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Price Dynamics and Market Liquidity: An Intraday Event Study on Euronext

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Summary

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Keywords: Liquidity, Limit order book, Price Dynamics, Japanese Candlesticks.

JEL Classification: G14.
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1 Introduction

Liquidity has recently become of utmost importance in finance. The liquidity black holes observed during the Subprime crisis, the recent emergence of liquidity dark pools, and the surge in high frequency trading have drawn the attention of an increasing number of researchers and practitioners. The flash crash of May 6th, 2010 has shown in particular that liquidity can be very unstable through time. In such a trading environment, the ability to find and estimate intraday liquidity in a fast and accurate way is extremely precious but also very challenging. Liquidity is indeed not unidimensional. As liquidity measures the ability to trade large quantities quickly at low cost with little price impact, several dimensions must be taken into account. Harris (2003) defines liquidity as "the ability to trade large size quickly, at low cost, when you want to trade" and attributes three mains dimensions to liquidity: immediacy, width and, depth before pointing resiliency (recovery from a liquidity shock) to be the fourth dimension. In this paper, we face this challenge by looking at intraday price dynamics observed on Euronext to determine whether they help characterize market liquidity in real time.

The seminal paper in this area of research is Kavajecz and Odders-White (2004) who first reveal some unexpected features of price movements with respect to liquidity on the NYSE. These authors study the information content of technical analysis for liquidity provision. They do not investigate the return predictability power of technical indicators but examine similarities between support and resistance levels and the level of depth in the limit order book. They also study moving average indicators and assess their information content in the order book. Their results show that signals in price charts are significantly related to the state of liquidity in the order book. They find that support and resistance levels and moving averages are strongly correlated with liquidity. The authors also conduct Granger causality tests, which reveal that technical analysis helps discover depth available in the book. However, their four liquidity measures are customized proxies that are not easily extracted from the limit order book. They also focus on 30-minute intervals without trying to extend their results to longer and shorter time frames. Furthermore, as support and resistance levels are often related to round prices limits, the relationship they outline may seem mechanical as limit orders submissions occur at these round prices, implying a higher depth for round price limits.1

In this paper, we extend their analysis to High-Low-Open-Close (HLOC) price dynamics that practitioners typically represent by drawing Japanese candlesticks. This method is an Eastern charting technique that is in essence very similar to bar charts. Candlestick charts give market participants a quick snapshot of buying and selling pressures, as well as turning points. This method is very different from support and resistance levels as well as from moving averages, that are investigated in Kavajecz and Odders-White (2004), as it is based on recent HLOC prices rather than historical information on closing prices.

1There is an extensive literature on round prices that we do not discuss in the paper. Ball et al. (1985), Harris (1991) and Kandel et al. (2001) are some examples.
Using market data on a sample of European stocks of three national indexes, we study the relationship between liquidity and price movements by applying an event study methodology on 15-minute intervals for the best-known candlesticks structures. As outlined by Kavajecz and Odders-White (2004), price dynamics are expected to be related to modifications in the state of the limit order book and with the supply of liquidity. For this purpose, we analyze different standard liquidity proxies: relative spread, one-sided displayed and hidden depth (at the best bid and offer, at the five best limits, and for the whole book), order imbalance, dispersion, and slope. We also analyze the following trading activity measures: number and size of buyer and seller-initiated trades, as well as trade imbalances for number of trades and volumes. We first focus our analysis on the Doji structures which are the most influential single lines in the literature on Japanese candlesticks. The Dojis are also expected to have a direct impact on liquidity given the succession of price pressures that drives these signals.

When a Doji appears on screen, our results suggest that liquidity is higher for all proxies although there is less trading activity at that particular time. This reinforces the hypothesis of price agreement for the security, as exposed in the literature on Japanese candlesticks. This consensus implies a narrower spread, higher depth and less dispersion due to higher competition that liquidity suppliers face. The duration of the liquidity changes depends on the proxy but the patterns are typically short-lived. The position of opening and closing prices on the candle is also related to different changes on bid and ask sides: bodies close to the highest price of the interval are linked to changes at the ask while bodies near the lowest price are related to changes at the bid. Using these dynamics might improve the execution of buy and sell decisions. Liquidity also seems to be higher when a Hammer or a Hanging Man occurs. In this respect, Japanese candlesticks may be used to quickly characterise the four dimensions of liquidity in a single chart, which may be very useful for traders, institutional or not, even if they have access to the raw information displayed in the limit order book. In a typical asset management firm, the decision to trade comes from the portfolio management team which then asks the broker to get the order executed in the best way. Trade execution could be improved by looking at these candlestick structures at the time of trade execution.

We investigate whether these results are related to the presence of informed trading, by using the PIN proposed by Easley et al. (1996). Our analysis shows that Dojis are moments where the PIN is lower, indicating that there are less informed traders at these moments.

We also conduct Granger causality tests in order to address the direction of the relationship between price movements and liquidity. Our results indicate that changes in liquidity proxies causes changes in the Close-Open range and that price movements are a good indicator for liquidity.

As robustness checks, we extend our analysis to other types of configurations. We also check the significance of our results when we consider 30-minute and 60-minute intervals. We find similar but less significant results indicating that the relationship is actually
shortlived.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the literature on price dynamics, technical analysis and liquidity. Section 3 describes the dataset and the different liquidity measures that are used. Section 4 presents the methodology that we apply. Section 5 reports the findings of the event study. Section 6 presents the results of the PIN analysis and, Section 7 is devoted to a causality analysis. Section 8 contains the robustness checks that are performed. The final Section concludes.

2 Literature review

2.1 Price dynamics and liquidity

The relationship between liquidity and price movements has not been well documented in the literature. Blume et al. (1989) study the interactions between liquidity and price dynamics by investigating the impact of order imbalances on stock price movements during the stock market crisis of October 19 and 20, 1987. The authors identify strong and positive correlation between order imbalances and price movements. They also enlighten a cascade effect of order imbalance on stock prices. The authors conclude that their results are consistent with the hypothesis that the stock decline was due to the incapacity of the market structure to absorb large selling orders. Using data from the Paris Bourse, Biais et al. (1995) investigate the supply and demand of liquidity as well as traders’ aggressiveness. They find that traders place orders inside the quotes when the spread or the depth (at the best quotes) is large. Chordia et al. (2001) empirically find that liquidity and trading activity are influenced by market returns and volatility. They also find that effective and quoted spreads increase dramatically in down markets. This effect is asymmetric because spreads do not decrease much in up markets. Chordia et al. (2002) reach the same results and identify a significant impact of daily order imbalance on both market returns and volatility. They also state that it is unwise to trade when the order book is highly imbalanced if waiting costs are low. Chordia and Subrahmanyam (2004) present a theoretical framework for Chordia et al. (2001) and obtain the same results at the individual stock level. Harris and Panchapagesan (2005) also outline a relationship between the limit order book and future price movements using the TORQ database. Chan (2005) find evidence that order placement strategies depend on previous returns, i.e. traders are more aggressive in buying and place fewer sell orders after positive returns and conversely, a decrease in price cause sellers to be more aggressive by placing more orders at the best quotes, larger orders, or by reducing the spread. More recently, Chordia et al. (2008) find that short-term return predictability is lower when liquidity (as measured by the bid-ask spread) is higher. They also pointed out that prices have been more efficient after the change to decimal tick size, supporting the positive relationship between liquidity and market efficiency. Cao et al. (2009) analyze the predictive power of limit order book information for 100 stocks quoted on the Australian Stock Exchange. They find evidence that
it facilitates price discovery and is associated with future short-term returns. Boudt et al. (2012) also consider the dynamics of liquidity around price jumps and the information content of window formation in intraday price charts with an event study. They find that liquidity drops sharply and is particularly low at the time of formation as well as in the following thirty minutes of the jump. All these studies investigate the returns based on the closing prices only, without taking into account HLOC dynamics which are directly related to trading activity, i.e. trading activity drives price changes. This paper fills that gap.

