High Frequency Trading and Price Jumps in the Stock Market

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Abstract

In this paper, we investigate liquidity supply and demand around price jumps in a pure order driven stock market using a detailed tick frequency data set on the Euronext 100 index. The advantage of this database is to allow us to disentangle two major evolutions in European financial markets: the emergence of high frequency trading and the implementation of multilateral trading facilities. We generate average 2-minute trading volume interval and assess liquidity dynamics through an extensive set of order book-based measures (liquidity supply) and trade-based measures (liquidity demand). Furthermore, we also consider order submission dynamics and investor types activity around price jumps. We find the origin of market disruptions lies in a low liquidity supply density at the inception of price jumps while at the opposite liquidity demand decreases. All our results suggest a higher involvement of high frequency trading activity in the market around price jumps. To emphasize our findings, we conduct bidirectional Granger causality tests that support our results.

JEL Classification: G14

Keywords: Intraday Liquidity, Microstructure, Investor Types, Price Jumps
1 Introduction

In the aftermath of the 2008 financial crisis and the 2010 liquidity-induced flash crash, market efficiency and financial system stability are prominent research topics for both practitioners and academics. Indeed, market disruptions, i.e. price jumps, have numerous implications in terms of risk management (Duffie and Pan, 2001; Bakshi and Panayotov, 2010), derivative pricing (Bates, 2000; Eraker et al., 2003) and portfolio allocation with its influence on the optimal strategy (Jarrow and Rosenfeld, 1984; Liu et al., 2003). While overall market quality improves lately (Castura et al., 2010), we observe an increasing of individual stock mini-crashes. Hendershott (2011) suggests those short-lived crashes could originate from several sources: high frequency trading activity, market structure changes, trading fragmentation and/or the disappearance of designed market makers.

In this paper, we investigate in-depth the root of price jumps in the stock market. For this purpose, we took a threefold perspective. First, we quantify liquidity demand and supply around price jumps. Second, we look at order submission dynamics that take place during market disruptions. Third, we investigate the behavior of investor types at that time.

Our methodology takes advantage of a unique database on the Euronext 100 Index that allows us to disentangle the effects of the two latest major evolutions in European financial markets: the emergence of high frequency trading as from the early 2000s and the implementation of multilateral trading facilities introduced by the MiFID directive as from 2007. We rely on a tick-by-tick trades, orders and quotes data set to quantify the liquidity dynamics through an extensive set of liquidity measures, both trade-based and order book-based. Furthermore, the database holds several undisclosed information such as broker identification, hidden orders and details on order submission. We then build fixed volume aggregation sampling that controls for trading volume effects and deals with non trading issues at high frequency aggregation. As for price jumps detection, we use jump tests robust to time-varying volatility and periodicity in financial markets.

We find the origin of market disruptions lies in a low liquidity supply density at the inception of price jumps while at the opposite liquidity demand decreases at the same time. Upside and
downside jumps impact liquidity dynamics the very same way and display similar abnormal patterns.

All our results suggest a higher involvement of high frequency trading activity in the market around price jumps. Liquidity supply displays an abnormal order book imbalance that implies a higher HFT activities (Brogaard et al., 2013). Order submission dynamics exhibit some widely known characteristics of high frequency trading such as high order cancellations/modifications and high order submission frequency as well.

Granger causality tests emphasize our initial findings in that causality is mainly found from liquidity supply to price jumps. Furthermore, we find back causal relationships that refer to some characteristics of high frequency trading activity such as order submission frequency, relative proportion of filled orders and order book imbalance.

Finally, we test the robustness of our findings on a higher time frame that is the 5-minute average trading volume aggregation sampling.

Our results bring support for several papers that outline a relationship between high frequency trading activity and stock specific volatility (Brogaard, 2012; Zhang, 2010; Kirilenko et al., 2011).

The remainder of the paper proceeds as follows. Section 2 provides a brief review of the literature on high frequency trading and price jumps. Section 3 describes the data set and the different liquidity measures implemented. Section 4 presents the applied methodology. Section 5 and 6 report respectively the event study results and Granger causality tests. Section 7 contains robustness checks on our initial findings. The final Section concludes.

2 Literature review

2.1 Price jumps and liquidity dynamics

Several papers document the relationship between order book imbalances and price movements. Chordia and Subrahmanyam (2004) report a positive correlation between daily order
book imbalance and stock returns and volatility. Chordia et al. (2008) also highlight that return predictability is higher when the spread is tight. Cao et al. (2009) also investigate the informational content of the order book and show it fosters price discovery in the market.

On higher frequency aggregation sampling, Harris and Panchapagesan (2005) confirm a relationship between the limit order book and future price movements. Hellström and Simonsen (2009) point out that the information content of the order book is short-lived. Indeed, they find predictive power at a 1 and 2-minute aggregation sampling on the Stockholm stock exchange while it vanishes on lower frequency sampling.

The relationship between market disruptions, i.e. price jumps, and liquidity provision remains unexplored in the literature. The origin of those market disruptions depends on the market.

