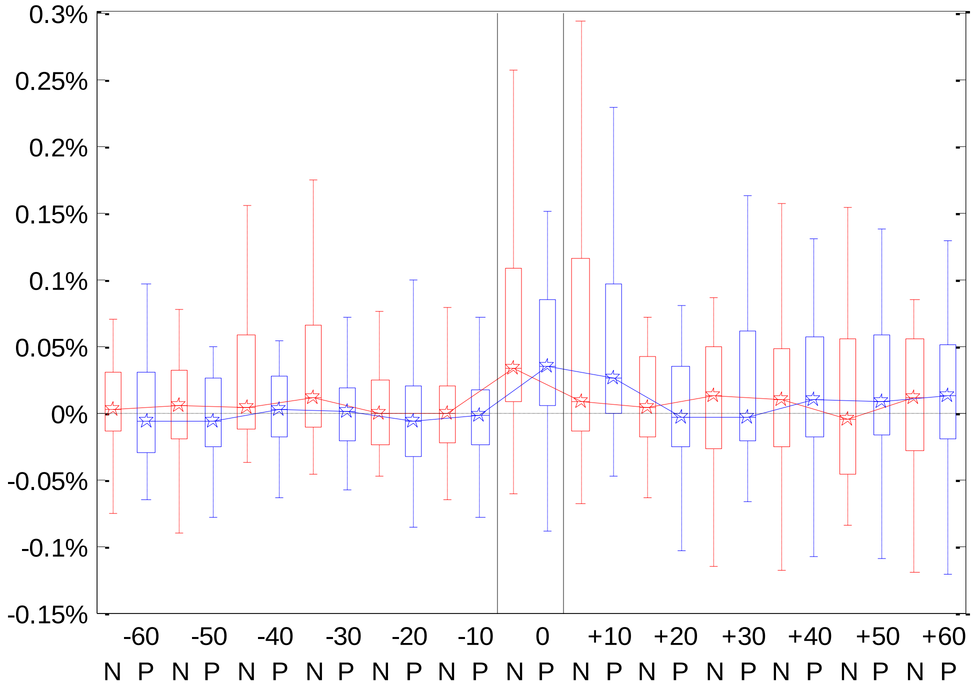

Figure 5: Bid-ask spread (SWPQS) for neg. (N)/ pos. (P) jumps during the event window.

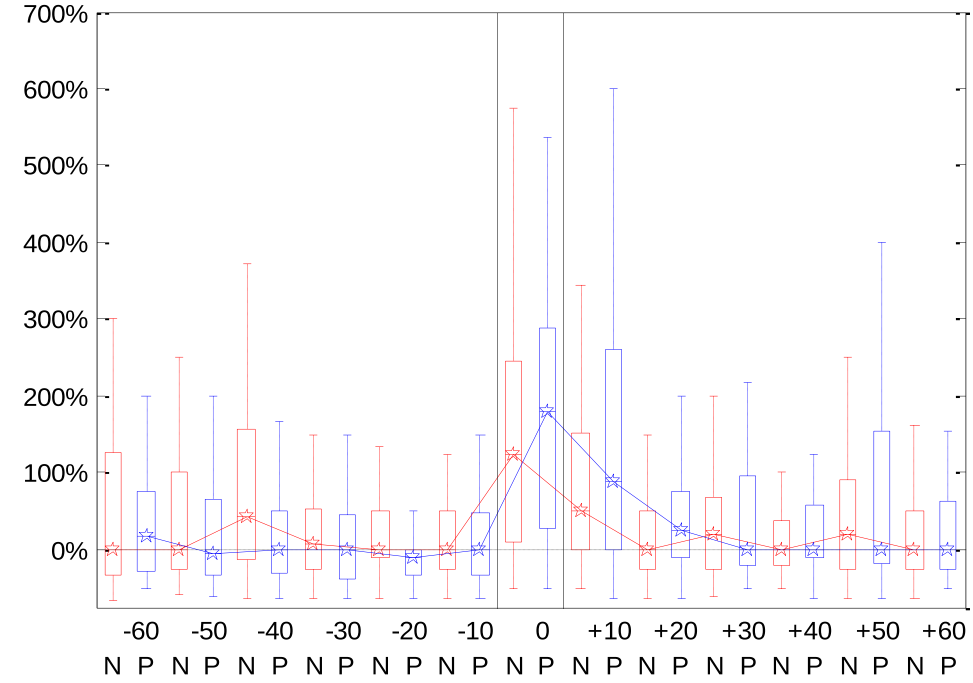

Figure 6: Volume traded (VOL) for neg. (N)/ pos. (P) jumps during the event window.

