Implicit transaction cost management using intraday price dynamics

Paolo Mazza[a] Mikael Petitjean[b]

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Abstract

Using the Exchange Liquidity Measure, we show that implicit transaction costs exhibit intraday regularities around specific price change signals for a sample of European blue chips publicly quoted on Euronext. Not only transaction costs follow a reverse J-shape throughout the day, but they also decrease significantly around specific patterns of price dynamics. By focusing on these signals during the trading day, liquidity traders may detect intraday windows of opportunities during which implicit transaction costs are lower.

JEL Classification: G14, G10

Keywords: XLM, Transaction costs, Liquidity, Execution

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[a] IESEG School of Management (LEM UMR 9221 CNRS). E-mail: p.mazza@ieseg.fr.
[b] IESEG School of Management (LEM UMR 9221 CNRS) and Louvain School of Management (LFIN Pole of IMMAQ, UCLouvain). E-mail: m.petitjean@ieseg.fr.
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1 Introduction

The microstructure of financial markets has raised a considerable amount of interest in both industry and academia. Since the seminal work of Demsetz (1968), transaction costs have been at the core of most studies in market microstructure. While there are explicit transaction costs which can be observed and known ex-ante (such as fees), investors also face implicit transaction costs, i.e. transaction costs that cannot be observed beforehand and are therefore subject to strong uncertainty. In this paper, we attempt to better anticipate the rise and fall of implicit transaction costs across time.

Past studies on liquidity dynamics across time have shown that intraday liquidity exhibits patterns and regularities. For instance, Biais et al. (1995) show that liquidity is influenced by order submission strategies in a rather systematic way. Other papers provide strong evidence of the existence of intraday seasonalities that affects liquidity (Admati and Pfleiderer, 1988; Chan et al., 1995; Hamao and Hasbrouck, 1995). A significant J or U-shape pattern for intraday liquidity is typically identified. Disregarding these regularities for execution purposes can be very costly, for example in the context of rebalancing needs. Our study builds on these findings with the ultimate goal of improving transaction cost management.

Research in market microstructure has also shown that valid liquidity proxies can be inferred from asset price series that are widely and easily available, as opposed to trade and order book data. For example, Roll (1984) proposes an estimate of the bid-ask spread based on daily high and low prices. Lesmond et al. (1999) also develop a liquidity proxy based on the occurrence of zero returns. More recently, Detollenaere and Mazza (2014) find that particular High-Low-Open-Close (HLOC) price dynamics help traders find pockets of liquidity. More specifically, they look at the occurrence of particular price changes as characterized by Japanese candlestick configurations and explain how they can help solve the trader's dilemma, i.e. the decision to split orders to incur lower market impact costs at the risk of higher market timing costs. These two components are essential in the management of trading costs. They find that these patterns in price changes fail to predict future returns and cannot therefore help reduce market timing when split orders are submitted. However, they show that market impact costs are lower when there is a consensus on the fundamental value of the security, as characterized by particular structures, such as the Doji configurations. Hence, easy-to-observe price dynamics may help find intraday periods of time during which transaction costs are lower. These outcomes are also consistent with previous theoretical models such as Chakravarty and Holden (1995) and Bloomfield et al. (2005), as well as empirical evidence such as Kavajecz and Odders-White (2004) and Mazza (2015). Kavajecz and Odders-White (2004) show that price dynamics, easily characterized by candlesticks, are expected to be related to modifications in the state of the limit order book and with the supply of liquidity while Mazza (2015) finds that liquidity is higher when some particular candlestick structures occur, indicating that a relationship does exist between limit order book variables and HLOC price movements.

We extend the existing literature by measuring implicit transaction costs around specific patterns of price variations while controlling for intraday liquidity seasonalities. We focus on consensus configurations as characterized by Dojis. This is motivated by both the theoretical and empirical findings in the existing literature suggested that only price consensus patterns matter when it comes to evaluating liquidity. For example, Mazza (2015) and Detollenaere and Mazza (2014) do not find significant results for other price configurations, confirming the experimental evidence provided by Bloomfield et al. (2005) on the behavior of informed traders.

In order to assess implicit transaction costs, we use the Exchange Liquidity Measure (XLM hereafter) which characterizes illiquidity conditions in the market by simulating order execution at each minute of trading (Gomber et al., 2015). To the best of our knowledge, no previous study on liquidity dynamics has assessed the information content of the XLM measure around price change signals. There are studies dealing with liquidity around various configurations of price dynamics, but liquidity measures are only investigated in turn. For example, Mazza (2015) analyzes various liquidity dimensions around specific configurations of price dynamics. Ex-ante liquidity proxies are captured by spread, depth, imbalance and slope measures. Volatility and trade dynamics are also taken into account. Unfortunately, there is no consensus in the literature on the best indicator to be used for each of the above-cited dimensions, as pointed out in Goyenko et al. (2009) and Aitken and Comerton-Forde (2003). Moreover, there is no attempt in this analysis at combining various liquidity dimensions into a more comprehensive liquidity indicator.

Even for transaction costs, there is no consensus on the best proxy to be used. For example, Detollenaere and Mazza (2014) study costs around specific configurations of price dynamics, but they only focus on the market timing and market impact costs in the specific framework of splitting order strategies. In contrast, we focus on the XLM measure which does not suffer from these drawbacks since it encompasses directly all the key liquidity dimensions.