On the one hand, there is a convergence of views to say that the frequency of jumps in the stock market cannot be fully explained by news, whether macroeconomic or firm specific. Boudt et al. (2012) assess that 70% of the jumps are related to liquidity in the DJIA index. Furthermore, they investigate the dynamics of the four dimensions of liquidity around price jumps. They find that the effective spread and the number of trades is informative of forthcoming jumps. Farmer et al. (2004)’s paper support those findings on the London Stock Exchange and outline the idea that large price fluctuations are driven by time-varying liquidity supply. Furthermore, it emphasizes that jump risks seem to be stock specific, illiquid stocks tend to suffer from jumps more often. Joulin et al. (2008) and Weber and Rosenov (2005) document, using U.S. market data, that a lower density of the order book is at the source of price jumps, instead of the surge of significant trading volume underlying the arrival of information in the stock market.

On the other hand, recent papers (Jiang et al., 2010; Miao et al., 2012) find that most jumps appear at pre-scheduled macroeconomic news in the US treasury bond market and in the stock index futures market.
2.2 High frequency trading and market stability

High frequency trading (henceforth HFT) is one of the latest major development in financial markets. As from 2005, HFT activity takes on a dominant role in the stock market (Smith, 2010). Zhang (2010) estimates that HFT accounts for 70% of dollar trading volume in the U.S. capital market in 2009. Lately HFT activity was under the spotlight following the liquidity-induced flash crash on May 6th, 2010 that cast doubt on the soundness of HFT activity and its externalities on market stability and price efficiency.

A comprehensive definition of what HFT activity includes remains elusive. According to Castura et al. (2010), it encompasses professional market participants that present some characteristics: high-speed algorithmic trading, the use of exchange co-location services and individual data feeds, very short investment horizon and the submission of a large number of orders during the continuous trading session that are often cancelled shortly after submission.

This last feature is well documented in the literature. Indeed, Hendershott et al. (2011) outline that over 90% of the order submitted by HFT are either cancelled or modified (cancelled and resubmitted) before being filled. More recently, Gai et al. (2012) show HFT increases the order cancellation/execution ratio and generates quote stuffing\(^1\), in the market. Finally, HFT activity is positively correlated to public information, market-wide movements and limit order book imbalances (Brogaard et al., 2013).

The impact of HFT activity is still widely unexplored.

On the one hand, several papers outline HFT activity improves overall market liquidity (Castura et al., 2010; Angel et al., 2010; Hasbrouck and Saar, 2011). It finds HFT activity went along with a reduction of the spread, a liquidity improvement and a reduction of intraday volatility. Hanson (2011) and Menkveld (2012) describe HFT as the new market makers in the U.S. financial market. Indeed, HFT acts mostly as liquidity providers and engages in price reversal strategies (Brogaard, 2011).

On the other hand, market quality improves mainly as from 2006 and is tough to relate

\(^1\)Quote stuffing consists in submitting a large number of orders followed immediately by a cancellation to generate order congestion.
directly to the emergence of HFT activity (Castura et al., 2010). Indeed, almost at the same
time, we implement major changes in the market structure both in the U.S. and in Europe
with respectively the implementation of RegNMS and the MiFID directive. Furthermore,
Hendershott (2011) documents that individual stock mini-crashes become more prominent
along with overall market quality improvement. The author puts forward several potential
origins of those liquidity-driven crashes among them high frequency trading activity.

Some papers report a tight relationship between high frequency activity and stock specific
volatility (Brogaard, 2012; Zhang, 2010; Kirilenko et al., 2011). Indeed, HFT generates the
majority of order flow while it displays periodicity in order submission and a high rate of order
cancellations and modifications. Significant changes in their market activity from liquidity
providers to liquidity takers suggest HFT may emphasize volatility and cause overreaction in
the market.

3 Data

3.1 Data and sample

The database pertains to the Euronext 100 index. This index represents 80% of the total
market capitalization of Euronext. It includes the 100 largest and most liquid stocks traded on
the exchange. The data spans 61 trading days from February 1, 2006 to April 30, 2006. This
time period shows the advantage to disentangle the effects of the two latest major evolutions in
European financial markets: the emergence of high frequency trading as from the early 2000s
and the implementation of multilateral trading facilities (uncentralized market) introduced by
the MiFID directive as from 2007.

We rely on a tick-by-tick trades, orders and quotes data set to quantify the liquidity dy-
namics through an extensive set of liquidity measures, both trade-based and order book-based.
Furthermore, the database holds several undisclosed information such as broker identification,
hidden orders and details on order submission.

We arrange our database in volume interval. This methodology allows us to control for
trading volume effects and avoid non trading issues at high frequency aggregation. For the sake of consistency, we set a fixed trading volume for each underlying stock that corresponds to the average 2-minute trading volume observed on the stock over the whole sample period. Several papers document that the 2-minute time frame strikes a balance between microstructure noise and the additional information content of higher frequency data (Andersen et al., 2010, 2012; Bajgrowicz and Scaillet, 2011; Boudt et al., 2012).

We filter our data set to ensure the robustness of our results. First, we eliminate the last interval of each trading day given the fixed trading volume might not be completed. Second, we remove the first and the last three intervals of each continuous trading day to avoid contagion effects in the event study. Finally, we tolerate slight variation in the fixed trading volume in order to avoid order splitting. Indeed, we set the trigger for a new interval as the trade that crosses the fixed volume threshold. Our filtered database consists in 1,104,880 intervals.