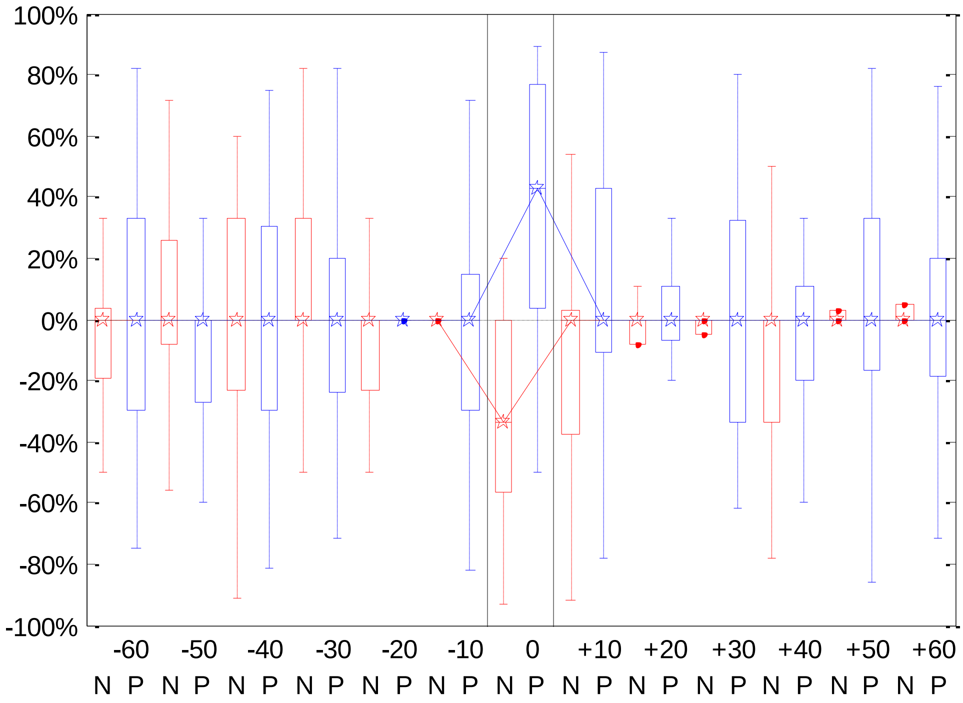

Figure 7: Order imbalance (OI) for neg. (N)/ pos. (P) jumps during the event window.

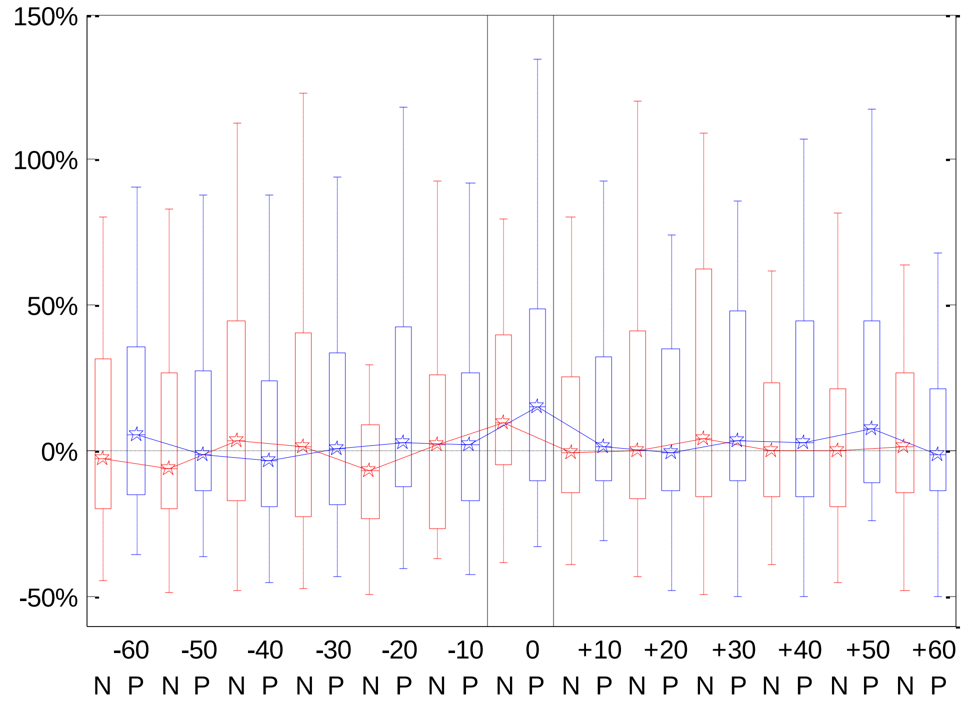

Figure 8: Mean bid depth at best quote ($BRDTH_B$) for neg. (N)/ pos. (P) jumps during the event window.