2.2 Price dynamics and Japanese candlesticks

Japanese candlesticks are a technical analysis charting technique based on High-Low-Open-Close prices.\(^1\) They are similar to bar charts but they are easier to interpret. The body is indeed black for negative days (yin day) and white for positive days (yang day). Bar charts do not contain this information. The formation process of candlesticks appears in Figure 1. There exist plenty of structures, formed by one to five candles, depending on the length of the shadows and the size and color of the bodies. These candlesticks emphasize what happened in the market at that particular moment. Each configuration can be translated into traders’ behaviors through price dynamics implied by buying and selling pressures.

Japanese candlesticks are interesting because they summarize a lot of information in one single chart: the closing price, the opening price as well as the lowest and highest prices. With the raising interest in high frequency trading and the narrowing of trading intervals, they have been increasingly used by practitioners to capture short term price dynamics. As for technical analysis, papers addressing candlesticks enter in the ”stock return predictability” category. For example, Marshall et al. (2006) and Marshall et al. (2008) find no evidence that candlesticks have predictive value for the Dow Jones Industrial Average stocks and for the Japanese equity market, respectively. They replicate daily data with a bootstrap methodology similar to the one used in Brock et al. (1992). However, intraday data is more relevant as traders do not typically wait for the closing of the day to place an order. Nevertheless, using intraday candlesticks charts on two future contracts (the DAX stock index contract and the Bund interest rate future), Fock et al. (2005) still find no evidence which suggests that candlesticks, alone or in combination with other methods, have a predictive ability. However, none of these papers looks at the relationships between candlestick configurations and order book dynamics. To our knowledge, this paper is the first research study that investigates the information content of HLOC price movements for intraday liquidity.

\(^2\)Even if Japanese candlesticks have been used for centuries in eastern countries, Steve Nison was the first to bring this method to the west in the nineties. Japanese candlesticks have been first used by Munehisa Homma who traded in the rice market during the seventeenth century. The original names of the candlestick structures come from the war atmosphere reigning in Japan at that time. At the beginning, there were only basic structures from one to three candles but more complex configurations have been identified since then. The predictive power of these configurations is still discussed. Nison (1991), Nison (1994), Morris (1995) and Bigalow (2001) are the best known and used handbooks of candlestick charting.
Previous research has outlined strong relationships between price movements and trade measures (e.g. Blume et al. (1989)). As candlesticks are good proxies for representing High-Low-Open-Close prices dynamics, we also expect a relationship between the occurrence of particular structures and trading activity measures. Fiess and MacDonald (2002) also argue in favor of that point. A relation between candlestick configurations and liquidity measures is also expected as trading activity measures are linked to the state of the order book, i.e. a trade occurs when supply meets demand and this matching is realized through the limit order book. The occurrence of some particular single lines should also be related to direct modifications in the book. This is the case of the Doji structures.

The Doji is one of the core structures of Japanese candlesticks. A Doji appears when the closing price is (almost) equal to the opening price. We observe different types of Dojis. The most frequent Doji is a "plus", i.e. no real body and almost equal shadows. If both closing and opening prices are also the highest price of the interval, the Doji becomes a Dragonfly Doji. By contrast, it becomes a Gravestone Doji when both closing and opening prices are equal to the lowest price of the interval. Another characteristic of the Doji is the position. A Doji may appear in a star position which means that a gap exists between the Doji and the previous candle. These Dojis are mostly part of the abandoned babies

4A description of the presented structures is available in Appendix.
structures. A Doji may also occur in a Harami position when it appears within the previous body.

The Doji denotes moments where there exists an agreement on the price of the stock. In this situation, traders are likely to situate the price of the stock inside the spread, leading to competition among traders which reduces the spread and the dispersion while increasing the slope and best quotes quantities. As a consequence, we expect liquidity to be higher and trading activity to be lower. We expect our results to be short-lived and the dynamics to appear in the window 30 minutes around the signal. We also expect different outcomes between Gravestone and Dragonfly Dojis as they come from different succession of price pressures: the Gravestone (Dragonfly) is made with a previous bullish (bearish) rally and ends up with a strong selling (buying) pressure. These expectations are opposed to the findings of Lesmond et al. (1999) who characterize zero-return days (Doji) as illiquid days with higher transaction costs. A zero-return interval may appear when no trader is willing to pay the best opposite price for the stock. The trader may however want to place the limit order and wait for execution. In this respect, zero-returns are not likely to be related to illiquidity. Furthermore, a Doji is a particular zero-return structure as some movement has occurred during the interval, indicating the presence of the willingness to trade, as opposed to the reasoning of Lesmond et al. (1999) based on the adverse selection framework of Glosten and Milgrom (1985) and Kyle (1985).

3 Data

3.1 Data and Sample

We use Euronext market data on 81 stocks belonging to three national indexes: BEL20, AEX and CAC40. We have tick-by-tick data for 61 trading days from February 1, 2006 to April 30, 2006. The key advantage of this dataset is to avoid the shift of volumes from national exchanges to Multilateral Trading Facilities (MTF) that has been occurring since the implementation phase of the MiFID directive. More recent datasets must instead include sufficient information from market data and MTFs to be representative of market activity. Needless to say, it has become extremely difficult to build such a reliable dataset in today’s decentralized trading environment. In addition, our dataset includes market members ID that we use to disentangle buyer-initiated and seller-initiated trades, without any error margin. Finally, we are also provided with undisclosed data on hidden orders.

We have rebuilt High-Low-Open-Close prices from this database for the 81 stocks over the whole sample period. As tick data are not adapted for candlestick analysis, we build 15-minute-intervals which leads to 34 intervals a day. This interval length is the best trade-off which allows to include intraday trends and to avoid noisy candlesticks patterns.

Hidden orders are orders that gradually display part of their total amount. For instance, a hidden order of 500 may appear on the book with a quantity of 100 and will automatically be refilled when 100 shares have been consumed.
resulting from non-trading intervals. We use the HLOC prices calculated above in order to identify candlestick configurations based on TA-Lib. We obtain a total of 167068 records (81 firms, 61 days, 34 intervals/day).

We filter the sample as follows. First, we remove ‘Four Prices Dojis’ because they are associated with non-trading patterns. Second, we only keep the events for which we do not observe any other structure in the previous and next three intervals in order to avoid any contagion effect in our measures. Therefore, there is only one event by analyzed window. As we study a moving window containing three 15-minute intervals before and after the signal, we do not consider events in the first and last three intervals for each day to avoid constructing event windows over different days. Finally, we only keep events types for which we have at least 30 event occurrences.

After the removal of all the possible contagious data, we have a total of 2959 Dojis, among which 653 are Dragonfly Dojis and 614 are Gravestone Dojis. Table 1 shows event occurrences.

<table>
<thead>
<tr>
<th>Name</th>
<th>Bull/Bear</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doji</td>
<td>1</td>
<td>2959</td>
</tr>
<tr>
<td>Bearish Dojistar</td>
<td>-1</td>
<td>111</td>
</tr>
<tr>
<td>Bullish Dojistar</td>
<td>1</td>
<td>121</td>
</tr>
<tr>
<td>Dragonfly Doji</td>
<td>1</td>
<td>653</td>
</tr>
<tr>
<td>Gravestone Doji</td>
<td>1</td>
<td>614</td>
</tr>
</tbody>
</table>

We look at the occurrences of the identified structures and check whether Dojis appear at a particular moment during the day. Figure 2 shows that the distribution of Dojis is

We observe too many non-trading intervals with 5-minute intervals. In the robustness checks section, we evaluate the sensibility of the results to a change in the interval length by analyzing 30-minute and 60-minute intervals.

