

Measuring Liquidity in an Emerging Market: The Tunis Stock Exchange

Emna Rouetbi¹

Institut Supérieur de Finance et Fiscalité Sousse,
Rue 18 janvier Sousse, Tunisia. Tel. 00 216 73 222 700,
Fax: 00 216 73 222 701. Email: erouetbi@yahoo.fr

Chokri Mamoghli

Institut des Hautes Etudes Commerciales,
2016 Carthage Présidence–Tunisia. Tel. 00 216 71 775 948,
Fax: 00 216 71 775 944. Email: chokri.mamoghli@essect.rnu.tn

ABSTRACT: In recent years, researches on microstructure have experienced considerable extensions. A major question that still has no precise answer is about measuring liquidity. Several measures were proposed in the literature in order to assess and understand this concept. This diversity of measures emanates from the main feature of liquidity which is multidimensionality. However, measuring liquidity constitutes the starting point for every research in this area. Indeed, the purpose of the present paper is to revisit the most complete measure of the intraday liquidity i.e. VNET and its main properties within an emerging market setting that is the Tunis Stock exchange.

Keywords: Microstructure; liquidity; emerging markets; ACD; EGARCH.

JEL Classifications: C22; C41; G10.

1. Introduction

Liquidity measuring has been the subject of many studies (Kyle, 1985; Harris, 1990; Engle and Lange, 2001; Amihud, 2002 among others). The challenge is to propose a more representative measure of this multidimensional concept. In fact, Harris (1990) completed the three dimensions initially proposed by Kyle (1985) namely, tightness, resiliency and depth when introducing the immediacy. Tightness reflects the cost of an immediate transaction. Resiliency refers to the speed of price level adjustment caused by a trade occurrence. Depth, on the other hand, denotes the volume available for transaction displayed by the order book. The time dimension (immediacy) evokes the possibility of immediately trading a desired quantity at the minimum trading price. These four dimensions are inter-related: time recalls tightness and immediacy. Price is related to cost and resiliency. The traded quantity is associated with depth and resiliency. This inter-relation complicates the measuring task and accordingly, the diversity of the proposed measures. At the intraday level, spread is the most used in the literature, it represents the width of the market as it is the difference between the best asks and bid prices.

Although the spread is an immediate measure of liquidity, it has some drawbacks. First, it is unable to account for the costs incurred by transactions larger than that presented by the best quotes. Anand and Martell (2001) argued that it is not a suitable measure for trades accruing beyond the best quotes especially for institutional traders seeking to rapidly trade large quantities. Additionally, it doesn't take into account the market maker's reaction to new information. In this context and considering the mid price (the average of bid and ask prices) as a benchmark, Lipson (2003)

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developed certain measures that are derived from such spreads as the effective, the proportional, and the relative spread².

These spreads, however, are not perfect measures of transaction cost. They can be considered as indicators of current pre-trading liquidity. Despite this criticism, these spreads are still the most frequently used measures to assess liquidity in different contexts. Lipson (2003), for example, used the effective spread to compare between the different market centres where NYSE listed stocks were traded. Bessembinder (2000) studied the reaction of liquidity after the tick reduction on NASDAQ. Ginglinger and Hamon (2004) used spreads measures to show the negative impact of the buyback on the liquidity of French stocks. Acker et al. (2001) retraced the evolution of the effective spread around the earnings announcement for the least liquid stocks of the LSE. Huang and Stoll (1996) also used the three spreads among other measures such as the cost of performance to study the differential costs between NASDAQ and NYSE.

In another vein, the liquidity temporal dimension refers to the speed at which transactions could be concluded. Thus a market is said to be liquid when providing traders with immediate exchange opportunities. For limit order markets, the shorter waiting time on the order book is the more liquid the market becomes. In this case, transactions are closely spaced in time, (see Dufour and Engle, 2000). According to Handa and Schwartz (1996), limit order traders are exposed to two types of risks: the non-execution risk which corresponds to a long waiting time on the book and an adverse selection risk that refers to the risk of being picked off by more informed agents. Copeland and Galai (1985) pointed out that these orders offer free options to insiders with reference to their mentioned prices.

Since the traded quantity indicates the presence of market information, volume and volatility can be correlated with the information itself. The asymmetric information theory suggests that large transactions are associated with high price fluctuations. According to Easley and O'Hara (1987), informed traders are encouraged to rapidly exchange large quantities before the private information revealed to the whole market. Thus uninformed traders and market makers interpret large trades as an evidence of new information occurrence. In this respect, French and Roll (1985) confirmed that the large volume of trade is associated with significant price movements. They argued that the opening volatility is caused by price adjustment to private information. Meanwhile, the size of trade reflects the quality of the signal. Blume et al. (1994) suggested that the trading volume is correlated with the quality and quantity of information.

When studying the behaviour of NYSE specialists, Kavajecz (1999) noticed that they proceed to quote revisions in 90% cases when they suspect the presence of new information. Similarly and in order to limit order traders on order driven market, they tried to decrease their adverse selection cost by reducing the proposed depth and widening the spread. Thus, we can note that tightness and depth are very much related. In this context, Kyle (1985) proposed a more complete measure of liquidity. The basic idea was to study the strategic behaviour of an informed agent when maximizing the profit from his informational advantage at the expense of other uninformed agents (liquidity traders). In a linear respect, and stating λ as the price variation caused by one unit increase of volume traded. The lower λ is, the more resilient and liquid is the market. Thus $1 / \lambda$ is a liquidity measure. However the linear relationship between price variations and the traded volume was challenged by Kempf and Korn (1999), who underlined that the informed traders' strategy depends on the non linearity relationship.