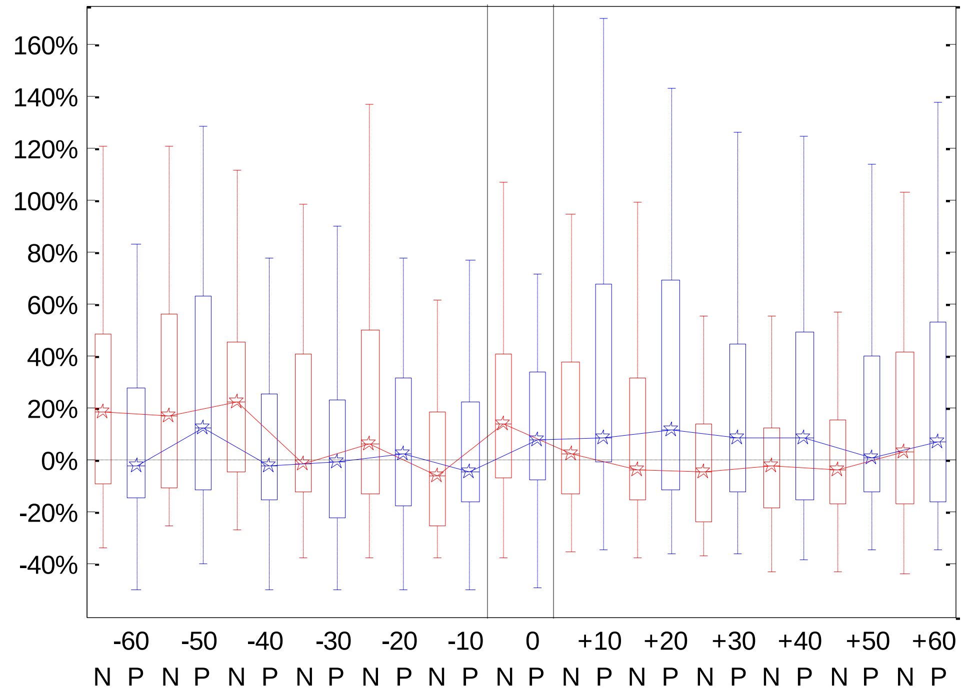

Figure 9: Mean ask depth at best quote (BRDTH$_A$) for neg. (N)/ pos. (P) jumps during the event window.

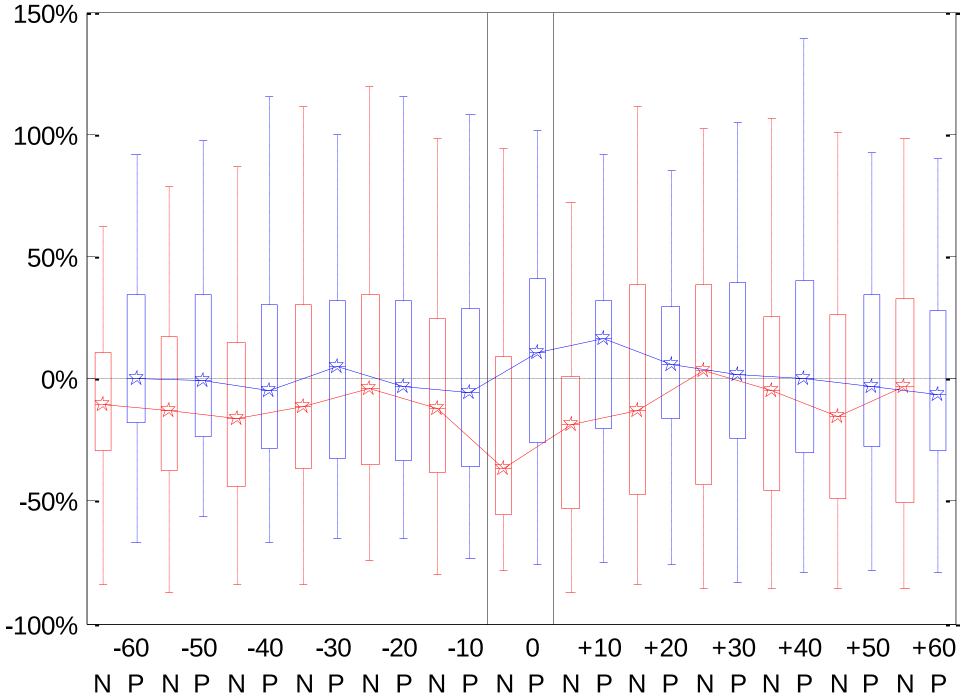

Figure 10: Mean bid depth (DPTH$_B$) for neg. (N)/ pos. (P) jumps during the event window.