Gomber et al. (2015) are the first to advocate the use of the XLM as a better proxy for transaction costs. These authors stress that the XLM provides a clear indication on the cost of pre-sized orders, a feature which is not covered by any other mainstream liquidity or transaction cost proxies. As they indicate, the use of the XLM measure for different order sizes provides 'a more complete analysis of the execution cost than is obtainable by only considering spread and depth data (as is done in many prior studies of resiliency).'[1]

Using market data on a sample of European blue chips included in three national indexes, we study the impact of particular price variations on the XLM. We focus on the most insightful price dynamics structure, i.e. the Dojis which characterize market consensus about a given security price. Confirming the experimental evidence provided by Bloomfield et al. (2005) on the behavior of informed traders, Mazza (2015) identifies a relationship between liquidity dynamics and specific price configurations, called the Dojis. Only Doji configurations seem to have a direct relationship to liquidity. This finding is confirmed by Detollenaere and Mazza (2014) who do not find any significant results for other patterns.

In this study, we estimate a fixed-effect panel regression model in which we use three different versions of the XLM as dependent variable; we correct for intraday transaction cost seasonality; and we add dummies for the occurrence of the above-mentioned Doji price change signal. Our main findings suggest that the XLM is lower when Dojis occur, suggesting that liquidity is higher and transaction costs lower when there is little if no price variation. We also find that transaction costs follow a reverse J-shape, implying that liquidity is lower shortly after the opening of the trading session. These results are most useful to practitioners who look for enhanced trading execution strategies. By focusing on these particular signals during the trading day, they may find windows of opportunities during which transaction costs are lower.

[1] On page 55, they write: 'In a liquid market there is an almost constant flow of (predominantly small) limit orders. After a liquidity shock a new limit order can quickly restore a small spread. If the new limit order is small, however, the order book remains thin. Consequently, assessing the resiliency of the market by considering the quoted spread may lead to an overstatement of the true liquidity in the market. The XLM measure, in contrast, is a summary measure of the total liquidity in the book and is thus better suited to address the issue of resiliency. A further advantage of the XLM measure is that it allows to assess the liquidity on the bid and the ask side of the market separately. The spread, in contrast, is by definition a symmetric measure.'

The remainder of the paper is organized as follows. Section 2 describes the sample, introduces price patterns and discusses the exchange liquidity measure. Section 3 is devoted to the presentation of the event study methodology and its results. Section 4 presents the panel regressions and documents their findings. The final section concludes.

2 Sample and Variables

We use Euronext market data on 81 stocks included in three national indexes, i.e. BEL20, AEX and CAC40. We have tick-by-tick data for 61 trading days from February 1, 2006 to April 30, 2006. The use of this dataset presents two key advantages. First, we have information on the full order book, including undisclosed data on hidden orders and market members' IDs. By using these IDs, we are able to disentangle buyer-initiated and seller-initiated trades without any error margin. In many market microstructure studies, the Lee and Ready (1991) algorithm is used to categorize buyer and seller-initiated trades. Although this algorithm has proved to be relatively efficient, misclassification still occurs. In our dataset, there is none since we know the order that initiates the transaction. Second, we avoid the volume shift and market fragmentation that have been occurring since the implementation phase of MiFID. As today's trading environment is much more decentralized than before, more recent datasets are often less representative and less reliable. Our sample of data includes all trading activities on these stocks, contrary to most recent studies in which there is insufficient information about the level of trading activity that prevails on the competing Multilateral Trading Facilities (MTFs) and dark pools.

2.1 HLOC price dynamics and Dojis

For these 81 stocks we rebuild High-Low-Open-Close prices over the whole sample period. As tick data are not suited for HLOC analysis, we use 15-minute intervals which leads to 34 intervals a day. Such an interval length offers the best trade-off between information and noise. While intraday trends must definitely be taken into account, it is also important to avoid noise in price dynamics resulting from non-trading intervals. We obtain a total of 167068 records, i.e. 81 firms during 61 days with 34 intervals per day.

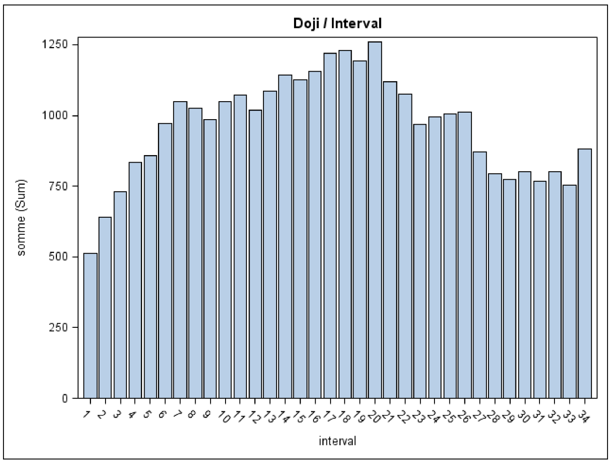
Among the different signals of price dynamics, we focus on the information content of Dojis for detecting potential patterns in implicit transaction cost variations. A Doji appears when the closing price is (almost) equal to the opening price.[2] We observe different types of Doji. The most frequent Doji looks like a "+" sign, i.e. it has no body and almost equal shadows. If both closing and opening prices are equal to 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 corresponds to the lowest price of the interval. Although Dojis are not helpful in predicting future returns (Duvinage et al., 2013), they constitute one of the most highly regarded structures in the HLOC literature. Recent research evidence has suggested that Dojis are related to periods of time during which liquidity is abundant in the order book. Mazza (2015) argues that the Doji is a consensus configuration during which informed traders do not trade aggressively and supply liquidity. In accordance with Bloomfield et al. (2005), informed traders become dealers when a Doji occurs because the fundamental value of the security is more likely to be located inside the spread. Detollenaere and Mazza (2014)

[2] Candlestick books refer to it as *the magic Doji* (Nison, 1991, 1994; Morris, 1995). A description of the patterns of price dynamics used in the paper is available in the appendix.

even show that Doji-based execution strategies bear significantly lower transaction costs than random ones, pointing to significant reductions in transaction costs.