The TA-lib library is compatible with the MATLAB Software. For each type of configuration and for each record, it returns "1" if the bullish part of the structure is identified, "-1" for the bearish part and "0" otherwise. As the structures are bullish, bearish or both, for each event type, the values that may appear are [0 ; 1], [-1 ; 0] or [-1 ; 0 ; 1]. The TA-lib allows some flexibility in the recognition of the configurations. As it is an open source library, we have been able to check the parametrization of the structures. Events are recognized according to the standard flexibility rules presented in Nison (1991) and Morris (1995). The TA-lib contains 61 pre-programmed structures. We however dropped 17 of them due to a lack of intraday significance. These 17 structures are meaningful when longer time periods are considered. However, they are too frequent on intraday data and do not give any signal. The list of these configurations is available upon request.

A Four Prices Doji occurs when all the prices are equal. When they occur in daily, weekly or monthly charts, they are a strong clue of a potential reversal. However, in intraday price charts, they represent non-trading intervals.

We keep the 44 configurations from the TA-lib for this filter.
roughly uniform with the most significant peaks occurring during lunch time and maybe resulting from non-trading. Dojis also seem to not occur frequently during the first two intervals of the day. This may be explained by the strong unidirectional movement that appears at that moment, as trends are at their beginning.

Figure 2: Dojis by Interval

This figure displays the number of Dojis in each time interval.

3.2 Liquidity Measures

We measure liquidity at the end of each trading interval, which enables us to measure the direct impact of the event on liquidity. We first calculate the traditional liquidity proxies such as relative spread, depths (displayed and hidden, in number of shares) and order imbalances (at different order book levels). We also use dispersion and slope measures which are respectively presented in Kang and Yeo (2008) and Næs and Skjeltorp (2006). Then, we compute trading activity measures as buyer and seller-initiated volumes and imbalances, in number of trades and quantities.\(^{10}\) Finally, we evaluate volatility using the High-Low measure for each time interval.\(^{11}\) Table 2 presents the different measures.

\(^{10}\) These measures are computed with the sum over each interval.

\(^{11}\) We also study the squared return as a volatility measure but the results are very similar.
**Table 2: Liquidity proxies and trading activity measures**

<table>
<thead>
<tr>
<th>Name</th>
<th>Median</th>
<th>Name</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantities at the Best Bid</td>
<td>1978.00</td>
<td>5 Best Limits Hidden Imbalance</td>
<td>0.04</td>
</tr>
<tr>
<td>Quantities at the Best Ask</td>
<td>1953.00</td>
<td>Imbalance Total</td>
<td>0.11</td>
</tr>
<tr>
<td>Quantities at the Best Bid (Hidden)</td>
<td>0.00</td>
<td>Imbalance Displayed</td>
<td>0.16</td>
</tr>
<tr>
<td>Quantities at the Best Ask (Hidden)</td>
<td>0.00</td>
<td>Imbalance Hidden</td>
<td>0.02</td>
</tr>
<tr>
<td>Displayed Depth 5 Best Bid</td>
<td>13409.00</td>
<td>Number of buyer-initiated trades</td>
<td>28.00</td>
</tr>
<tr>
<td>Displayed Depth 5 Best Ask</td>
<td>13612.00</td>
<td>Quantities of buyer-initiated trades</td>
<td>12785.00</td>
</tr>
<tr>
<td>Hidden Depth 5 Best Bid</td>
<td>1559.00</td>
<td>Number of seller-initiated trades</td>
<td>31.00</td>
</tr>
<tr>
<td>Hidden Depth 5 Best Ask</td>
<td>1800.00</td>
<td>Quantities of seller-initiated trades</td>
<td>13508.00</td>
</tr>
<tr>
<td>Displayed Depth Bid</td>
<td>312453.50</td>
<td>Imbalance Number of Trades</td>
<td>-0.05</td>
</tr>
<tr>
<td>Displayed Depth Ask</td>
<td>361465.00</td>
<td>Imbalance Traded Quantities</td>
<td>-0.03</td>
</tr>
<tr>
<td>Hidden Depth Bid</td>
<td>130558.50</td>
<td>High - Low</td>
<td>0.00</td>
</tr>
<tr>
<td>Hidden Depth Ask</td>
<td>143938.00</td>
<td>Squared Return</td>
<td>0.00</td>
</tr>
<tr>
<td>Total Depth Bid</td>
<td>169410.00</td>
<td>Dispersion Bid</td>
<td>0.02</td>
</tr>
<tr>
<td>Total Depth Ask</td>
<td>212337.00</td>
<td>Dispersion Ask</td>
<td>0.02</td>
</tr>
<tr>
<td>Depth First Limits (Bid+ask)</td>
<td>4541.50</td>
<td>Dispersion</td>
<td>0.02</td>
</tr>
<tr>
<td>Hidden Depth First Limits (Bid+ask)</td>
<td>453.00</td>
<td>Imbalance Dispersion</td>
<td>0.00</td>
</tr>
<tr>
<td>Depth 5 First Limits (Bid+ask)</td>
<td>27908.00</td>
<td>Bid Slope</td>
<td>4245.62</td>
</tr>
<tr>
<td>Hidden Depth 5 First Limits (Bid+ask)</td>
<td>8410.50</td>
<td>Ask Slope</td>
<td>4269.39</td>
</tr>
<tr>
<td>Total depth (Bid+ask)</td>
<td>387121.50</td>
<td>Slope</td>
<td>4302.42</td>
</tr>
<tr>
<td>Hidden Total depth (Bid+ask)</td>
<td>280698.00</td>
<td>Relative Spread</td>
<td>0.07</td>
</tr>
<tr>
<td>First Limits Imbalance</td>
<td>0.00</td>
<td>Buy-side Aggressiveness</td>
<td>-0.42</td>
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<tr>
<td>First limits Hidden Imbalance</td>
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<td>Sell-side Aggressiveness</td>
<td>-0.37</td>
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<tr>
<td>5 Best Limits Imbalance</td>
<td>0.01</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

"Quantities at the best bid (ask)" denotes the amount of shares displayed at the best bid (ask) limit. "Hidden" indicates the quantities that are not displayed. "Displayed Depth 5 Best Bid (Ask)" represents the total amount displayed at the five best bid (ask) limits. "Hidden Depth 5 Best Bid" denotes the total hidden amount at the five best bid (ask) limits. "Displayed Depth Bid (ask)" stands for the total amount of shares that is displayed on the bid (ask) side of the order book. "Hidden Depth Bid (ask)" only includes hidden quantities at the bid (ask) while "Total Depth Bid (ask)" is the sum of both displayed and hidden total depths at the bid (ask). "Depth First Limits (Bid+ask)" is the sum of displayed best bid and offer quantities. "Hidden Depth First Limits (Bid+ask)" only takes into account hidden quantities. Depth 5 First Limits (Bid+ask) and Hidden Depth 5 First Limits (Bid+ask) are computed across the five best price limits while Total depth (Bid+ask)" and "Hidden Total depth (Bid+ask)" consider the whole book. "First limits Imbalance" is the best limits displayed imbalance \( \text{Imbalance}_{i,t} = \frac{\text{Depth Bid}_{i,t} + \text{Depth Ask}_{i,t}}{2} \), where \( i \) denotes a given security and \( t \) a given interval. "First limits Hidden Imbalance" only considers hidden quantities. The same measures are computed for the five best limits ("5 Best Limits Imbalance" and "5 Best Limits Hidden Imbalance") as well as for the whole book ("Imbalance Displayed" and "Imbalance Hidden"). "Imbalance Total" is the total imbalance, summing displayed and hidden quantities.
Dispersion  Kang and Yeo (2008) present two measures to quantify the density of the limit order book, i.e. how limits are far from each other or from the quoted midpoint. One of these two measures is the dispersion:

\[ Dispersion_{i,t} = \frac{1}{2} \left( \sum_{j=1}^{n} w_{i,j,t} D_{st}^{Bid}_{i,j,t} + \sum_{j=1}^{n} w_{i,j,t} D_{st}^{Ask}_{i,j,t} \right), \]  

(1)

where, for security \( i \) and interval \( t \), \( w_{i,j,t} \) are the weights which are equal to quantities, offer and bid sizes, at the \( j \)th price limit normalized by the total depth of the five best limits, \( D_{st}^{Bid}_{i,j,t} = (\text{Price}_{Bid}^{i,j,t} - 1) / p_{0} \) and, \( D_{st}^{Ask}_{i,j,t} = (\text{Price}_{Ask}^{i,j,t} - 1) / p_{0} \). The midquote is used for the distance of the first best limits.