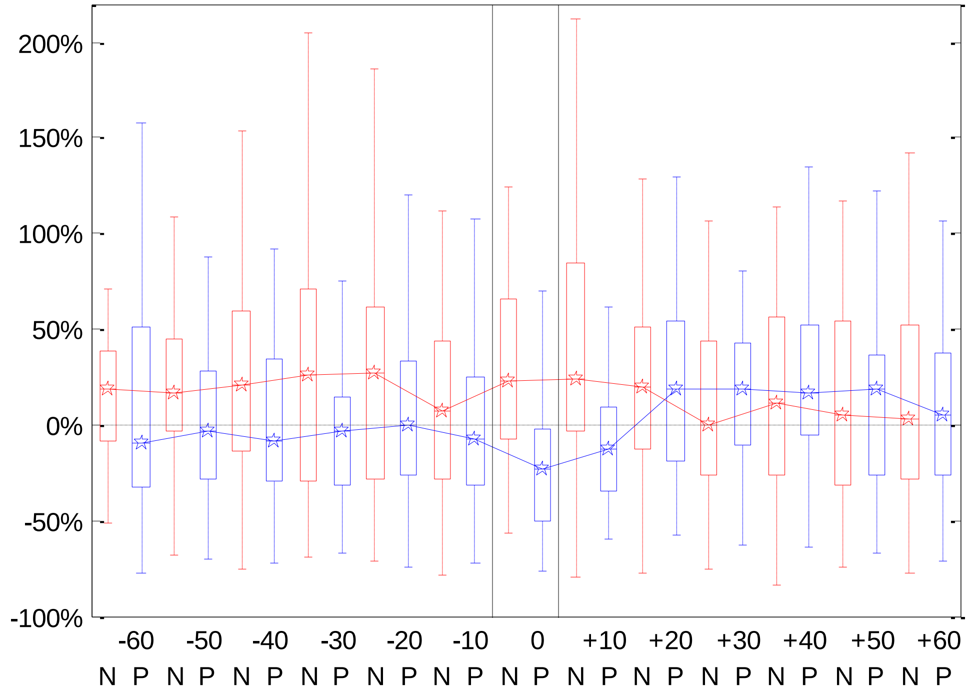

Figure 11: Mean ask depth ($DPTH_A$) for neg. (N)/ pos. (P) jumps during the event window.

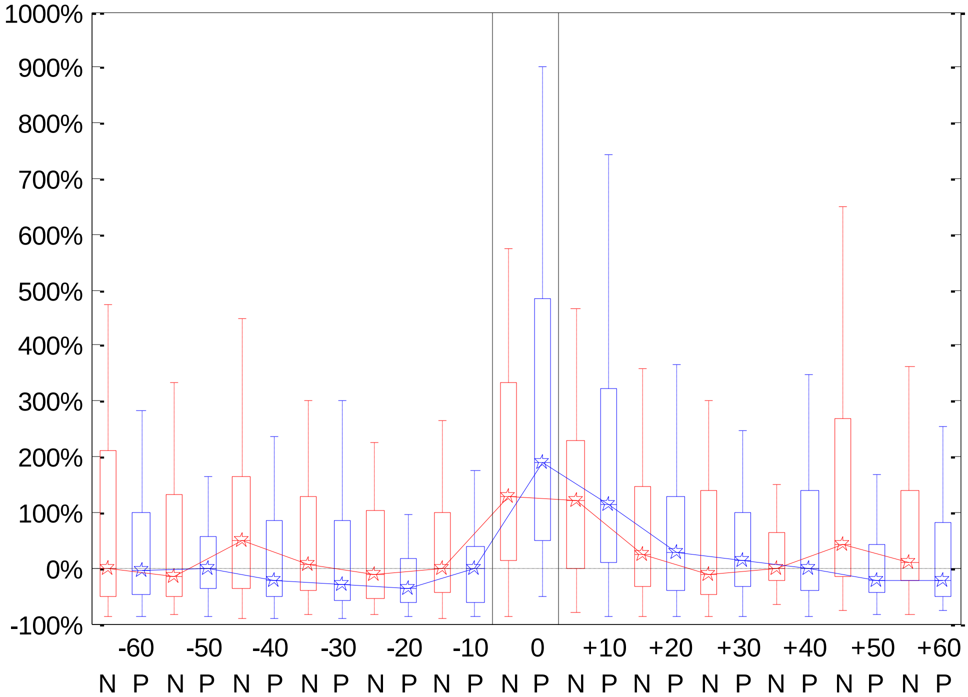

Figure 12: Volume of lim. buy orders (LO_B) for neg. (N)/ pos. (P) jumps during the event window.