We first examine the occurrence of Doji configurations across the day. Figure 1 shows that the distribution of Dojis is roughly uniform with the most significant peaks occurring during lunch time, potentially resulting from quiet trading. Doji structures occur most infrequently during the first couple of intervals of the day. This may be explained by the rather stronger level of volatility that typically characterizes the early trading activities of the day. Table 2.1 presents the number of each structure which is identified in our dataset.

Figure 1: Doji by interval



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

Table 1: Number of signals

Structure	Count
Doji	29828
Dragonfly Doji	7071
Gravestone Doji	7557

2.2 Implicit transaction costs and the XLM measure

We focus on the Exchange Liquidity Measure (XLM) developed by Gomber et al. (2015) that measures the cost of a round trip trade for an order of a given size. The XLM is computed for every stock i and day d at each minute m in interval t, i.e. $XLM_{i,d,m,t}$. It requires treating simulated buy and sell orders separately such that

$$XLM^{V}_{i,d,m,t,b} = \frac{AEP^{V}_{i,d,m,t,b} - M_{i,d,m,t}}{AEP^{V}_{i,d,m,t,b}} * 10000, \tag{2.1}$$

$$XLM^{V}_{i,d,m,t,s} = \frac{M_{i,d,m,t} - AEP^{V}_{i,d,m,t,s}}{AEP^{V}_{i,d,m,t,s}} * 10000, \tag{2.2}$$

where $AEP^{V}_{i,d,m,t,b}$ and $AEP^{V}_{i,d,m,t,s}$ respectively denote the average execution price of a buy order and sell order, of a size V, with M being the midquote. We simulate three different order sizes V: EUR 25000, 50000 and 100000. The XLM measure is then aggregated for all orders such that $XLM_{i,d,m,t} = XLM_{i,d,m,t,b} + XLM_{i,d,m,t,s}$. Note that the XLM is computed in basis points.

Summary statistics of the XLM are provided in Table 2 for each stock index and simulated order size. N represents the number of fully executed orders at the five best limits. The mean, the median and the standard deviation of the XLM are computed by pooling all the 1-minute XLMs across intervals, days, and stocks of the same stock exchange. As expected, both the mean and median of the XLM measure increase with the simulated order size on each of the three exchanges, while the number of fully executed orders decreases with it. When we compare the three exchanges in terms of execution costs, we clearly observe that the Paris Bourse offers the cheapest transaction costs irrespective of the simulated order size, while the Brussels Stock Exchange seems to be more expensive.

Table 2: Descriptive statistics for the XLM variable

AEX	N	$Mean$	$Median$	STD
XLM25	686591	10.03	8.30	7.19
XLM50	686413	10.87	8.66	7.75
XLM100	683987	12.55	10.24	8.83
BEL20				
XLM25	441770	14.69	11.23	11.44
XLM50	440617	16.61	13.35	12.63
XLM100	427875	20.06	16.29	14.63
CAC40				
XLM25	1213838	8.52	6.84	5.49
XLM50	1210871	9.23	7.49	6.03
XLM100	1193909	10.57	8.82	6.84

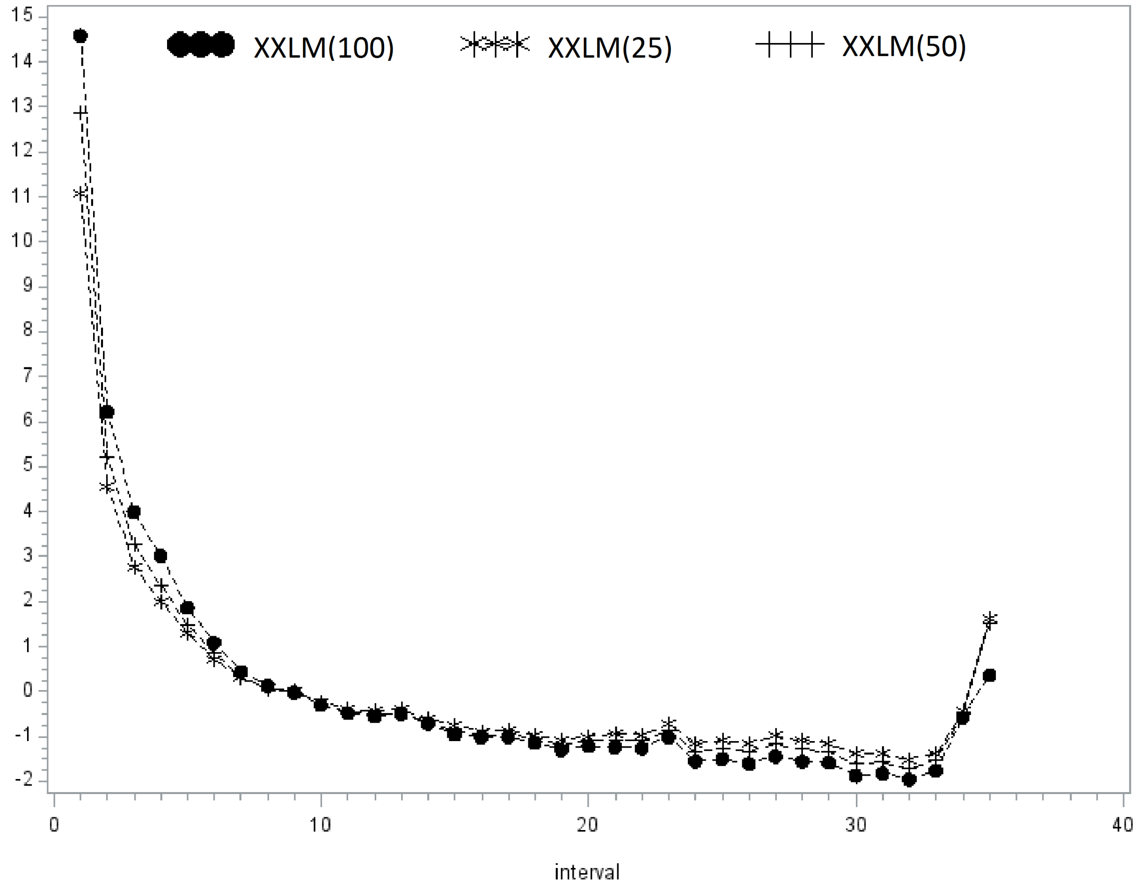
The XLM is computed every minute for each stock index by using all the N fully executed orders at the 5 best limits for three different order sizes (EUR 25K, 50K, and 100K). The $Mean$, $Median$ and STD are based on the pooling of all the 1-minute XLMs across intervals, days, and stocks of the same index.