As Kang and Yeo (2008) outline, dispersion is small under fierce competition as each trader wants to gain price priority.

Slope  The slope is computed by averaging the price elasticity of quantities over the five best quotes. We calculate the slope of the book following Næs and Skjeltorp (2006), that is:

\[ SLOPE_{i,t} = \frac{DE_{i,t} + SE_{i,t}}{2}, \]  

(2)

where \( DE_{i,t} \) and \( SE_{i,t} \) are the demand and supply elasticities respectively and are computed as:

\[ DE_{i,t} = \frac{1}{5} \left( \frac{v_{B}^{i}}{p_{B}^{i} / p_{0} - 1} + \sum_{\tau=1}^{4} \frac{v_{B+1}^{i} / v_{B}^{i} - 1}{p_{B+1}^{\tau} / p_{B}^{\tau} - 1} \right). \]  

(3)

\[ SE_{i,t} = \frac{1}{5} \left( \frac{v_{A}^{i}}{p_{A}^{i} / p_{0} - 1} + \sum_{\tau=1}^{4} \frac{v_{A+1}^{i} / v_{A}^{i} - 1}{p_{A+1}^{\tau} / p_{A}^{\tau} - 1} \right). \]  

(4)

\( p_{B}^{\tau} \) and \( p_{A}^{\tau} \) are the prices, respectively at the bid and at the ask, appearing at the quote \( \tau \). \( p_{0} \) denotes the quoted midpoint. Finally, \( v_{B}^{i} \) and \( v_{A}^{i} \) are the natural logarithm of accumulated total share volume at the limit \( \tau \) respectively for the bid and the ask.\(^{12}\)

A steep slope represents an order book where volumes are concentrated at a given limit (low elasticity) while a gentle slope denotes an order book where volumes are not aggregated at a given limit (high elasticity). A steep slope also means that traders agree about the value of the security while a more gentle slope indicates that traders have different estimations of the fair price of the security.

\(^{12}\)By accumulated, we mean the sum of the quantities outstanding at that limit and the sum of all quantities outstanding at each better quote.
Trade Imbalance In order to calculate trade imbalance, we first have to sign transactions. Most empirical studies use Lee and Ready (1991)’s algorithm, which categorizes buyer and seller-initiated trades based on the position of the transaction price relative to the bid-ask spread. With our database, we are able to match for each transaction the orders that generate the trade. Then, the sign of the transaction is found by comparing the submission time of the orders, i.e. the last order being the determinant of the transaction. After that, we compute the total number of trades and quantities respectively for buyer and seller-initiated trades. With these variables, we compute two trade imbalance measures:

\[
\text{Imbalance}_N^{i,t} = \frac{N\text{Trades}_{Buy}^{i,t} - N\text{Trades}_{Sell}^{i,t}}{N\text{Trades}_{Buy}^{i,t} + N\text{Trades}_{Sell}^{i,t}} 
\]

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

\[
\text{Imbalance}_Q^{i,t} = \frac{Q_{Buy}^{i,t} - Q_{Sell}^{i,t}}{Q_{Buy}^{i,t} + Q_{Sell}^{i,t}} 
\]

where \( Q_{Buy}^{i,t} \) is the sum of the volume of all buyer-initiated trades occurring at the \( t^{th} \) interval for stock \( i \) and \( Q_{Sell}^{i,t} \) is the sum of the volume of all seller-initiated trades occurring at the \( t^{th} \) interval for stock \( i \).

These measures are computed separately for each interval and for each security. As we also dispose on the buyer and seller-initiated quantities and number of trades, we also include them in the analysis.

Aggressiveness We compute our aggressiveness measure separately for bid and ask sides. Our measure captures the number of aggressive orders, i.e. orders that consume liquidity and generate a trade, compared to the total number of orders that occurs during a given time interval:

\[
\text{Aggressiveness}_{B}^{i,t} = \frac{N\text{bAggressive}_{Buy}^{i,t} - N\text{bPassive}_{Buy}^{i,t}}{N\text{bAggressive}_{Buy}^{i,t} + N\text{bPassive}_{Buy}^{i,t}} 
\]

where \( N\text{bAggressive}_{Buy}^{i,t} \) is the total number of marketable buy orders occurring at the \( t^{th} \) interval for stock \( i \) and \( N\text{bPassive}_{Buy}^{i,t} \) is the total number of non-marketable buy orders occurring at the \( t^{th} \) interval for stock \( i \). A similar process is applied to sell orders.
4 Methodology

With our extended dataset containing HLOC prices, candlestick identification variables and liquidity proxies, we perform intraday event studies of liquidity behavior around candlestick structures. This original median-based event study methodology has been proposed by Boudt et al. (2012). Our event is the occurrence of a Doji. The null hypothesis of this event study is: The occurrence of Dojis is not related to a change in the liquidity proxy. The alternative hypothesis postulates that: The occurrence of Dojis is related to a positive or negative change in the liquidity proxy. We focus on an event window of $[-3,+3]$ containing seven observations: three observations before the signal, the time of the signal and three observations after the signal. This leads us to consider liquidity behavior 45 minutes before and after the apparition of the event. As we have different types of measures, we compute our abnormal measures depending upon the nature of the variables, as suggested by Boudt et al. (2012).

For spreads, imbalances and aggressiveness measures, we compute the abnormality as follows:

$$ Abnormal_{i,t,p} = Proxy_{i,t,p} - Median_{i,t,p}^{NE}, $$

where $Proxy_{i,t,p}$ is the analyzed liquidity proxy $p$ for stock $i$ for the time interval $t$ and $Median_{i,t,p}^{NE}$ is the median of the proxy $p$ for stock $i$ across all non-events occurring during the time interval $t$.

For the other measures, the calculation method is:

$$ Abnormal_{i,t,p} = \frac{Proxy_{i,t,p} - Median_{i,t,p}^{NE}}{Median_{i,t,p}^{NE}}, $$

where $Proxy_{i,t,p}$ is the analyzed liquidity proxy for stock $i$ for the time interval $t$ and $Median_{i,t,p}^{NE}$ is the median of the proxy $p$ for stock $i$ across all non-events occurring during the time interval $t$.

We apply these processes separately for each liquidity measure. We then aggregate the results obtained for each stock to form median patterns of liquidity behavior around each event and for each proxy. We choose the median as it is a more robust measure of central tendency, compared to the mean, as the distributions of liquidity proxies is heavily skewed. We analyze these patterns to check whether the abnormality is significantly different from zero. For this purpose, we use a standard non parametric sign test that does not need any assumptions about the shape of the distribution. Our null hypothesis postulates that the median of the abnormal measure equals zero. The alternative hypothesis postulates the

---

13 The 17 dropped pre-programmed structures have been included in the non-event sample as they are too frequent on intraday data and are not linked to any particular signal.
opposite. The statistic $M$ is computed as follows:

$$M = \frac{N_+ - N_-}{2},$$

where $M$ follows a binomial distribution, $N_+$ is the number of positive values and $N_-$ is the number of negative values. Values equal to zero are discarded.

We then analyze the p-values of each time interval of the window and check whether the differences are significant or not. If the p-value at the signal interval is significant, the structure is associated to a particular state of (il)liquidity. This signal may thus lead to a given configuration of the limit order book. If p-values are significant before the signal, the signal may be a response to a particular state of liquidity. If p-values are significant after the signal, a change in liquidity may correspond to a response to the signal.