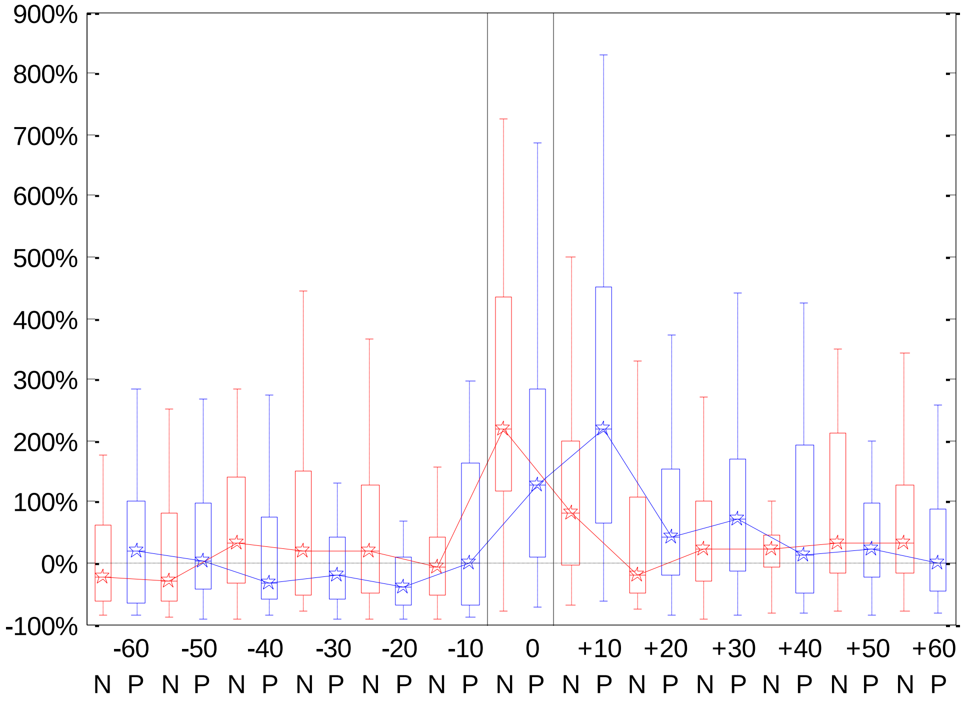

Figure 13: Volume of lim. sell orders (LO_S) for neg. (N)/ pos. (P) jumps during the event window.

Appendix I: Definition of Liquidity Measures

SWPQS	The size-weighted proportional quoted spread, defined as the weighted average of the quoted spread per 10 minute interval. The weighting scheme uses the quantities available at the prevailing quotes as the weight.
NT	Number of trades, defined as the total number of transaction per 10 minute interval.
VOL	Trading volume, defined as the total transaction volume by value per 10 minute interval.
OF	(Transaction) Order flow, defined as the signed trading volume per 10 minute interval.
OI	Order flow imbalance, defined as the ratio of transaction order flow to the total transaction volume by value per 10 minute interval.
$DPTH_B$	Mean depth at the bid side, defined as the average quantity available at the bid side of the limit order book over all quotes per 10 minute interval.
$DPTH_A$	Mean depth at the ask side, defined as the average quantity available at the ask side of the limit order book over all quotes per 10 minute interval.
DI	Depth imbalance, defined as the difference between $DPTH_A$ and $DPTH_B$ scaled by the sum of $DPTH_A$ and $DPTH_B$ per 10 minute interval.
$BRDTH_B$	Mean breadth at the bid side, defined as the average quantity available at the best bid of the limit order book over all quotes per 10 minute interval.
$BRDTH_A$	Mean breadth at the ask side, defined as the average quantity available at the best ask of the limit order book over all quotes per 10 minute interval.
BI	Breadth imbalance, defined as the difference between $BRDTH_A$ and $BRDTH_B$ scaled by the sum of $BRDTH_A$ and $BRDTH_B$ per 10 minute interval.
LO_B	Limit buy order submitted, defined as the quantities (volume) of newly placed limit buy orders per 10 minute interval.
LO_S	Limit sell order submitted at the best price, defined as the quantities (volume) of newly placed limit sell orders per 10 minute interval.
LOI	Limit order imbalance, defined as the difference between LO_B and LO_S, scaled by the sum of LO_B and LO_S per 10 minute interval.
LO_{BB}	Limit buy order submitted at the best price, defined as the quantities (volume) of newly placed limit buy orders at the best price per 10 minute interval.
LO_{SB}	Limit sell order submitted at the best price, defined as the quantities (volume) of newly placed limit sell orders at the best price per 10 minute interval.
LOI_B	Limit order imbalance at the best price, defined as the difference between LO_{BB} and LO_{SB}, scaled by the sum of LO_{BB} and LO_{SB} per 10 minute interval.