### 3.2 Liquidity measures

In order to evaluate liquidity supply and demand around price jumps, we compute an extensive set of order book and trade-based measures that account for the multidimensional aspect of liquidity.

**Liquidity supply** We assess liquidity supply through the tightness and depth dimension of liquidity and their resiliency around price jumps. The snapshot of the order book state is taken at the end of each interval.

The liquidity supply measures include respectively the relative spread ($RS_{i,t}$), the dispersion ($Dispersion_{i,t}$), the cost of round trip ($CRT_{i,t}$), the displayed and hidden depth at the first and five best bid and ask quotes ($Q_{n_{i,t}}$), and the absolute depth imbalance at the five best quotes ($AbsImb_{5_{i,t}}$). They are computed as follows:

$$RS_{i,t} = \frac{P_{A1,i,t} - P_{B1,i,t}}{MQ_{i,t}},$$
where $P_{A1,i,t}$ is the best ask and $P_{B1,i,t}$ is the best bid for stock $i$ at the end of interval $t$ and $MQ_{i,t}$ is the midquote at the end of interval $t$ for stock $i$.

Kang and Yeo (2008)’s dispersion measure is used to quantify the density of the order book. The lower the dispersion, the higher the liquidity.

$$\text{Dispersion}_{i,t} = \frac{1}{2} \left( \frac{\sum_{j=1}^{n} w_{i,j,t}^\text{Bid} D_{st}^{\text{Bid}}_{i,j,t}}{\sum_{j=1}^{n} w_{i,j,t}^\text{Bid}} + \frac{\sum_{j=1}^{n} w_{i,j,t}^\text{Ask} D_{st}^{\text{Ask}}_{i,j,t}}{\sum_{j=1}^{n} w_{i,j,t}^\text{Ask}} \right), \quad (3.1)$$

where $w_{i,j,t}$ are the bid and ask quantities available for security $i$ and interval $t$ at the $j$th price limit normalized by the total depth of the five best quotes, $D_{st}^{\text{Bid}}_{i,j,t} = (\text{Price}_{\text{Bid}}^{i,j,t} - \text{Price}_{\text{Bid}}^{i,j-1,t})$ and, $D_{st}^{\text{Ask}}_{i,j,t} = (\text{Price}_{\text{Ask}}^{i,j,t} - \text{Price}_{\text{Ask}}^{i,j-1,t})$. The midquote is used for the distance of the first best quotes.

The cost of round trip measure takes the five best limit quotes of the order book into account and then assumes a perfect elasticity of prices beyond as it is usually done in the literature (Jain et al., 2011). The trade size is lined up with the time frame of the event chart, that is the 2-minute average trading volume on the underlying stock.

$$CRT_{i,t} = \frac{\left| \sum_{k=1}^{5} I_{k}^\text{Buy} \left( \text{Midquote}_{i,t} - P_{k}^\text{Buy} \right) + \sum_{k=1}^{5} I_{k}^\text{Sell} \left( P_{k}^\text{Sell} - \text{Midquote}_{i,t} \right) \right|}{T \times \text{Midquote}_{i,t}},$$

where $I_{k}$ is the number of shares bought or sold respectively at the $k$th price limit of the order book and $P_{k}$ is the price of the $k$th order book price limit. $T$ is the total number of shares to be bought or sold.

with

- $I_{k}^h = Q_k^h$ if $T > \sum_{j=1}^{k} Q_j^h$,
- $I_{k}^h = (T - \sum_{j=1}^{k-1} Q_j^h)$ if $T > \sum_{j=1}^{k-1} Q_j^h$ and $T < \sum_{j=1}^{k} Q_j^h$,
- $I_{k}^h = 0$ otherwise,

where $h \in [\text{Buy}, \text{Sell}]$, $Q_j^h$ is the committed quantity at the $j$th price limit of the order book and $T$ is the total number of shares to be bought or sold.
\[ Q_{n,i,t} = \sum_{j=1}^{n} Q_{B,j,i,t} + Q_{A,j,i,t}, \]

where \( Q_{nB,j,i,t} \) is the committed bid quantities and \( Q_{nA,j,i,t} \) is the committed ask quantities display at the \( j^{th} \) best price limit for stock \( i \) at the end of interval \( t \).

\[ \text{AbsImb}_{i,t} = \frac{|\sum_{k=1}^{5} Q_{B,k,i,t} - Q_{A,k,i,t}|}{\sum_{k=1}^{5} Q_{B,k,i,t} + Q_{A,k,i,t}}, \]

where \( Q_{B,i,t} \) is the displayed committed bid quantities and \( Q_{A,i,t} \) is the displayed committed ask quantities for stock \( i \) at interval \( t \). \( k \) is the \( k^{th} \) price limit of the order book.

**Liquidity demand** We estimate liquidity demand through three trade-based liquidity measures that are summed over the interval: the number of trades (\(#\text{Trades}_{i,t}\)), the trade duration (\(\text{TradeDuration}_{i,t}\)) and the number of trades imbalance (\(\text{ImbalanceN}_{i,t}\)).

In the framework of our volume aggregation sampling, the number of trades for a given trading volume represents the average trading size in the market.

\[ #\text{Trades}_{i,t} = \sum_{j=1}^{J} N_{i,j,t}, \]

where \( N \) is the number of trades for stock \( i \) during interval \( t \).