5 Results

5.1 Overall picture

The general conclusion of the event study is that liquidity is higher when a Doji appears. Higher liquidity and fewer trades mean that a consensus build around the stock price and that buyers and sellers are not willing to trade at a different price level. A Doji is an indication of the presence of liquidity on each side of the book. The strategy of placing liquidity-taking orders at that moment in time is likely to cost less in terms of implicit costs. Liquidity providers are also numerous and, as a result, face more competition to supply liquidity. Interestingly, these results do not hold when jumps occur. As pointed out by Boudt et al. (2012), jumps are linked to illiquid states of the book. As a result, candlesticks in Harami positions would be related to liquidity while those in star positions (i.e. those with jumps) would be related to illiquidity. We test this hypothesis by comparing Harami Dojis and Doji Stars and confirm that Dojis in star positions are linked to less liquid states of the book than Harami Dojis.

The identification of the different types of Dojis also brings interesting information about the thickness of each side of the book. The Dragonfly Doji seems to be associated with more significant changes at the ask while the Gravestone Doji seems to rather affect the bid. These movements occur about 15 minutes before the occurrence of these Dojis, implying that the Doji itself is the consequence of depth dynamics. This result is confirmed by imbalances which show that the order book is imbalanced before these Dojis and comes back to equilibrium after the occurrence of the Dojis. These findings show that price

\footnote{We disentangle Bullish and Bearish parts of the configurations as they may have a totally different impact.}

\footnote{The drop in liquidity is effective in terms of spread, depth, dispersion and slope. These results are not reported here but are available upon request.}
dynamics are related to the state of the limit order book and confirm previous evidence of such a relationship, as in Kavajecz and Odders-White (2004) or Chordia et al. (2002).

We also observe disparities in trading activity. While buyer-initiated trades are less frequent and smaller in size when there is a Gravestone Doji, seller-initiated trades are less frequent and smaller in size when a Dragonfly Doji occurs. Buy orders are also more aggressive after a Dragonfly Doji while sell orders are more aggressive when a Gravestone Doji appears.

Our analysis finally shows that liquidity is negatively correlated with volatility as the High-Low is significantly lower while liquidity seems to be higher when a Doji appears.

5.2 Details

The spread significantly drops when a Doji appears. The recovery is fast after the trough in all cases. This is perfectly in line with what we expected as a Doji occurs when there is a consensus on the price. Traders seem to agree on a price for the stock and situate it inside the spread. A reduction of the spread confirms this consensus.

The quantities at the best bid are significantly higher, at a 1% confidence level, at the time of the signal. Quantities at the best bid are also significantly higher just before the apparition of a Gravestone Doji. The pattern at the ask is more noisy but indicates that the Dragonfly Doji presents a significantly higher best ask depth just before its occurrence. These Dojis seem to be the consequences of a particular state of liquidity in the limit order book as the pattern starts in t-1. The Gravestone Doji is likely to occur just after an accumulation of depth at the bid that does not translate into more trades. The Dragonfly Doji seems to appear when depth at the ask is higher and when there are less trades. The results of the bid side are confirmed if we consider the five best quotes. However it is not the case for the ask side. If we look at the sum of both sides, we also observe a peaking depth for the first quote and for the five best quotes. This is interesting as the reduction of the spread does not take place at the cost of a lower depth. Liquidity is higher over these two dimensions.

The Gravestone Doji presents a peak in hidden depth at the bid just before its apparition while depth at the ask peaks just before the Dragonfly Doji. These findings indicate that the position of the real body (near the highest or lowest price of the time interval) on the candle has a one-sided impact on depth, hidden or not.

We observe opposite patterns for the Dragonfly and Gravestone Dojis. Order book imbalance is significantly higher just before and when a Gravestone Doji appears while it is significantly lower before and when a Dragonfly Doji occurs. The simple Doji does not exhibit any particular pattern.

The dispersion drops when a Doji appears, meaning that the competition in the book is higher at that particular moment and that the limits are closer from each other. This is consistent with the idea of consensus. Traders are also competing to gain price priority implying a narrower spread. If we disentangle ask and bid sides, we observe that dispersion
is significantly lower at the bid for the Dragonfly Doji and at the ask for the Gravestone Doji while it remains unchanged on the other side. These findings are also coherent with the philosophy behind these two Dojis: a strong buying pressure creates the Dragonfly Doji while the Gravestone Doji appears after a selling rally. This is also in line with the one-sided impact that occurs for depth.

The slope significantly peaks at the moment of the Doji, on both supply and demand sides. These outcomes are consistent with the agreement on the price and with dispersion measures which show an increase in order book density when these signals appear.

The number of trades is lower when the signal appears, whatever the direction of the trade. After the signal, there is a quicker return to normal values for buy trades than for sell trades which remain low 15 minutes after the signal. Traders seem to delay buying and selling activities when these signals occur, even if liquidity is higher. As depth does not fall and even increase, there are more pending orders in the book. If we investigate the pattern for the Gravestone and the Dragonfly Doji and keeping in mind the philosophy behind these structures, we observe that buy trades are less numerous and less big for the Gravestone Doji compared to sell trades while we observe the opposite pattern for the Dragonfly Doji. Since, the Gravestone Doji appears when a selling rally follows a strong buying pressure, our results suggest that the selling rally does not come from an increased sell volume but from a decrease in buy volume. The opposite interpretation may be done for the Dragonfly Doji. Trade imbalances confirm these findings with a sharp drop for the Gravestone Doji and a significant peak for the Dragonfly Doji.

Sell orders are more aggressive when a Doji appears while buy orders are more aggressive only 15 minutes after the apparition of the Doji. Traders seem to place more marketable orders than they usually do, even if trading activity is lower. This suggest that buy traders become aggressive after the apparition of the Doji. Sellers react quicker than buyers do. The results also suggest that sellers are even more aggressive when the Doji is a Gravestone Doji and buyers seem to be even more aggressive in the case of a Dragonfly Doji. These results are at first sight not consistent with the lower trading activity around these structures. Yet, even if traders are less numerous, they are more aggressive but their aggressiveness does not erode depth at the opposite side.

Whatever the Doji structure, the High-Low volatility measure sharply falls when the signal appears. The level is significant at 1%. A Doji is thus linked to lower volatility, which is consistent with the consensus on the price implied by the Doji. This also indicates that high volatility Dojis, Doji with very long shadows, are very rare in our dataset.
Full, dotted and dashed lines represent the intra-window median pattern for the abnormal spread respectively for the Doji, the Dragonfly Doji and the Gravestone Doji. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.
Figure 4: Abnormal liquidity around Doji

(a) Spread

(b) Hidden five best limits Imbalance

(c) Dispersion : Bid side

(d) Dispersion : Ask side

(e) Dispersion

(f) Slope

Full, dotted and dashed lines represent the intra-window median pattern for each of the abnormal dispersion respectively for the Doji, the Dragonfly Doji and the Gravestone Doji. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.
Figure 5: Abnormal Number of trades around Doji

(a) Number of buy trades

(b) Number of sell trades

(c) Imbalance

(d) High-Low

(e) Buyers’s aggressiveness

(f) Sellers’s aggressiveness

Full, dotted and dashed lines represent the intra-window median pattern for this trading activity measure respectively for the Doji, the Dragonfly Doji and the Gravestone Doji. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis respectively at the 99%, 95% and 90% confidence levels.
6 Detecting the Presence of Informed Trading

As outlined in the previous section, when a Doji occurs, liquidity is higher and trading activity is lower. A possible explanation may be found in the microstructure literature on informed trading. As the intraday return is close to zero, Dojis seem to be related to moments without significant news. Informed traders should not be active in the market at these particular moments and the activity should be mainly driven by uninformed trades. If some information is made available, informed traders place their orders on the same side, generating high order and trade imbalances.

In the following analysis, we use the PIN indicator to check whether there is less informed trading when Dojis occur. The PIN measure, which quantifies the probability of information-based trading, has already been extensively discussed in the literature [Easley and O'Hara (1987), Easley and O'Hara (1992), Easley et al. (1996), Easley et al. (1997), Easley et al. (1998), Easley et al. (2002), Easley et al. (2008) and, Easley et al. (2012)]. There are many possible computations of the PIN measure. In this paper, we use the one provided in Easley et al. (1996), as it is usually done in the literature. We also use the factorization method of the log-likelihood function presented in Easley et al. (2008).