Appendix II: Standardization of the liquidity measures

It is well known in the empirical literature that liquidity measures have seasonal patterns at the daily and intraday level whether they are compounded with news announcements or not (eg. see figure 1 Fleming & Remolona 1999). Therefore, liquidity measures need to be standardized to make them comparable across days and intraday periods. Moreover, the empirical distribution of liquidity measures is highly skewed to the right at the intraday level as pointed out by Plerou *et al.* (2005) among others. Motivated by the applications in Boudt and Petitjean (201x); Boudt *et al.* (2011), we favor median value rather than mean value for standardizing purpose, which deviates from previous literature ((Fleming & Remolona 1999; Jiang *et al.* 2011; Gomber *et al.* 2013).

Following Boudt and Petitjean (201x), we assume that all the liquidity measures except spread and imbalance measures follow a multiplicative specification: On non-jump days, the intraday value of the liquidity measure (denoted as $LM_{i,j}$) is the product of a latent daily factor LM_i and a deterministic intradaily factor LM_j and an *i.i.d.* error term $\varepsilon_{i,j}$ with median 1.

$$LM_{i,j} = LM_i LM_j \varepsilon_{i,j} \tag{AII.1}$$

On jump days, however, the above specification is augmented by an additive component $\delta_{i,j}$ associated with jumps:

$$LM_{i,j} = LM_i LM_j \varepsilon_{i,j} + \delta_{i,j} \tag{AII.2}$$

Given the above assumptions, the sample counterpart of the daily factor ($\widehat{LM}_i$) is proxied by the median value of the intraday liquidity measure on day *i*, while the sample intraday factor ($\widehat{LM}_j$) is estimated as the sample median of all the observed intraday liquidity values in interval *j* on non-jump days (*NJD*), scaled by their respective daily factor.

$$\widehat{LM}_j = median_{i\in NJD} \frac{\widehat{LM}_{i,j}}{\widehat{LM}_i} \tag{AII.3}$$

It is thus straightforward to calculate the percentage deviation of the liquidity value from its normal (expected) level via the following equation.

$$\widetilde{LM}_{i,j} = \frac{\widehat{LM}_{i,j}}{\widehat{LM}_i \widehat{LM}_j} - 1 \tag{AII.4}$$

where the first term in the RHS of the equation is the standardized liquidity measure.

As the imbalance measures are bounded in (-1, +1), we opt for an additive process with the following specification:

$$LM_{i,j} = LM_i + LM_j + \varepsilon_{i,j} + \delta_{i,j} \tag{AII.5}$$

with $\varepsilon_{i,j}$ as an *i.i.d.* error term with zero median and $\delta_{i,j}$ as an additive component due to jumps. In the same token, the estimated daily factor ($\widehat{LM}_i$) is proxied by the median value of the intraday liquidity measure on day *i*. The sample intraday factor ($\widehat{LM}_j$), however, is estimated as the sample median of all the observed intraday liquidity values in interval *j* on non-jump days (*NJD*), net of their respective daily factor:

$$\widehat{LM}_j = median_{i\in NJD}\left(\widehat{LM}_{i,j} - \widehat{LM}_i\right) \tag{AII.6}$$

The deviation of the liquidity value is thus:

$$\widetilde{LM}_{i,j} = \widehat{LM}_{i,j} - \widehat{LM}_i - \widehat{LM}_j \tag{AII.7}$$

Therefore, we use the above equation to estimate the deviation for liquidity measures including depth imbalance, order imbalance, imbalance of newly placed limit orders and spread.

For either of the model specification, we would expect the median value of $\widetilde{LM}_{i,j}$ to be zero in case of no (significant) jump effect on liquidity.

List of References

Acharya, V.V., Pedersen, L.H., 2005. Asset pricing with liquidity risk. Journal of Financial Economics 77, 375-410

Admati, A., Pfleiderer, P., 1988. A theory of intraday patterns: volume and price variability. Review of Financial Studies 1, 3-40

Ahn, H.-J., Bae, K.-H., Chan, K., 2001. Limit Orders, Depth, and Volatility: Evidence from the Stock Exchange of Hong Kong. The Journal of Finance 56, 767-788

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31-56

Anand, A., Venkataraman, K., 2013. Should Exchanges Impose Market Maker Obligations? Available at SSRN: http://ssrn.com/abstract=2179259 or http://dx.doi.org/10.2139/ssrn.2179259