Figure 2 shows strong intraday seasonality in the XLM. Our results reveal a reverse-J shape, with a lower level of liquidity during the morning, as evidenced by higher transaction costs after the opening of the trading session. To reveal such a pattern, we do not simply pool all 1-minute XLMs across intervals, days, and stocks.[3] First, we aggregate the 1-minute XLMs within 15-minute intervals, which gives $XLM_{i,d,t} = \sum_{m=1}^{15} XLM_{i,d,t,m}/15$. Second, we compute a mean-centered value for $XLM_{i,d,t}$ and then compute a simple average of the demeaned XLM variable across each of the 61 trading days, which gives $XXLM_{i,t} = \sum_{d=1}^{61} (XLM_{i,d,t} - XLM_{i,t})/61$ where $XLM_{i,t} =$

[3] In contrast to Goodfellow et al. (2010), we do not compute the mean across the whole sample in order to control for the intraday seasonality in the XLM, which is oubvious on Figure 2.

$\sum_{d=1}^{61} XLM_{i,d,t}/61$. Finally, we aggregate the cross-day average of the demeaned XLM variable across stocks, which gives $XXLM_t = \sum_{i=1}^{81} XXLM_{i,t}/81$. We therefore end up with 34 measures of XLM since there are 34 intervals of 15 minutes in a trading day.

Figure 2: Demeaned XLM value for each 15-minute interval of the trading day



$XXLM_t$ is computed for each 15-minute interval t during the trading day. It is computed in three steps. First, we aggregate the 1-minute XLMs within 15-minute intervals. Second, we compute a mean-centered value before computing a simple average of the demeaned XLM variable across each of the 61 trading days. Third, we aggregate the cross-day average of the demeaned XLM variable across stocks. Each plotted line refers to a different order size, i.e. EUR 25K, 50K and 100K.

3 Intraday Event Study

We first conduct an event study to characterize the evolution of the XLM measure around different types of Dojis at the intraday level. An event is represented by the occurrence of one of the following patterns of price dynamics: Doji, Dragonfly Doji or Gravestone Doji. The event window contains seven intervals: the interval during which the event occurs, as well as three intervals before and after it.

We first compute $XLM_{i,d,t} = \sum_{m=1}^{15} XLM_{i,d,t,m}/15$ and then obtain $XLM_{i,t} = \sum_{d=1}^{61} XLM_{i,d,t}/61$. To compute the abnormal value of the XLM for stock i at interval t, we proceed as follows:

$$AXLM_{i,t} = \frac{XLM_{i,t} - Median_{i,t}^{NE}}{Median_{i,t}^{NE}},$$

where $Median_{i,t}^{NE}$ is the median of the XLM for stock i across all non-events occurring during the same time interval t (within which the non-events have been pooled across minutes and days before). The use of the median is justified given the skewed and leptokurtic distribution of most liquidity measures. Following Boudt and Petitjean (2014) as well as Mazza (2015), we replicate this procedure for the three simulated order sizes and aggregate all events across stocks to form graphs for each of these sizes (see Figure 3 below).

We also check whether the event window contains no more than one pattern of price dynamics to avoid contamination: If two events were to occur within the [-3,+3] window, the after-effects of the first event would much probably affect observations near the second event. Finally, we test whether the AXLM is significantly different within the [-3,+3] window. As in Mazza (2015), we use a standard non parametric sign test which does not require any assumption about the shape of the distribution. The null hypothesis specifies that the abnormal measure has a median equal to zero. The alternative hypothesis postulates the opposite. The test statistic M is computed as: $M = \frac{N_+ - N_-}{2}$, where M follows a binomial distribution, N_+ is the number of positive values and N_- is the number of negative values.

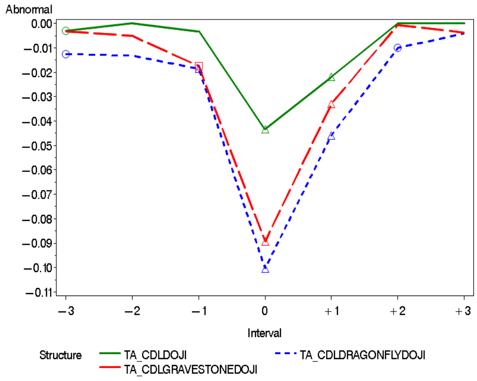
We apply this event study methodology to compute the XLM based on the three simulated order sizes: EUR 25K, 50K, and 100K. As a robustness check, we also use the median (instead of the mean) to aggregate the 1-minute XLMs within the same 15-minute interval, which gives $XLM^*_{i,d,t}$ corresponding to the average between the 7th and 8th largest XLM value within the 15-minute interval.