We compute the PIN associated to each day for each stock of our sample, as it is done in previous literature. We compare days with Dojis to days without Dojis and check whether days with Dojis exhibit a lower PIN. We count the number of Dojis per days and exclude days where there are more than 10 Dojis. Then, we conduct a non-parametric comparison Kruskal-Wallis test whose null hypothesis postulates that the mean scores of the subsamples are equal while the alternative hypothesis postulates that they are different. The results of the test are presented in Table 3.

\[16\] Details on the computation of the PIN are not presented here but are available in these papers.
Table 3: Non-parametric tests on the relationship between PIN and the number of Dojis per day.

<table>
<thead>
<tr>
<th>Number of Dojis</th>
<th>Count</th>
<th>Sum of Scores</th>
<th>Mean Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>28</td>
<td>79624</td>
<td>2843.714</td>
</tr>
<tr>
<td>1</td>
<td>117</td>
<td>278484.5</td>
<td>2380.209</td>
</tr>
<tr>
<td>2</td>
<td>283</td>
<td>671048.5</td>
<td>2371.196</td>
</tr>
<tr>
<td>3</td>
<td>487</td>
<td>1121739</td>
<td>2303.364</td>
</tr>
<tr>
<td>4</td>
<td>690</td>
<td>1614494</td>
<td>2339.846</td>
</tr>
<tr>
<td>5</td>
<td>732</td>
<td>1776181</td>
<td>2426.477</td>
</tr>
<tr>
<td>6</td>
<td>692</td>
<td>1672226</td>
<td>2416.512</td>
</tr>
<tr>
<td>7</td>
<td>546</td>
<td>1318298</td>
<td>2414.464</td>
</tr>
<tr>
<td>8</td>
<td>429</td>
<td>1075123</td>
<td>2506.113</td>
</tr>
<tr>
<td>9</td>
<td>309</td>
<td>807164.5</td>
<td>2612.183</td>
</tr>
<tr>
<td>10</td>
<td>198</td>
<td>519593</td>
<td>2624.207</td>
</tr>
</tbody>
</table>

This table presents the results of the non-parametric Kruskal-Wallis test which tests whether there are differences in the mean scores across the different subsamples, stratified by the number of Dojis per day. The first column denotes the 10 subsamples that correspond to a fix number of Dojis per day. The second column presents the number of days in the subsample. The third and fourth column respectively display the sum of scores and the mean scores of the Kruskal-Wallis test. The p-value associated to the Chi-square statistic of the test is equal to 0.0062 indicating that the null hypothesis is rejected, i.e. the scores of the 10 subsamples are significantly different from each other.

These results show that the mean score of the first row is higher than the nine other rows, indicating that the PIN is effectively higher when there is no Doji. This finding states that the lower trading activity occurring with Dojis may be due to less informed trading rather than less uninformed trading. This is consistent with the explanation we provided on information-based trading. The p-value of the test is also highly significant (0.0062).

7 Granger causality

In this section, we test the Granger causality between each liquidity proxy and a price movement variable that represents the occurrence of a Doji. This variable measures the absolute value of the difference between opening and closing prices and therefore characterizes the size of the real body, i.e. \( OC_t = |Close_t - Open_t| \), where \( Range_{Mid_t} = \frac{High_t + Low_t}{2} \). These tests enables us to check whether the Doji is a cause or consequence of a change in liquidity or both of these relationships (Bidirectional causality).

Toda and Yamamoto (1995) present a procedure to produce efficient and unbiased estimators of VAR models when the processes are integrated. This methodology helps to produce unbiased Granger causality tests, as it is similar to testing zero-restrictions on a given set parameters of a VAR specification. Their first step suggests that we check for the order of integration of the time series. We use stationarity tests, ADF and Phillips-Perron statistics, and conclude that all our time series were stationary. In this case, the Wald test statistic may be directly used instead of going through the process presented in Toda and Yamamoto (1995).
Our unrestricted VAR models are specified as follows:

\[
OC_t = \alpha_0 + \alpha_1 OC_{t-1} + \alpha_2 OC_{t-2} + \ldots + \alpha_p OC_{t-p} + \beta_1 L_{t-1} + \beta_2 L_{t-2} + \ldots + \beta_p L_{t-p} + u_t,
\]  

(11)

\[
L_t = \alpha_0 + \alpha_1 L_{t-1} + \alpha_2 L_{t-2} + \ldots + \alpha_p L_{t-p} + \beta_1 OC_{t-1} + \beta_2 OC_{t-2} + \ldots + \beta_p OC_{t-p} + u_t,
\]  

(12)

where \(L_t\) denotes one of the liquidity proxies that is investigated, \(p\) denotes the number of lags and \(u_t\) is an error term. The optimal lag length, \(p\), is determined through an optimization process based on Akaike’s Information Criterion (AIC).

The null hypothesis of Granger Causality tests characterizes non-causality, i.e. "\(L_t\) does not Granger-cause \(OC_t\)" for the first VAR model and "\(OC_t\) does not Granger-cause \(L_t\)" for the second one. This test consists in testing that all the \(\beta\) of the models equal 0.

We compute the F-test statistic as follows:

\[
S_1 = \frac{(RSS_r - RSS_u)/p}{RSS_u/(T-2p-1)} \sim F_{p,T-2p-1},
\]  

(13)

where \(RSS_r\) and \(RSS_u\) are the residual sums of squares respectively for the restricted and unrestricted models. \(T\) and \(p\) respectively denote the number of observations and the lag length. If the result of this test statistic is greater than the specified critical value, we reject the null hypothesis that specifies that there is no Granger-Causality.

An asymptotically equivalent test is specified as follows\(^{17}\):

\[
S_1 = \frac{T(RSS_r - RSS_u)}{RSS_u} \sim \chi^2(p).
\]  

(14)

Table 4 presents the results of the Granger causality tests, based on the asymptotically equivalent statistic. The first column indicates the p-value of the causality from the prices to the book while the second one displays the p-value from the book to the prices. The results show that the p-values are more significant from liquidity to HLOC prices meaning that HLOC prices dynamics are a response to a particular state of liquidity. This is consistent with the findings of Kavajecz and Odders-White (2004). The results are however not valid at the first limit and for displayed imbalances. We also observe a bidirectional causality for relative spread, dispersion and slope measures. In these cases, liquidity causes modifications of \(OC_t\) which in turns causes changes in liquidity.

\(^{17}\)When lagged dependent variables are included, the test is only valid asymptotically. Further information may be found in Lütkepohl (2006).
Table 4: Granger causality tests

<table>
<thead>
<tr>
<th></th>
<th>OC $\rightarrow$ Liquidity</th>
<th>Liquidity $\rightarrow$ OC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantities at the Best Bid</td>
<td>0.32754</td>
<td>0.51789</td>
</tr>
<tr>
<td>Quantities at the Best Ask</td>
<td>0.07330</td>
<td>0.56609</td>
</tr>
<tr>
<td>Quantities at the Best (Hidden)</td>
<td>0.23496</td>
<td>0.04968</td>
</tr>
<tr>
<td>Depth First Limits (Bid+ask)</td>
<td>0.00507</td>
<td>0.40818</td>
</tr>
<tr>
<td>Hidden Depth First Limits (Bid+ask)</td>
<td>0.88486</td>
<td>0.11814</td>
</tr>
<tr>
<td>Displayed Depth 5 Best Bid</td>
<td>0.05838</td>
<td>0.00015</td>
</tr>
<tr>
<td>Displayed Depth 5 Best Ask</td>
<td>0.10212</td>
<td>0.00010</td>
</tr>
<tr>
<td>Hidden Depth 5 Best Bid</td>
<td>0.24773</td>
<td>0.38075</td>
</tr>
<tr>
<td>Hidden Depth 5 Best Ask</td>
<td>0.28121</td>
<td>0.00003</td>
</tr>
<tr>
<td>Depth 5 First Limits (Bid+ask)</td>
<td>0.13820</td>
<td>0.00000</td>
</tr>
<tr>
<td>Hidden Depth 5 First Limits (Bid+ask)</td>
<td>0.72686</td>
<td>0.00005</td>
</tr>
<tr>
<td>First Limits Imbalance</td>
<td>0.39725</td>
<td>0.37709</td>
</tr>
<tr>
<td>First limits Hidden Imbalance</td>
<td>0.29162</td>
<td>0.00000</td>
</tr>
<tr>
<td>5 Best Limits Imbalance</td>
<td>0.15460</td>
<td>0.27104</td>
</tr>
<tr>
<td>5 Best Limits Hidden Imbalance</td>
<td>0.57127</td>
<td>0.00000</td>
</tr>
<tr>
<td>Dispersion</td>
<td>0.00780</td>
<td>0.00024</td>
</tr>
<tr>
<td>Slope</td>
<td>0.00017</td>
<td>0.00000</td>
</tr>
<tr>
<td>Relative Spread</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
</tbody>
</table>