Andersen, T.G., Bollerslev, T., Diebold, F.X., 2007a. Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. Review of Economics and Statistics 89, 701-720

Andersen, T.G., Bollerslev, T., Dobrev, D., 2007b. No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and iid noise: Theory and testable distributional implications. Journal of Econometrics 138, 125

Andersen, T.G., Bollerslev, T., Frederiksen, P., Ørregaard Nielsen, M., 2010. Continuous-time models, realized volatilities, and testable distributional implications for daily stock returns. Journal of Applied Econometrics 25, 233-261

Bajgrowicz, P., Scaillet, O., 2011. Jumps in High-Frequency Data: Spurious Detections, Dynamics, and News. SSRN eLibrary

Banti, C., Phylaktis, K., Sarno, L., 2012. Global liquidity risk in the foreign exchange market. Journal of International Money and Finance 31, 267-291

Barndorff-Nielsen, O.E., Shephard, N., 2004. Power and Bipower Variation with Stochastic Volatility and Jumps. Journal of Financial Econometrics 2, 1-37

Barndorff-Nielsen, O.E., Shephard, N., 2006a. Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation. Journal of Financial Econometrics 4, 1-30

Barndorff-Nielsen, O.E., Shephard, N., 2006b. Impact of jumps on returns and realised variances: econometric analysis of time-deformed Levy processes. Journal of Econometrics 131, 217-252

Beine, M., Lahaye, J., Laurent, S., Neely, C.J., Palm, F.C., 2007. Central bank intervention and exchange rate volatility, its continuous and jump components. International Journal of Finance & Economics 12, 201

Biais, B., Hillion, P., Spatt, C., 1995. An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse. The Journal of Finance 50, 1655-1689

BIS, 1996. Triennial central bank survey: report on global foreign exchange market activity in 1996. Bank for International Settlements, www.bis.org

BIS, 2005. Triennial central bank survey: report on global foreign exchange market activity in 2005. Bank for International Settlements, www.bis.org

BIS, 2010. Triennial central bank survey: report on global foreign exchange market activity in 2010. Bank for International Settlements, www.bis.org

Bloomfield, R., O'Hara, M., Saar, G., 2005. The "make or take" decision in an electronic market: Evidence on the evolution of liquidity. Journal of Financial Economics 75, 165-199

Boudt, K., Croux, C., Laurent, S., 2011. Robust estimation of intraweek periodicity in volatility and jump detection. Journal of Empirical Finance 18, 353-367

Boudt, K., Petitjean, M., 201x. Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks. Journal of Financial Markets, forthcoming
Campbell, J.Y., Grossman, S.J., Wang, J., 1993. Trading Volume and Serial Correlation in Stock Returns. The Quarterly Journal of Economics 108, 905-939
Cao, C., Hansch, O., Wang, X., 2008. Order Placement Strategies in a Pure Limit Order Book Market. Journal of Financial Research 31, 113-140
Cohen, K.J., Maier, S.F., Schwartz, R.A., Whitcomb, D.K., 1981. Transaction Costs, Order Placement Strategy, and Existence of the Bid-Ask Spread. Journal of political economy 89, 287-305
Copeland, L.S., 2005. Exchange Rates and International Finance. Prentice Hall, Harlow.
Covrig, V., Ng, L., 2004. Volume autocorrelation, information, and investor trading. Journal of Banking & Finance 28, 2155-2174
Dungey, M., McKenzie, M., Smith, L.V., 2009. Empirical evidence on jumps in the term structure of the US Treasury Market. Journal of Empirical Finance 16, 430-445
Eisler, Z., Bouchaud, J.-P., Kockelkoren, J., 2011. The price impact of order book events: market orders, limit orders and cancellations. Quantitative Finance 12, 1395-1419
Evans, K.P., 2011. Intraday jumps and US macroeconomic news announcements. Journal of Banking & Finance 35, 2511-2527
Evans, M.D.D., Lyons, R.K., 2002. Informational integration and FX trading. Journal of International Money and Finance 21, 807-831
Evans, M.D.D., Lyons, R.K., 2005. Meese-Rogoff Redux: Micro-Based Exchange-Rate Forecasting. The American economic review 95, 405-414
Fleming, M.J., Remolona, E.M., 1999. Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information. The Journal of Finance 54, 1901-1915
Foucault, T., 1999. Order flow composition and trading costs in a dynamic limit order market. Journal of Financial Markets 2, 99-134
Foucault, T., Kadan, O., Kandel, E., 2005. Limit Order Book as a Market for Liquidity. Review of Financial Studies 18, 1171-1217
Foucault, T., Kadan, O., Kandel, E., 2013. Liquidity Cycles and Make/Take Fees in Electronic Markets. The Journal of Finance 68, 299-341
Frömmel, M., Kiss M, N., Pintér, K., 2011. Macroeconomic announcements, communication and order flow on the Hungarian foreign exchange market. International Journal of Finance & Economics 16, 172-188
Frömmel, M., Van Gysegem, F., 2012. Spread Components in the Hungarian Forint-Euro Market. Emerging Markets Finance & Trade 48, 52-69
Gereben, Á., Kiss M., N., 2006. A Brief Overview of the Characteristics of Interbank Forint/Euro Trading. MNB Bulletin 1:2
Glosten, L.R., 1994. Is the Electronic Open Limit Order Book Inevitable? The Journal of Finance 49, 1127-1161
Goettler, R.L., Parlour, C.A., Rajan, U., 2005. Equilibrium in a Dynamic Limit Order Market. The Journal of Finance 60, 2149-2192
Gomber, P., Schweickert, U., Theissen, E., 2013. Liquidity Dynamics in an Electronic Open Limit Order Book: an Event Study Approach. European Financial Management, n/a-n/a
Griffiths, M.D., Smith, B.F., Turnbull, D.A.S., White, R.W., 2000. The costs and determinants of order aggressiveness. Journal of Financial Economics 56, 65-88
Harris, L., 1998. Optimal Dynamic Order Submission Strategies in Some Stylized Trading Problems. Financial Markets, Institutions & Instruments 7, 1-76
Hautsch, N., Huang, R., 2012. The market impact of a limit order. Journal of Economic Dynamics and Control 36, 501-522