Results on Figure 3 clearly indicate that the XLM measure sharply drops when any of these structures appears, irrespective of the order size. We also identify some persistence in liquidity after and before these events, as evidenced by the level of significance of liquidity variations around them. These findings are insensitive to the use of the median (instead of the mean) to pool the 1-minute XLMs within the 15-minute interval. The Gravestone Doji ranks first in terms of its information content for implicit transaction cost management. Submitting liquidity-demanding orders when such configurations of price dynamics occur leads to significantly lower transaction costs.

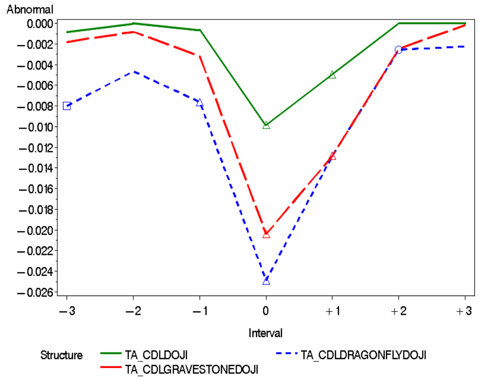
4 Panel Regression Analysis

We also test the usefulness of these configurations of price dynamics for implicit transaction cost management by estimating a fixed-panel regression model for each of the three simulated order sizes.

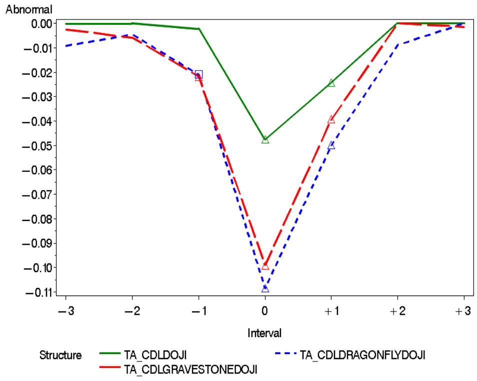
Figure 3: Abnormal XLM around Dojis



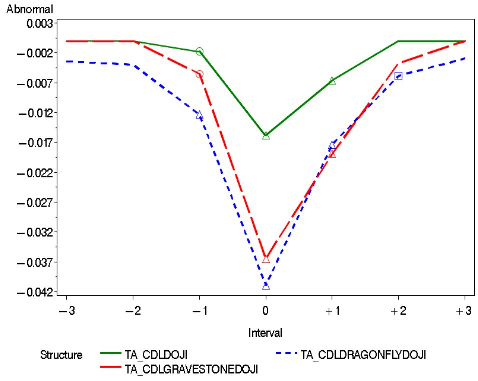
(a) AXLM25 - Mean



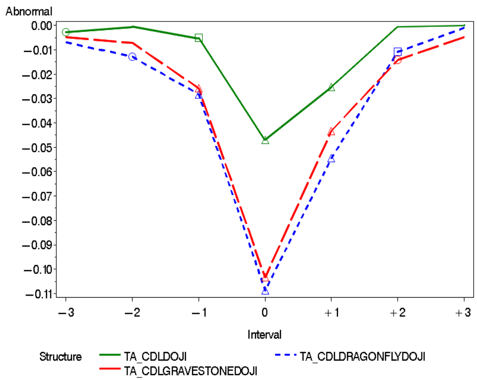
(b) AXLM25 - Median



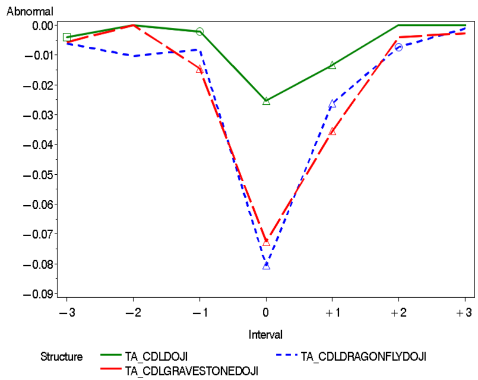
(c) AXLM50 - Mean



(d) AXLM50 - Median



(e) AXLM100 - Mean



(f) AXLM100 - Median

Full, dotted and dashed lines represent the intra-window pattern of the abnormal XLM for different order sizes around the Doji (TA_CDLDOJI), the Dragonfly Doji (TA_CDLDRAGONFLYDOJI), and the Gravestone Doji (TA_CDLGRAVESTONEDOJI) respectively. Triangles (△), squares (□), and circles (○) indicate a rejection of the null hypothesis at the 99%, 95% and 90% confidence levels respectively.

The dependent variable is $DXLM_{i,t}$ for a stock i at interval t. As a reminder, we first compute $XLM_{i,d,t} = \sum_{m=1}^{15} XLM_{i,d,t,m}/15$ and then compute an average across days such that $XLM_{i,t} = \sum_{d=1}^{61} XLM_{i,d,t}/61$. As a robustness check, we also compute another variant based on the median in the interval; we call it $XLMM_{i,d,t}$ for which we also compute an average across days. We use the first difference of these variables because autoregressive coefficients are close to 0.8 in almost every case, pointing to high persistence in the dependent variable.[4]

We include dummy variables to capture the effect of the Doji structures on implicit transaction costs. The dummy is equal to 1 when the structure occurs during interval t (meaning the structure starts at the end of the $(t-1)^{th}$ interval and ends at the end of t^{th} interval) and 0 otherwise.