The trade duration measures the time needed to complete the fixed trading volume. It estimates the aggressiveness of market participants in the market.

\[ \text{TradeDuration}_{i,t} = \text{EndTime}_{i,t} - \text{StartTime}_{i,t}, \]

where \( \text{EndTime}_{i,t} \) is the closing time in seconds and \( \text{StartTime}_{i,t} \) is the opening time in seconds of the fixed volume interval for stock \( i \) at interval \( t \).

As for the number of trades imbalance, we aggregate buyer and seller-initiated trades during an interval in number of trades. Then, we compute an absolute imbalance as follows:
\[ \text{Imbalance}_N(i, t) = \frac{\left| \sum_{j=1}^{J} \# \text{Trades}^\text{Buy}_{i,t} - \sum_{k=1}^{K} \# \text{Trades}^\text{Sell}_{i,t} \right|}{\sum_{j=1}^{J} \# \text{Trades}^\text{Buy}_{i,t} + \sum_{k=1}^{K} \# \text{Trades}^\text{Sell}_{i,t}}, \]

where \( \# \text{Trades}^\text{Buy}_{i,t} \) is the number of buyer-initiated trades for stock \( i \) during interval \( t \) and \( \# \text{Trades}^\text{Sell}_{i,t} \) is the number of seller-initiated trades for stock \( i \) during interval \( t \).

4 Methodology

4.1 Price jump detection

Reliable jump identification is of paramount importance. In this paper, we rely on Boudt et al. (2011) that extend the Lee and Mykland (2008)’s jump test. Aside of being typically designed for high frequency data, this non parametric jump test allows us to account for time-varying volatility and periodicity in the stock market.

Lee and Mykland (2008)’s jump test assumes log prices follow a continuous time brownian process. Based on this price model, the authors use absolute return standardized by a jump-robust estimate of the local volatility to test the null hypothesis that the return is unaffected by a jump. The test rests on the realized bipower variation to compute the average daily volatility. Indeed, Barndorff-Nielsen and Shephard (2004) show the realized bipower variation converges, under weak conditions, to the integrated variance. The Lee and Mykland (2008)’s test assumes that the local volatility is constant over the entire window used to compute it. Given those windows typically expand on days for intraday aggregation sampling, this assumption introduces a significant bias in the jump test. To cope with this issue, Boudt et al. (2011) develop a filtered test and advocate the use of the weighted standard deviation (henceforth JM WSD) as a periodicity filter. This periodicity filter improves the jump detection accuracy. Indeed, spurious jump detection may arise from neglecting intraday volatility periodicity.

The jump test statistic \( J_{i,t} \) informs us on the precise timing of a jump as well as its size.

\[ J_{i,t} = \frac{|r_{i,t}|}{\xi_{i,t} f_{i,t}}, \quad (4.1) \]
where \( r_{i,t} \) is the return for stock \( i \) at interval \( t \), \( \xi_{i,t} \) is the square root of the realized bipower variation and \( f_{i,t} \) is the periodicity estimate for stock \( i \) at interval \( t \).

The length of the rolling window used to compute the local volatility depends on the sampling frequency. It should account for both, time-varying volatility and jump-robust local volatility estimate. Lee and Mykland (2008) propose to set the length of the rolling window to \( \sqrt{252 \times obs} \), where \( obs \) is the number of intraday observations. Indeed, the authors show through simulation that an increasing of the window size beyond this threshold brings only marginal contribution while increasing the computational burden.

Finally, Lee and Mykland (2008) suggest to set the critical level to reject the null hypothesis of no jump based on a quantile function of a standard Gumbel distribution. We reject the null of no jump with a 10% type 1 error probability, such as in Boudt et al. (2012), which is a conservative approach.

The main time frame of the paper, that is the average 2-minute trading volume on the underlying stock, is set to strike a balance between market microstructure noises and the additional information content resulting from higher frequency aggregation sampling. Indeed, several papers outline the 2-minute aggregation sampling offers a good compromise (Andersen et al., 2010, 2012; Bajgrowicz and Scaillet, 2011; Boudt et al., 2012). Table 1 reports the number of events, i.e. price jumps, at the average 2-minute trading volume sampling aggregation and the splitting of the events between upside and downside jumps.

<table>
<thead>
<tr>
<th>Table 1: Descriptive Statistics</th>
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<tr>
<td><strong>Average 2-minute trading volume</strong></td>
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<td></td>
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<tr>
<td>JM,LM</td>
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<td>JM,WSD</td>
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</table>

The table reports the total number of jumps as well as the count of upside and downside jumps for our main time frame that is the 2-minute average trading volume on the underlying stock. The jumps displayed here are the Lee and Mykland (2008)’s jump test (JM LM) and its variant that account for seasonality (JM WSD).
4.2 Event study

We investigate the impact of price jumps on three dimensions: liquidity supply and demand, order submission dynamics and investor types activity. Our event study focuses on the three intervals before and after the price jump occurrence. Relying on Boudt et al. (2012), we standardize our different measures using the median. Indeed, the skewness of our measures makes median a better central tendency estimator. We carry out a statistical hypothesis testing relying on the Mann-Whitney non parametric sign test. Our null hypothesis is that price jumps have no impact on our measure and the alternative hypothesis is that our measure is abnormally high or low around the inception of price jumps.