Hollifield, B., Miller, R.A., Sandås, P., 2004. Empirical Analysis of Limit Order Markets. The Review of Economic Studies 71, 1027-1063
Huang, X., 2007. Macroeconomic News Announcements, Financial Market Volatility and Jumps.
Huang, X., Tauchen, G., 2005. The Relative Contribution of Jumps to Total Price Variance. Journal of Financial Econometrics 3, 456-499
Jiang, G.J., Lo, I., Verdelhan, A., 2011. Information Shocks, Liquidity Shocks, Jumps, and Price Discovery: Evidence from the US Treasury Market. Journal of Financial and Quantitative Analysis 46, 527-551
Jiang, G.J., Oomen, R.C.A., 2008. Testing for jumps when asset prices are observed with noise–a "swap variance" approach. Journal of Econometrics 144, 352-370
Kaniel, R., Liu, H., 2006. So What Orders Do Informed Traders Use? The Journal of Business 79, 1867-1913
Kyle, A.S., 1985. Continuous Auctions and Insider Trading. Econometrica 53, 1315-1335
Lahaye, J., Laurent, S., Neely, C.J., 2011. Jumps, Cojumps and Macro Announcements. Journal of Applied Econometrics 26, 893-921
Lee, S.S., Mykland, P.A., 2008. Jumps in Financial Markets: A New Nonparametric Test and Jump Dynamics. Review of Financial Studies 21, 2535-2563
Liu, W., 2006. A liquidity-augmented capital asset pricing model. Journal of Financial Economics 82, 631-671
Mazza, P., 2013. Rethinking Zero Returns in the Liquidity Puzzle. In: Working Paper
Neely, C.J., 2011. A Survey of Announcement Effects on Foreign Exchange Volatility and Jumps. Federal Reserve Bank of St. Louis Review 93, 361-385
Parlour, C., 1998. Price dynamics in limit order markets. Review of Financial Studies 11, 789-816
Pástor, Ľ., Stambaugh, Robert F., 2003. Liquidity Risk and Expected Stock Returns. Journal of political economy 111, 642-685
Plerou, V., Gopikrishnan, P., Stanley, H.E., 2005. Quantifying fluctuations in market liquidity: Analysis of the bid-ask spread. Physical Review E 71, 046131
Ranaldo, A., 2004. Order aggressiveness in limit order book markets. Journal of Financial Markets 7, 53-74
Rime, D., 2000. Private or Public Information in Foreign Exchange Markets? An Empirical Analysis. SSRN eLibrary
Roşu, I., 2009. A Dynamic Model of the Limit Order Book. Review of Financial Studies 22, 4601-4641
Sager, M.J., Taylor, M.P., 2006. Under the microscope: the structure of the foreign exchange market. International Journal of Finance & Economics 11, 81-95
Sandås, P., 2001. Adverse Selection and Competitive Market Making: Empirical Evidence from a Limit Order Market. Review of Financial Studies 14, 705-734
Seppi, D., 1997. Liquidity provision with limit orders and a strategic specialist. Review of Financial Studies 10, 103-150
Wang, J., 1994. A Model of Competitive Stock Trading Volume. Journal of political economy 102, 127-168