In line with Kavajecz and Odders-White (2004) and Wang et al. (2012) who point to higher liquidity supply around technical signals, we expect $XLM_{i,t}$ to be lower when one of these structures occur, implying a negative sign for the dummy variables. This is also suggested by Mazza (2015) who follow Bloomfield et al. (2005) in showing that this type of structures is associated with a higher level of liquidity in the order book. When Dojis occur, a market consensus is reached, with the fundamental value being potentially located inside the bid-ask spread, leading in turn informed traders to supply liquidity in the order book. Detollenaere and Mazza (2014) also argue in favor of such a relationship after examining two components of transaction costs, i.e. market impact and timing costs.

The first fixed effects model that we test is specified as follows:

[4] We do not report the tables to save space but they are available upon request.

$$DXLM_{i,t} = \beta_0 + \beta_1 D_{i,t} + \sum_{i=2}^{81} \alpha_i S_i + \varepsilon_{i,t},$$

where $XLM_{i,t}$ is the implicit transaction cost measure computed at time t for stock i and $D_{i,t}$ is a dummy equal to 1 if any of the (Classical) Doji, Gravestone Doji and Dragonfly Doji occurs at time t for stock i. $\sum_{i=2}^{81} \alpha_i S_i$ denotes the stocks' fixed-effects.

We test another model specification by including three dummies, i.e. one dummy for each type of Dojis. The goal is to test whether the information content for transaction cost management differs between them. The specification is:

$$DXLM_{i,t} = \beta_0 + \beta_1 CL_{i,t} + \beta_2 GR_{i,t} + \beta_3 DR_{i,t} + \sum_{i=2}^{81} \alpha_i S_i + \varepsilon_{i,t},$$

where $CL_{i,t}$ is a dummy equal to 1 if the (Classical) Doji occurs at time t for stock i; $GR_{i,t}$ is a dummy equal to 1 if the Gravestone Doji occurs at time t for stock i; and $DR_{i,t}$ is a dummy equal to 1 if the Dragonfly Doji occurs at time t for stock i.

These models are estimated with the clustering approach that controls for within cluster correlation, following the recommendations of Petersen (2009). Estimating panel models with traditional estimation methods, such as OLS, results in inaccurate standard errors that significantly affect the outcomes. As outlined by Petersen (2009), this method produces unbiased standard errors when there is a firm-specific effect and is superior to White, Newey-West, and Fama-MacBeth correction methods.

We also analyze the relationship between the XLM measure and lagged signals in order to check whether the XLM is actually lower after a Doji structure has occurred. According to Detollenaere and Mazza (2014), Dojis may indeed have an impact on transaction costs during the next 15 minutes.

Finally, we test the sensitivity of our results to the inclusion of several classical control variables identified in the literature. We add the market capitalization of each stock at the beginning of year i (LNC_i), the stock return at time t (RET_t), the change in the number of buy trades (DNB_t) and sell trades at time t (DNS_t), as well as a lagged value of the dependent variables (Y_{t-1}) to control for any remaining autocorrelation dynamics.

Table 3 show the results for the contemporaneous panel regressions. As expected, we find a significant negative relationship between Dojis and XLM. When considering all dojis together (as captured by D_t), we obtain a p-value below 1% in 11 cases out of 12. The use of the mean or the median in the computation of the XLM has no impact on the statistical significance of the results. The inclusion of the five control variables does not change the significance neither. Results are also robust to the order sizes. From an economic point of view, the ceteris paribus effect of a doji on liquidity is nevertheless around five times lower when the median is used to compute the XLM in an interval (instead of the mean). When dojis are classified in three different categories, we find that the most and least insightful dojis are the classical doji (i.e. the '+' signal) and dragonfly doji (i.e. the 'T' signal) respectively. All these results are clearly consistent with the fact that liquidity improves in the limit order book when such patterns of price dynamics occur, in line with Mazza (2015) or Kavajecz and Odders-White (2004).

From an economic perspective, the occurrence of dojis has a positive and significant effect as well. For example, we see in column 2 that the average XLM variation decreases by around 2 to 3 basis points when there is consensus on prices, as characterized by the dojis. The economic significance is lower when the median XLM variation is considered, close to 0.5 basis points. This difference may be explained by the improvement in liquidity being concentrated around a few minutes within the 15-minute interval, possibly