This table presents the results of the Granger causality tests conducted for both directions, i.e. HLOC prices to liquidity and liquidity to HLOC prices. The values are the p-values returned by the asymptotically equivalent test. "Quantities at the best bid (ask)" denotes the amount of shares displayed at the best bid (ask) limit. "Hidden" indicates the quantities that are not displayed. "Displayed Depth 5 Best Bid (Ask)" represents the total amount displayed at the five best bid (ask) limits. "Hidden Depth 5 Best Bid" denotes the total hidden amount at the five best bid (ask) limits. "Depth First Limits (Bid+ask)" is the sum of displayed best bid and offer quantities. "Hidden Depth First Limits (Bid+ask)" only takes into account hidden quantities. "Depth 5 First Limits (Bid+ask)" and "Hidden Depth 5 First Limits (Bid+ask)" are computed across the five best price limits. "First limits Imbalance" is the best limits displayed imbalance ($\text{Imbalance}_{i,t} = \frac{\text{DepthBid}_{i,t} - \text{DepthAsk}_{i,t}}{\text{DepthBid}_{i,t} + \text{DepthAsk}_{i,t}}$, where $i$ denotes a given security and $t$ a given interval.). "First limits Hidden Imbalance" only considers hidden quantities. The same measures are computed for the five best limits ("5 Best Limits Imbalance" and "5 Best Limits Hidden Imbalance").

8 Robustness checks

In this section, we first investigate other types of dynamics by looking at Hammer-like configurations. Among Hammer-like structures, there are four structures that are characterized by a long shadow and a small real body.\footnote{A description of the presented structures is available in appendix.} The Hammer appears at the end of a downtrend and is made of a very small real body with (almost) no upper shadow and a very long lower shadow. The same structure may appear at the end of an uptrend but, in that case, it is called a Hanging Man. Inverting the shadows, i.e. the upper shadow becomes the lower shadow and vice-versa, we obtain an Inverted Hammer at the end of a downtrend or a Shooting Star at the end of an uptrend. This group of figures is interesting for many purposes. First, as these figures are said to be strong reversal structures, we expect a high correlation between changes in trade imbalances and the occurrence of these structures. Regarding liquidity, the results should be linked to previous findings on the
Gravestone and Dragonfly Dojis if the size of the real body has little impact. Indeed, a Dragonfly Doji may be a particular Hammer or Hanging Man while a Gravestone Doji may be a particular Inverted Hammer or Shooting Star, depending on their position on the price chart. If we observe differences between these structures, the size of the real body has an influence on liquidity behavior. We also expect a difference between bullish and bearish signals. Hammers and Inverted Hammers should present some similarities in their results as well as Hanging Men and Shooting Stars.

Then, we conduct the same analysis on candlesticks generated from 30-minutes and 60-minutes price series. By doing this, we create two new sets of events. This enables us to check whether our findings are the consequence of the choice of the time interval.19

8.1 The Hammer, the Hanging Man, the Inverted Hammer and the Shooting Star

To sum up, our results confirm the literature on Japanese candlesticks which states that Hammer-like configurations are strong reversal structures as they really break the intra-window pattern. We observe a higher liquidity just before the formation of the Hammer but this liquidity is not provided by more depth: the book is more dense and the spread is lower. The Hanging Man also shows similar outcomes but only after it has fully appeared on the chart. The results we discuss here may come from the configuration type, i.e. the size of the shadows. This is confirmed by the order imbalance results which show that the order imbalance is more in favor of the ask when the lower shadow is longer. Trading activity and aggressiveness measures are totally in line with the bearish or bullish reversal potential of the structure. We also observe lower volatility when these structures appear. The results are summarized in Table 3.

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19 All the graphs of this analysis are not presented here but are available upon request.
Table 5: Liquidity dynamics around Hammer-like configurations

<table>
<thead>
<tr>
<th></th>
<th>Hammer (625)</th>
<th>Inverted Hammer (175)</th>
<th>Hanging Man (469)</th>
<th>Shooting Star (91)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1</td>
<td>0</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>Spread</td>
<td>-3</td>
<td>-1</td>
<td>-2</td>
<td>-1</td>
</tr>
<tr>
<td>Bid depth</td>
<td>-3</td>
<td>-3</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Ask depth</td>
<td>+3</td>
<td>+3</td>
<td>1</td>
<td>+3</td>
</tr>
<tr>
<td>Imbalance</td>
<td>-3</td>
<td>-1</td>
<td>3</td>
<td>-3</td>
</tr>
<tr>
<td>Dispersion - Bid</td>
<td>+3</td>
<td>3</td>
<td>-1</td>
<td>-3</td>
</tr>
<tr>
<td>Dispersion - Ask</td>
<td>-3</td>
<td>3</td>
<td>-1</td>
<td>-3</td>
</tr>
<tr>
<td>Slope - Bid</td>
<td>+3</td>
<td>3</td>
<td>-1</td>
<td>-3</td>
</tr>
<tr>
<td>Slope - Ask</td>
<td>+3</td>
<td>-1</td>
<td>3</td>
<td>-3</td>
</tr>
</tbody>
</table>

This table presents the results obtained for the four Hammer-like structures for each liquidity measure. Each panel represents a [-1;+1] time window around the occurrence of the event. "+" and "-" signs denote positive and negative values for the abnormal measure. "++" and "--" signs denote bigger positive and negative variations. "+++" and "--" signs denote peaks and trough over the time window. The exponents denote the significance: 1 for 10% significance, 2 for 5% significance and 3 for 1% significance.

The results clearly indicate that liquidity is higher before the apparition of the Hammer and when the Hanging Man occurs. Liquidity seems also to be lower for the Inverted Hammer and the Shooting Star. Depth results suggest that changes in liquidity around these structures are only one-sided. These outcomes are similar to those of the Doji structures for which bid and ask quantities evolve differently depending on the position of the price on the candle (near the highest or lowest of the interval). The imbalance significantly drops just before a Hammer or a Hanging Man. The book seems to be imbalanced in favor of the ask side when these configurations appear, confirming previous results. Regarding dispersion, we observe that the Hammer present a sharp drop in dispersion at the ask just before its occurrence. This may suggest that the length of the shadows has also an impact on dispersion. A Hammer is likely to occur when the density of the ask side increases, i.e. price limits are closer from each other. This is consistent with an agreement on the minimum price and the end of the bearish rally. As expected, these structures exhibit changes in dispersion given their high reversal potential. Slope results are totally in line with dispersion results. Number of buy and sell trades, trade imbalance, aggressiveness and volatility measures are consistent with the literature on Japanese candlesticks and with the price pressures that drive these signals. There are thus not reported here.
8.2 Changing the time interval

Table 6 presents the number of occurrences for each structure for both 30-minutes and 60-minutes price series.