The standardized abnormal measure is computed as follows:

\[
\text{StandardizedMeasure}_{i,t,j} = \frac{\text{Measure}_{i,t,j} - \text{Median}^{NE}_{i,t,j}}{\text{Median}^{NE}_{i,t,j}},
\]

where \(\text{Measure}_{i,t,j}\) is the analyzed measure \(j\) for stock \(i\) at interval \(t\) and \(\text{Median}^{NE}_{i,t,j}\) is the median of the measure \(j\) for stock \(i\) across all non-events occurring at interval \(t\).

A significant abnormal level of some measures around price jumps implies potential causality. Indeed, it might be that price jumps cause our measure to display abnormal patterns or at the opposite that our measure is a consequence of price jumps.

To investigate causality, we rely on the jump size to conduct bidirectional Granger causality tests between our measures and price jumps.

Our unrestricted VAR models are specified as follows:

\[
JM_t = \alpha_0 + \alpha_1 JM_{t-1} + \alpha_2 JM_{t-2} + \ldots + \alpha_p JM_{t-p} \\
+ \beta_1 M_{t-1} + \beta_2 M_{t-2} + \ldots + \beta_p M_{t-p} + \epsilon_t,
\]

\[
M_t = \alpha_0 + \alpha_1 M_{t-1} + \alpha_2 M_{t-2} + \ldots + \alpha_p M_{t-p} \\
+ \beta_1 JM_{t-1} + \beta_2 JM_{t-2} + \ldots + \beta_p JM_{t-p} + \epsilon_t,
\]
where $M_t$ denotes one of our investigated measures, $p$ denotes the number of lags and $\varepsilon_t$ is an error term.

The lag length of our VAR models is set through a minimization of the Akaike information criteria (Akaike, 1974). The Granger causality test null hypothesis is that the significance of all the explanatory variables of the VAR model are jointly zero, that is no causality.

5 Results

5.1 Summary

All in all, we find strong evidence of a low liquidity supply density at the inception of price jumps while at the opposite liquidity demand decreases at the same time. Upside and downside jumps impact liquidity dynamics the very same way and display similar abnormal patterns.

As for liquidity supply, we observe strong resiliency of both tightness and depth dimension. Even though, tightness and depth remain respectively abnormally high and low around the occurrence of price jumps, the abnormal measures quickly recover to their pre-jump levels.

At the opposite, liquidity demand exhibits a sudden and short-lived slowdown during price jumps. While trading activity is fairly high around price jumps, trade duration spike when a jump occurs. Even if this spike is not significant, it pictures a decreasing in trading activity. Along with a lower trading activity, the number of trades significantly spikes during market disruptions indicating that the average trading size is significantly smaller at that time. Finally, the trade imbalance in number of trades is abnormally high before the occurrence of disruptions and then quickly reverts to normal after jumps.

We also investigate the order submission frequency. It highlights a significant abnormal peak in order submission frequency both in number of orders and in volume before the occurrence of price jumps that reverts to normal as from the inception of jumps.

As for the order state, we mention a strong decreasing of filled orders during the price jump interval. At the same time, we observe a significant abnormal increasing of modified orders.
both in number and in volume. Number of cancelled orders spike during price jumps as well
but cancelled orders remain low which suggest that the average size of cancelled orders is small.

Our last focus point is on investor types that are active during market disruptions. Our
finding suggests that brokerage firms are less active at that time. Brokerage firms still submit
almost the same relative number of orders in the market but lower their trading size.

All our results suggest a higher involvement of high frequency trading activity in the mar-
et around market disruptions. Liquidity supply displays an abnormal order book imbalance
that implies a higher HFT activities (Brogaard et al., 2013). Order submission dynamics
exhibit some widely known characteristics of high frequency trading such as high order can-
cellations/modifications and high order submission frequency. Our findings bring support for
several papers that outline a relationship between high frequency trading activity and volatility
(Brogaard, 2012; Zhang, 2010; Kirilenko et al., 2011).

Granger causality tests emphasize our initial findings in that causality is mainly found from
liquidity supply to price jumps. Furthermore, we find causal relationships that refer to some
characteristics of high frequency trading activity such as order submission frequency, relative
proportion of filled orders and order book imbalance.

5.2 Details on liquidity supply and demand around price jumps

Liquidity dynamics around price jumps reveal some interesting insight. We find strong evidence
of a low liquidity supply density at the inception of price jumps while at the opposite liquidity
demand drops at the same time. Upside and downside jumps impact liquidity dynamics the
very same way and display similar patterns.

As for liquidity supply, we observe strong resiliency of both tightness and depth dimension.
Even though, tightness and depth remain respectively abnormally high and low around the
occurrence of price jumps, the abnormal measures quickly recover to their pre-jump levels.

Concerning the tightness dimension, the spread is significantly higher, at a 1% confidence
level, during the all window. Furthermore, it displays a spike around the event in [-2,+1]
window. The dispersion and the cost of round trip trade exhibit very similar patterns with positive abnormal measures and a peak the interval prior to price jumps inception.