Table 3: Panel regressions results - Contemporaneous signals

	D_t	CL_t	DR_t	GR_t	LNC_i	RET_t	DNB_t	DNS_t	Y_{t-1}
DXLM100	-0.031^{***}								
DXLM100	-0.034^{***}				-0.002	0.017	0.000	-0.001	-0.314^{***}
DXLM100		-0.037^{***}	0.005	0.024^{**}					
DXLM100		-0.039^{***}	-0.003	0.024^{**}	-0.002	0.017	0.000	-0.001	-0.314^{***}
DXLM50	-0.027^{***}								
DXLM50	-0.034^{***}				-0.016	-0.005	0.000	-0.001	-0.309^{***}
DXLM50		-0.034^{***}	0.006	0.026^{**}					
DXLM50		-0.040^{***}	-0.000	0.025^{**}	-0.016	-0.005	0.000	-0.001	-0.309^{***}
DXLM25	-0.021^{***}								
DXLM25	-0.031^{***}				-0.026^{*}	-0.023	0.001	-0.001	-0.305^{***}
DXLM25		-0.028^{***}	0.004	0.023^{**}					
DXLM25		-0.036^{***}	-0.002	0.023^{**}	-0.026^{*}	-0.023	0.001	-0.001	-0.305^{***}
DXLMM100	-0.006^{***}								
DXLMM100	-0.007^{***}				-0.006^{***}	0.024	0.000	-0.000	-0.243^{***}
DXLMM100		-0.007^{**}	0.000	0.003					
DXLMM100		-0.007^{**}	-0.001	0.001	-0.006^{***}	0.025	0.000	-0.000	-0.243^{***}
DXLMM50	-0.005^{**}								
DXLMM50	-0.007^{***}				-0.008^{***}	0.029	0.001	-0.000	-0.259^{***}
DXLMM50		-0.006^{**}	0.000	0.004					
DXLMM50		-0.007^{**}	-0.003	0.001	-0.008^{***}	0.029	0.001	-0.000	-0.259^{***}
DXLMM25	-0.003								
DXLMM25	-0.006^{**}				-0.011^{***}	0.028	0.001	-0.000	-0.269^{***}
DXLMM25		-0.004	-0.001	0.003					
DXLMM25		-0.005^{*}	-0.005	0.001	-0.011^{***}	0.028	0.001	-0.000	-0.269^{***}

We use three order sizes to compute the XLM: EUR 25,000 (XLM25), EUR 50,000 (XLM50) and EUR 100,000 (XLM100). $DXLM$ (resp. $DXLMM$) measures the change in the XLM when the mean (resp. median) is used to compute its value during the 15-minute interval. D, CL, GR and DR are candlesticks identification dummies, respectively for all Dojis, Classical Dojis, Gravestone Dojis and Dragonfly Dojis. Control variables include the market capitalization of each stock at the beginning of year i (LNC_i), the stock return at time t (RET_t), the change in the number of buy trades (DNB_t) and sell trades at time t (DNS_t), as well as a lagged value of the dependent variables (Y_{t-1}). The models are estimated with clustered standard errors. *,**,*** indicate that the results are significant at 10%, 5% and 1%, respectively. P-values for the F-test of global significance are always below 5%, except in the two DXLMM25 equations without control variables. The adjusted R-squared ranges from 0.36 and 0.53 when the first lag of the dependent variable is included, and from 0.06 and 0.13 when it is not, except in the same two DXLMM25 equations.

as soon as the dojis take shape. The use of data at higher frequency would be needed to make to a definitive statement.

When we examine lagged signals in Table 4, we observe that some coefficient estimates for the dojis remain significant, but this is only due to the information content of the classical doji and it is only verified when the mean is used to compute the XLM during the interval. This suggest that gain in liquidity is probably not long-lived enough to enable traders to profit from these patterns of price dynamics over more than 15 minutes.

Table 4: Panel regressions results - Lagged signals

	D_{t-1}	CL_{t-1}	DR_{t-1}	GR_{t-1}	LNC_i	RET_t	DNB_t	DNS_t	Y_{t-1}
DXLM100	-0.020^{***}								
DXLM100	-0.025^{***}				-0.002	0.018	0.001	-0.001	-0.314^{***}
DXLM100		-0.022^{***}	0.013	-0.006					
DXLM100		-0.025^{***}	0.007	-0.006	-0.002	0.018	0.001	-0.001	-0.314^{***}
DXLM50	-0.017^{***}								
DXLM50	-0.023^{***}				-0.016	-0.004	0.001	0.000	-0.309^{***}
DXLM50		-0.018^{**}	0.016	-0.010					
DXLM50		-0.023^{***}	0.009	-0.009	-0.016	-0.004	0.001	-0.000	-0.309^{***}
DXLM25	-0.014^{**}								
DXLM25	-0.022^{***}				-0.025^{*}	-0.022	0.001	-0.000	-0.305^{***}
DXLM25		-0.014^{*}	0.014	-0.016					
DXLM25		-0.020^{**}	0.006	-0.014	-0.025^{*}	-0.022	0.001	-0.000	-0.305^{***}
DXLMM100	-0.001								
DXLMM100	-0.004				-0.006^{***}	0.025	0.000	0.000	-0.243^{***}
DXLMM100		-0.002	0.002	0.003					
DXLMM100		-0.005^{*}	0.002	0.002	-0.006^{***}	0.025	0.000	0.000	-0.243^{***}
DXLMM50	-0.000								
DXLMM50	-0.003				-0.008^{***}	0.029	0.001	-0.000	-0.259^{***}
DXLMM50		-0.002	0.006	0.001					
DXLMM50		-0.004	0.005	-0.000	-0.008^{***}	0.029	0.001	-0.000	-0.259^{***}
DXLMM25	0.001								
DXLMM25	-0.002				-0.011^{***}	0.028	0.001	-0.000	-0.269^{***}
DXLMM25		0.000	0.005	-0.002					
DXLMM25		-0.003	0.004	-0.002	-0.011^{***}	0.028	0.001	-0.000	-0.269^{***}

We use three order sizes to compute the XLM: EUR 25,000 (XLM25), EUR 50,000 (XLM50) and EUR 100,000 (XLM100). $DXLM$ (resp. $DXLMM$) measures the change in the XLM when the mean (resp. median) is used to compute its value during the 15-minute interval. D, CL, GR and DR are candlesticks identification dummies, respectively for all Dojis, Classical Dojis, Gravestone Dojis and Dragonfly Dojis. Control variables include the market capitalization of each stock at the beginning of year i (LNC_i), the stock return at time t (RET_t), the change in the number of buy trades (DNB_t) and sell trades at time t (DNS_t), as well as a lagged value of the dependent variables (Y_{t-1}). The models are estimated with clustered standard errors. *,**,*** indicate that the results are significant at 10%, 5% and 1%, respectively. P-values for the F-test of global significance are always below 5% in the DXLM equations as well as in the DLXMM equations including the first-order lag of the dependent variable. The adjusted R-squared ranges from 0.23 and 0.48 when the first lag of the dependent variable is included, and from 0.04 and 0.10 when it is not, except in all DXLMM25 equations without control variables.