<table>
<thead>
<tr>
<th>Name</th>
<th>Bull/Bear</th>
<th>Count 30 minutes</th>
<th>Count 60 minutes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Doji</td>
<td>1</td>
<td>1511</td>
<td>1103</td>
</tr>
<tr>
<td>Bearish Dojistar</td>
<td>-1</td>
<td>34</td>
<td>34</td>
</tr>
<tr>
<td>Bullish Dojistar</td>
<td>1</td>
<td>43</td>
<td>36</td>
</tr>
<tr>
<td>Dragonfly Doji</td>
<td>1</td>
<td>254</td>
<td>198</td>
</tr>
<tr>
<td>Gravestone Doji</td>
<td>1</td>
<td>283</td>
<td>197</td>
</tr>
<tr>
<td>Hammer</td>
<td>1</td>
<td>268</td>
<td>225</td>
</tr>
<tr>
<td>Hanging Man</td>
<td>-1</td>
<td>209</td>
<td>159</td>
</tr>
<tr>
<td>Inverted Hammer</td>
<td>1</td>
<td>73</td>
<td>47</td>
</tr>
<tr>
<td>Shooting Star</td>
<td>-1</td>
<td>42</td>
<td>27</td>
</tr>
</tbody>
</table>

If we consider 30-minutes intervals, Doji structures display very similar liquidity, trading activity and volatility patterns over the whole window. The conclusions of 15-minutes price series are also applicable. This is also true for 60-minutes intervals even if the patterns are more noisy. The results support all our findings. This indicates that the relationships between price dynamics and liquidity are still significant for longer periods.

While looking at Hammer-like configurations, the conclusions of 30-minutes and 60-minutes intervals are very similar. Liquidity measures outcomes are much less significant for all measures, except for the dispersion and the slope whose conclusions remain unchanged. The spread still drops in case of a Hammer or a Hanging Man. We however observe fluctuations in the time window but without significance. Trading activity, aggressiveness and volatility measures display similar patterns as for 15-minutes price series but with much more noisy results. When intervals are longer, buying and selling pressures are always struggling, leading to more noise in the results.

To sum up, robustness checks results confirm the outcomes of our core study. The relationships between liquidity and price movements outlined in our study are thus applicable to time intervals up to 60 minutes. The Doji structures do not present different results. This confirms that the consensus on the price that appears on the chart also appears in the order book whatever the time interval from 15 to 60 minutes. These checks also confirms the "one-sided" impact that has been previously outlined. However, we also observe that Hammer-like configurations patterns are not as significant for longer intervals as for smaller ones.
9 Conclusion

In this paper, we investigate the relationship between price movements and liquidity in order to check whether it is possible to have a quick view on the state of liquidity in the limit order book by extracting information out of price dynamics. We focus on HLOC prices and the best known Japanese candlesticks charting method to characterize price dynamics. We use an event study methodology on 15-minute intervals in order to check how liquidity is affected by the occurrence of a given candlestick structure. After filtering for contagious effects and non-relevant events, we focus on traditional, Dragonfly and Gravestone Dojis which are the most influential single lines identified in the literature on Japanese candlesticks. These structures imply a consensus between buyers and sellers on the price of the security.

We look at several liquidity and trading activity measures: spread, depth, order imbalance, dispersion, slope, trade imbalance, aggressiveness and volatility. We disentangle bid and ask sides as we expect the book to be affected differently on each side. Liquidity seems to be higher over all dimensions when a Doji appears. We also find that there is less trading activity at that moment. Traders seem to agree on the price of the security and only a few of them is willing to hit the best opposite quote. A liquidity-taking order placed at that particular moment may thus incur a lower market impact, implying lower implicit costs.

We also outline that the position of the real body on the candle seems to have an impact on the behavior of liquidity. A Dragonfly Doji is likely to be linked to a bigger depth variation on the ask side and a Gravestone Doji to a bigger depth variation on the bid side just before their occurrences. This also enables us to argue on causality, as in Kavajecz and Odders-White (2004). These Dojis seem to be the answer to particular liquidity and trading activity dynamics. These results have to be further discussed as these structure may appear at the end of either an uptrend or a downtrend. It would be interesting to analyze how valid is this pattern if we disentangle bullish signals from bearish signals. Our results also show that Dojis appearing in star positions are linked to less liquid states of the order book than for traditional Dojis.

We further investigate what are the possible determinants of these outcomes by analyzing whether Dojis are negatively related to informed trading. No particular information events should arise as the return is close to zero. We therefore compute the PIN measure, which identifies the probability of informed trading during a given period, as proposed in Easley et al. (1996) and compare days with Dojis to days without Dojis. We find that the PIN is lower when Dojis occur and even more lower when the number of Dojis during the day increases. These findings are consistent with our previous outcomes as less informed trading naturally results in lower trading activity and higher liquidity.

We also conduct Granger causality tests which indicate that changes in liquidity proxies causes changes in the Close-Open range. This measure is similar to identify the occurrence of Dojis. We find that our price measure is a consequence of the state of liquidity and
is therefore an indicator of liquidity in the short run. The results are consistent with the findings of Kavajecz and Odders-White (2004) which show that prices help characterize the state of the limit order book.

We perform two types of robustness checks. We first look at other influential candlesticks configurations among the Hammer-like family. We observe interesting results on Hammers and Hanging Men which indicates that liquidity is higher before the occurrence of a Hammer and when a Hanging Man appears. However this increase in liquidity is not provided by more depth. Placing a large liquidity-taking order at the time of the Hammer may thus not necessarily cost less as a higher density does not provide lower market impact, if quantities do not increase. The Hanging Man, which looks like to the Hammer, i.e. small real body, no upper shadow and a very long lower shadow, presents similar outcomes but it only displays higher liquidity at the time of occurrence. Moreover, the Hanging Man appears after an uptrend, in opposition to the Hammer. This may suggest that the trend has little impact on liquidity. We do not investigate further trading activity and aggressiveness measures as they are totally in line with the buying and selling price pressures that drive the signals. Finally, our results confirm previous findings on Doji structures which suggest that the position of the real body in comparison to the highest and lowest price of the interval has a one-sided influence on liquidity. When the body is near the highest, there seem to be more liquidity at the ask and conversely, liquidity is higher at the bid when the real body is near the lowest price of the time interval. This is even more true when the real body is short, i.e. in case of Dojis.

We then change our interval length in order to validate our results for longer time intervals. With 30-minutes and 60-minutes price series, the results are very similar for Doji structures. Hammer-like configurations do not present very different patterns but display much less significance, except for dispersion and slope measures. The patterns are not as significant for this second category. As expected, all the patterns contain more noise, given the longer period taken into consideration, but still outline a relationship between price dynamics and our measures.

All our results suggest that market participants may benefit from candlesticks analysis as a way to better time their order submissions and improve their transaction costs management. Dojis are likely to summarize the information content of the four liquidity dimensions present in the limit order book. All things being equal, placing a marketable order when a Doji appears is likely to lead to better order execution. The magnitude of the potential gains on transaction costs and the economic significance as well as the resulting optimal execution are beyond the scope of this analysis and are left for further research.

References


The Doji presents a closing price (almost) equal to the opening price. It occurs when there is an agreement on the fair value of the asset and where markets are 'on a rest'. The Doji indicates the end of the previous trend. The most traditional Doji is a ‘plus’ sign but Dragonfly and Gravestone Dojis are also frequent. A Dragonfly Doji appears when a strong buying pressure directly follows a strong selling pressure implying an upper shadow almost equal to zero. The Gravestone Doji occurs when the buyers have dominated the first part of the session and the sellers, the second one. The Hammer and the Hanging Man appear when sellers dominate the first part of the session and buyers, the second part. By construction, they present a long lower shadow and almost no upper shadow. The Hammer occurs at the end of a downtrend while the Hanging Man puts an end to an uptrend. The Inverted Hammer and the Shooting Star are made with a small real body, a very long upper shadow and almost no lower shadow. The Inverted Hammer appears at the end of a downtrend and the Shooting Star occurs at the end of an uptrend. These structures are said to be strong reversal ones.