The depth dimension remains significantly abnormally low during the entire investigated window but it displays less obvious patterns. The hidden quantities at the best bid and ask quotes drop significantly around the occurrence of price jumps. Moreover, the absolute depth imbalance exhibits a significant spike that vanishes quickly after the occurrence of price jumps. This finding would suggest a higher high frequency trading activity in the stock market at that moment. Indeed, Brogaard et al. (2013) document that high frequency trading activities are positively correlated with order book imbalances.

At the opposite, liquidity demand exhibits a sudden and short-lived slowdown during price jumps. While trading activity is fairly high around price jumps, trade duration spike when a jump occurs. Even if this spike is not significant, it pictures a decreasing in trading activity. By the same token, the number of trades significantly spikes during market disruptions indicating that the average trading size is significantly smaller at that time. Finally, the trade imbalance, in number of trades, is abnormally high before the occurrence of price jumps and then quickly revert to normal after jumps.

All in all, liquidity dynamics show that liquidity supply gaps are responsible for price jumps instead of a high liquidity demand. Our results suggest the presence of information asymmetry around jumps as well as a higher involvement of high frequency trading activity in the market.
Figure 1: Liquidity supply around price jumps: Tightness dimension

(a) Relative spread
(b) Dispersion
(c) Cost of Round Trip (CRT)

Full, dotted and dashed lines represent the intra-window median pattern for liquidity supply measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels. Liquidity measures are detailed in Section 3.2.
Figure 2: Liquidity supply around price jumps: Depth dimension

Full, dotted and dashed lines represent the intra-window median pattern for liquidity supply measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels. Liquidity measures are detailed in Section 3.2.
5.3 Details on order submission dynamics around price jumps

During the inception of upside price jumps, we observe a lower rate of limit orders submission, both in number of orders and in volume which is not the case for downside price jumps. Market orders are abnormally low but they exhibit a significant spike in volume after the market disruption, even though it remains well below its median pattern. This result outlines stop loss order type are not liable for market disruptions in our data sample.
We also investigate the order submission frequency around price jumps. It highlights a significant abnormal peak in order submission frequency both in number of orders and in volume before the occurrence of price jumps that reverts to normal as from the inception of price jumps.

As for the order state around price jumps, we mention a strong decreasing of filled orders during the price jump interval. At the same time, we observe a significant abnormal increasing of modified orders both in number and in volume. Number of cancelled orders spike during price jumps as well but cancelled orders remain low which suggest that the average size of cancelled orders is small.

To sum up, order submission dynamics seem to corroborate our insight from liquidity dynamics. Again, we find some key characteristics of high frequency trading activity in the order submission dynamics. In fact, the order cancellation/execution ratio spikes during the price jump interval and the higher order submission frequency suggests quote stuffing strategies before the occurrence of market disruptions.
Figure 4: Order submission dynamics around price jumps: Order types and order frequency

(a) Relative number of limit orders
(b) Relative quantity of limit orders
(c) Relative number of market orders
(d) Relative quantity of market orders
(e) Number of orders by second
(f) Quantity of orders by second

Full, dotted and dashed lines represent the intra-window median pattern for order submission dynamics measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.
Figure 5: Order submission dynamics around price jumps: Order state

(a) Relative number of filled orders
(b) Relative quantity of filled orders
(c) Relative number of modified orders
(d) Relative quantity of modified orders
(e) Relative number of cancelled orders
(f) Relative quantity of cancelled orders

Full, dotted and dashed lines represent the intra-window median pattern for order submission dynamics measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.
5.4 Details on investor types around price jumps

Our last focus point is on investor types that are active during market disruptions. For this purpose, we take advantage of the richness of our data set and split order between brokerage firms own account orders and customer orders. In terms of number of orders submitted, there is no obvious pattern except for downside jumps where it displays more customer orders and less proprietary orders before price jumps at a 1% confidence level. Concerning the volume of orders, customer and proprietary orders are respectively abnormally high and low during the entire window with a spike/low during the jump interval.

Our finding suggests that brokerage firms are less active around price jumps. Brokerage firms still submit almost the same relative number of orders in the market but lower their trading size. This suggests the presence of information asymmetry around price jumps and supports our initial observations on liquidity dynamics.
Figure 6: Investor types around price jumps

(a) Relative number of customer orders
(b) Relative quantity of customer orders
(c) Relative number of proprietary orders
(d) Relative quantity of proprietary orders

Full, dotted and dashed lines represent the intra-window median pattern for investor types measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

6 Granger causality

Table 2 presents the results of the Ganger causality tests. As mentioned in the section 4, we test the bidirectional Granger causality, that is on the one hand, jumps Granger-cause our measure and our measure Granger-causes jumps. A small p-value indicates that Granger causality exists between the measure and price jumps. Most Granger causality is found from our measures to price jumps.
We find some Granger causality from liquidity supply to price jumps. Indeed, the relative spread at a 99% confidence level and to a lower extend, the absolute depth imbalance, at a 90% confidence level, Granger-cause price jumps. As for liquidity demand, we observe a bidirectional Granger causality between the average trading size and price jumps. In other words, price jumps lead to small average trading size while at the same time small average trading size leads price jumps.

Concerning order submission dynamics, we highlight that the percentage of filled orders Granger-causes price jumps both in number of orders and in volume. At a 90% confidence level, we also observe that the number of orders frequency causes price jumps. Finally, investor types activity does not significantly Granger-causes price jumps at a 10% critical level.