5 Concluding remarks

Our study is an attempt to improve the management of implicit transaction costs across time. We use the Exchange Liquidity Measure (XLM) to measure the implicit cost of a round-trip trade and we identify patterns and regularities at the intraday level. Following past studies suggesting that asset price series provide useful information about liquidity dynamics, we study the variations in the XLM around specific price change signals.

We investigate the informational content of three specific configurations related to the same consensus structure, i.e. the Doji, which occurs when the opening and closing prices in a given time interval are almost equal, whatever the timescale. The three configurations under scrutiny in this paper are the Classical Doji ("+"), the Dragonfly Doji ("T") and the Gravestone Doji (Inverted "T").

In the event study, we find that transaction costs estimated by the XLM on three order sizes (25k, 50k and 100k) are significantly lower when one of these structures occurs, whatever the order size. We also observe some persistence around these events, with highly significant results whatever the order size.

We further investigate this relationship through panel regression models, with a clustering approach to correct for correlation as proposed by Petersen (2009). We regress the first difference of the XLM measure on contemporaneous signals for the three above-mentioned order sizes. The results of our panel regression models are consistent with the event study, pointing to a significant decrease in transaction costs when consensus structures occur. They also support empirical evidence found in Mazza (2015), Detollenaere and Mazza (2014) and Kavajecz and Odders-White (2004). We redo the analysis with lagged signals and find that statistical significance vanishes, showing that liquidity gains are rather short-lived and become marginal after 15 minutes.

We conclude that it may be wise for practitioners to pay more attention to the occurrence of these patterns of price dynamics should they want to better manage implicit transaction costs at the intraday level and execute orders at lower costs.

References

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

Aitken, M. and C. Comerton-Forde (2003). How should liquidity be measured? *Pacific-Basin Finance Journal 11*, 45–59.

Biais, B., P. Hillion, and C. Spatt (1995). An empirical analysis of the limit order book and the order flow in the Paris bourse. *The Journal of Finance 50*(5), 1655–1689.

Bloomfield, R., M. O'Hara, and G. Saar (2005). The 'make or take' decision in an electronic market: Evidence on the evolution of liquidity. *Journal of Financial Economics 75*(1), 165–199.

Boudt, K. and M. Petitjean (2014). Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks. *Journal of Financial Markets 17*, 121–149.

Chakravarty, S. and C. W. Holden (1995). An Integrated Model of Market and Limit Orders. *Journal of Financial Intermediation 4*(3), 213–241.

Chan, K., W. Christie, and P. Schultz (1995). Market structure and the intraday pattern of bid-ask spreads for NASDAQ securities. *Journal of Business 68*(1), 35–60.

Demsetz, H. (1968). The Cost of Transacting. *Quarterly Journal of Economics 82*, 33–53.

Detollenaere, B. and P. Mazza (2014). Do Japanese candlesticks help solve the trader's dilemma? *Journal of Banking and Finance 48*, 386–395.

Duvinage, M., P. Mazza, and M. Petitjean (2013). The intraday performance of market timing strategies and trading systems based on Japanese candlesticks. *Quantitative Finance 13*(7), 1059–1070.

Gomber, P., U. Schweickert, and E. Theissen (2015). Liquidity dynamics in an electronic open limit order book: an event study approach. *European Financial Management 21*(1), 52–78.

Goodfellow, C., D. Schiereck, and T. Verrier (2010). How do trading costs vary across the day? a note on the innovative xlm measure for small caps at the frankfurtstock exchange. *The Journal of Trading 5*(4), 78–87.

Goyenko, R., C. Holden, and C. Trzcinka (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics 92*(2), 153–181.

Hamao, Y. and J. Hasbrouck (1995). Securities trading in the absence of dealers: Trades and quotes on the tokyo stock exchange. *Review of Financial Studies 8*(3), 849–878.

Kavajecz, K. A. and E. R. Odders-White (2004). Technical analysis and liquidity provision. *Review of Financial Studies 17*(4), 1043–1071.

Lesmond, D., J. Ogden, and C. Trzcinka (1999). A new estimate of transaction costs. *Review of Financial Studies 12*(5), 1113–1141.

Mazza, P. (2015). Price dynamics and market liquidity: An intraday event study on Euronext. *The Quarterly Review of Economics and Finance 56*, 139–153.

Morris, G. (1995). *Candlestick Charting Explained: Timeless Techniques for Trading Stocks and Futures*. New–York: McGraw-Hill Trade.

Nison, S. (1991). *Japanese Candlestick Charting Techniques: A Contemporary Guide to the Ancient Investment Technique of the Far East*. New–York: New York Institute of Finance.

Nison, S. (1994). *Beyond Candlesticks: New Japanese Charting Techniques Revealed.* New-York: John Wiley and Sons.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies 22*(1), 435–480.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance 39*(4), 1127–1139.

Wang, Z.-M., C. Chiao, and Y.-T. Chang (2012). Technical analyses and order submission behaviors: Evidence from an emerging market. *International Review of Economics and Finance 24*(0), 109–128.