Our Granger causality tests emphasize our initial findings in that causality is mainly found from liquidity supply to price jumps. Furthermore, the causal relationships refer to some characteristics of high frequency trading activity such as order submission frequency, relative proportion of filled orders and order book imbalance.
Table 2: Granger causality tests

<table>
<thead>
<tr>
<th>Measure</th>
<th>$M_t \rightarrow JM$</th>
<th>$JM \rightarrow Measure$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative spread</td>
<td>0.1496</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Dispersion</td>
<td>0.3664</td>
<td>0.2369</td>
</tr>
<tr>
<td>Cost of round trip</td>
<td>0.9940</td>
<td>0.9441</td>
</tr>
<tr>
<td>Displayed Q1 (Both sides)</td>
<td>0.9704</td>
<td>0.7035</td>
</tr>
<tr>
<td>Displayed Q5 (Both sides)</td>
<td>0.9143</td>
<td>0.4030</td>
</tr>
<tr>
<td>Hidden Q1 (Both sides)</td>
<td>0.8063</td>
<td>0.6466</td>
</tr>
<tr>
<td>Hidden Q5 (Both sides)</td>
<td>0.8061</td>
<td>0.3995</td>
</tr>
<tr>
<td>Absolute depth imbalance</td>
<td>0.9445</td>
<td>0.0573</td>
</tr>
<tr>
<td>Number of trades</td>
<td>0.0191</td>
<td>0.0026</td>
</tr>
<tr>
<td>Number of trades imbalance</td>
<td>0.7037</td>
<td>0.4756</td>
</tr>
<tr>
<td>Trade duration</td>
<td>0.7456</td>
<td>0.5669</td>
</tr>
<tr>
<td>Relative number of limit orders</td>
<td>0.8064</td>
<td>0.1474</td>
</tr>
<tr>
<td>Relative quantity of limit orders</td>
<td>0.5134</td>
<td>0.4404</td>
</tr>
<tr>
<td>Relative number of market orders</td>
<td>0.7506</td>
<td>0.3501</td>
</tr>
<tr>
<td>Relative quantity of market orders</td>
<td>0.5369</td>
<td>0.4404</td>
</tr>
<tr>
<td>Number of orders by second</td>
<td>0.5298</td>
<td>0.0618</td>
</tr>
<tr>
<td>Quantity of orders by second</td>
<td>0.7400</td>
<td>0.8268</td>
</tr>
<tr>
<td>Relative number of filled orders</td>
<td>0.4612</td>
<td>0.0479</td>
</tr>
<tr>
<td>Relative quantity of filled orders</td>
<td>0.3993</td>
<td>0.0505</td>
</tr>
<tr>
<td>Relative number of modified orders</td>
<td>0.7676</td>
<td>0.3591</td>
</tr>
<tr>
<td>Relative quantity of modified orders</td>
<td>0.6608</td>
<td>0.5127</td>
</tr>
<tr>
<td>Relative number of cancelled orders</td>
<td>0.3788</td>
<td>0.5667</td>
</tr>
<tr>
<td>Relative quantity of cancelled orders</td>
<td>0.4907</td>
<td>0.3692</td>
</tr>
<tr>
<td>Relative number of customer orders</td>
<td>0.9147</td>
<td>0.1075</td>
</tr>
<tr>
<td>Relative quantity of customer orders</td>
<td>0.6610</td>
<td>0.5044</td>
</tr>
<tr>
<td>Relative number of proprietary orders</td>
<td>0.8390</td>
<td>0.1564</td>
</tr>
<tr>
<td>Relative quantity of proprietary orders</td>
<td>0.4214</td>
<td>0.1772</td>
</tr>
</tbody>
</table>

The table reports the bidirectional Granger causality tests, that is Price jumps Granger-cause the measure and the measure Granger-causes price jumps. The results displayed are the p-value, small p-values means there is Granger causality. Liquidity measures are detailed in Section 3.2. "Q1" includes the sum of bid and ask quantities available at the best quote. "Q5" is the sum of bid and ask quantities at the 5 best bid and ask quotes."Absolute depth imbalance" is the depth imbalance at the 5 best quotes. "Number of trades" sums up the number of trades during the interval. In the framework of a volume chart, it represents the average trading size. "Number of trades imbalance" is the imbalance in the number of trades during the interval. As for order submission dynamics and investor types activity, the table reports both the relative number of orders and the relative quantity of orders.
Robustness checks

To test the robustness of our results, we investigate two variants of our initial findings.

First, we consider the basic Lee and Mykland (2008)’s test to identify price jumps. This
delivers very similar results and is therefore not detailed in the paper.

Second, we implement the very same methodology on a higher time frame, that is the
5-minute average trading volume on the underlying stock over the whole sample period. The
detailed results are reported in appendix.

All in all, liquidity supply and demand dynamics around price jumps look very similar
to our initial results. Indeed, the tightness dimension is significantly higher and the depth
dimension significantly lower over the entire investigated window. Again, we mention a strong
depth imbalance at the 5 best quotes of the order book before the occurrence of price jumps.
The striking observation that is made here, is the fact that the spike in the tightness dimension
occurs during the price jumps instead of right before the event in our main time frame while
the depth dimension behaves similarly as in our main time frame. This indicates that the
informational content of liquidity lies well in high frequency data.

Regarding liquidity demand, we observe the very same phenomenon that is a higher trading
activity that slowdown during price jumps along with a significantly smaller average trading
size. We mention as well abnormal trade imbalance before the jump occurrence that recovers
very fast as from the inception of a price jump.

Finally, order submission dynamics display much more ambiguous patterns, upside and
downside jumps tend to exhibit opposite patterns, upside jumps seem to be followed by a higher
resiliency than downside jumps. Lower frequency price jumps seem to indicate that brokerage
firms are more active during price jumps for their own account than for their customer account
which is the opposite as in the 2-minute trading volume time frame.

To sum up, we still found a significant relationship between price jumps and liquidity
that hold in higher time frame. As for order submission dynamics and investor types, the
relationship seems to be much more ambiguous. Upside and downside jumps that display
very similar patterns in our main time frame disentangle at a 5-minute average trading volume aggregation sampling. Thus, our observations on order submission dynamics and investor types only hold on pretty high frequency aggregation sampling.

8 Conclusion

In this paper, we use average 2-minute trading volume interval to carry out an in-depth analysis of the origin of high frequency price jumps in the stock market. Our event study considers the three intervals before and after the price jump and focuses on a threefold perspective. First, we analyse the dynamics of liquidity supply and demand around the occurrence of price jump. Second, we capture the behavior of market participants through order submission dynamics. Finally, we split market participants between brokerage firms customer account and proprietary account.

We take advantage of the richness of our data set to compute an extensive set of order book-based or trade-based. This database allows us to disentangle the effects of the two latest major evolutions in European financial markets: the emergence of high frequency trading as from the early 2000s and the implementation of multilateral trading facilities introduced by the MiFID directive as from 2007. We rely on a tick frequency trades, orders and quotes data set to quantify the liquidity dynamics through an extensive set of liquidity measures, both trade-based and order book-based. Furthermore, the database holds several undisclosed information such as broker identification, hidden orders and details on order submission. We then build average 2-minute trading volume aggregation sampling that controls for trading volume effects and deals with non trading issues at high frequency aggregation. As for price jumps detection, we use jump tests robust to time-varying volatility and periodicity in financial markets.

We find strong evidence of a low liquidity supply density at the inception of price jumps while at the opposite liquidity demand decreases at the same time. Upside and downside jumps impact liquidity dynamics the very same way and display similar abnormal patterns. Granger causality tests emphasize our initial findings in that causality is mainly found from liquidity supply to price jumps. Furthermore, we find causal relationships that refer to some
characteristics of high frequency trading activity such as order submission frequency, relative proportion of filled orders and order book imbalance.

We test the robustness of our findings on a higher time frame that is the average 5-minute trading volume aggregation sampling.

While liquidity supply and demand dynamics around price jumps look very similar to our initial results, order submission dynamics display much more ambiguous pattern. Indeed, upside and downside jumps tend to display opposite patterns, upside jumps seem to be followed by a higher resiliency than downside jumps. Lower frequency price jumps seem to indicate that brokerage firms are more active during price jumps for their own accounts than for their customer accounts which is the opposite as in our main time frame. Overall, the informational content of market microstructure tends to vanish at lower frequency aggregation.

All our results suggest a higher involvement of high frequency trading activity in the market around market disruptions. Liquidity supply displays an abnormal order book imbalance that implies a higher HFT activities (Brogaard et al., 2013). Order submission dynamics exhibit some widely known characteristics of high frequency trading such as high order cancellations/modifications and high order submission frequency. Our findings bring support for several papers that outline a relationship between high frequency trading activity and volatility (Brogaard, 2012; Zhang, 2010; Kirilenko et al., 2011).

References


9 Appendix

Figure 7: Liquidity supply around price jumps: Tightness dimension

(a) Relative spread
(b) Dispersion
(c) Cost of Round Trip (CRT)

Full, dotted and dashed lines represent the intra-window median pattern for liquidity supply measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels. Liquidity measures are detailed in Section 3.2.
Figure 8: Liquidity supply around price jumps: Depth dimension

Full, dotted and dashed lines represent the intra-window median pattern for liquidity supply measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels. Liquidity measures are detailed in Section 3.2.
Figure 9: Liquidity demand around price jumps: Immediacy dimension

(a) Number of trades
(b) Number of trades imbalance
(c) Trade duration

Full, dotted and dashed lines represent the intra-window median pattern for liquidity demand measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels. Liquidity measures are detailed in Section 3.2.
Figure 10: Order submission dynamics around price jumps: Order state

(a) Relative number of filled orders
(b) Relative quantity of filled orders
(c) Relative number of modified orders
(d) Relative quantity of modified orders
(e) Relative number of cancelled orders
(f) Relative quantity of cancelled orders

Full, dotted and dashed lines represent the intra-window median pattern for order submission dynamics measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.

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Figure 11: Investor types around price jumps

(a) Relative number of customer orders
(b) Relative quantity of customer orders
(c) Relative number of proprietary orders
(d) Relative quantity of proprietary orders

Full, dotted and dashed lines represent the intra-window median pattern for investor types measures respectively for all the jumps, upside jumps and downside jumps. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.