In the same context, Engle and Lange (2001) shed light on the importance of factors influencing short time prices behaviour. They defined depth as the number of traded shares causing a minimum price variation. In other words, it corresponds to the volume traded during certain price duration. Their contribution consists in stating a relationship between this measure and the trading related variables such as the number of trades, volume, spread...etc.

² Effective spread is twice the difference between the transaction and Mid prices multiplied by (-1) for seller initiated orders and (1) for a buyer initiated ones. The effective proportional spread is twice the quoted spread side divided by the Mid price. The realized spread is twice the difference between the traded price and Mid price recorded 5 minutes after the trade occurrence multiplied by (-1) for seller initiated orders and (1) for a buyer initiated ones.

Despite the diversity of proposed measures, one could be validated only if it is sensitive to information and trading environment evolutions. In this context, we propose to extend Engle and Lange (2001) measure and suggest studying liquidity variations determinants. To validate this one, we propose to express its conditional volatility in terms of pre-trading and post-trading variables. We also suggest dealing with such problematic in the context of an emerging market i.e. the Tunis Stock Exchange (BVMT). It belongs to the MENA region and has received less attention from empirical studies although it represents a favourable field for microstructure ones. As an order driven market, it has been the subject of successive reforms in order to improve the trading environment and attract order flow³.

Therefore and in the context of the BVMT, we propose to empirically validate the following assumptions:

For pre-trading variables: As explained above, and according to the microstructure literature, spread reports the cost of an immediate transaction made at one of the best order book limits. Given the simplicity of calculation it was considered as an ex-ante measure of liquidity in several studies such as that of Hamon (1997). Thus we can assume a positive relationship between liquidity variation and the spread. When immediate transaction is expensive, liquidity becomes more volatile.

H1: There is a positive relationship between the volatility of liquidity and spread.

According to Chordia et al. (2002), limit orders concentration on the order book executes a pressure on prices and encourages its evolution in a particular direction. In other words, when a stock is requested, a price increase is expected. Black (1971) added that buyers are often more informed than sellers; in this respect, we can expect a positive relationship between long bid orders queue and the probability of new information occurrence. Given the relationship between liquidity and asymmetric information stipulated by Easley et al (1996), we can formulate the hypothesis H2:

H2: The liquidity becomes more volatile when the order book is longer at the bid side.

Post-trading variables: Among the post-trade variables, volume is very special as it was considered by the microstructure literature as an indicator of information asymmetry. Indeed, according to Easley and O'Hara (1992) informed agents buy (sell) the undervalued securities (over-valued). Similarly, Admati and Pfleiderer (1988) noted that the informed agents intervene when the market is able to absorb the volume of their trades. Meanwhile, uninformed agents react by reducing their liquidity supply and widening the spread. Hence the following hypothesis is introduced:

H3: There is a positive relationship between volatility of liquidity and traded volume.

According to Jones et al (1994) and Chan and Fong (2000) returns' volatility is more responsive to an increase of the number of transactions than that of the trading volume. In addition, Cornell and Sirri (1992), when studying the behaviour of 38 insiders trading on the NYSE, showed that relative trades accounted for 78.2% of small and medium sized transactions. Thus, these traders can hide the informational content of their transactions. Therefore, we can postulate the following hypothesis:

H4: There is a positive relationship between the volatility of liquidity and the number of trades.

Dufour and Engle (2000) stated that long periods between trades indicate the intervention of negative information that may discourage uninformed agents from trading (see Diamond and Verrecchia (1987)). However, Admati and Pfleiderer (1988) showed that discretionary traders (uninformed and liquidity providers) concentrate their transactions over time in order to reduce the supported adverse selection cost. Given this reasoning, we can state the hypotheses H5 and H6 as follows:

H5: There is a positive relationship between the volatility of liquidity and price fluctuations.

H6: There is a positive relationship between the volatility of liquidity and the trade duration.

2. Data and Methodology

Engle and Lange (2001) proposed an innovative liquidity measure namely VNET defined as the net volume necessary to provoke a minimum price variation. Every price variation is associated with two interrelated variables, namely; volume and price duration.

VNET = (Volume traded by the buyer-volume traded by the sellers) measured during a period price.

³ See Rouetbi and Mamoghli (2013, 2014).

The following equation (1) illustrates the VNET calculation steps necessary to measure the variable VNET. We begin by choosing the minimum MID price (average of bid and ask prices) variations. After several trials, and given our data properties, we selected 5 tick variations. 5 ticks variations (positive and negative) of the MID price are then considered as events. Accordingly, we calculated the time duration of every event and the net volume that contributed to their achievement.

$$VNET = \log|\sum_{i=1}^n(d_i vol_i)| \quad (1)$$

Where d_i direction indicator transaction i ,
 $d_i = 1$ (-1) for the trades initiated by buyers (sellers)
 vol_i is the number of traded stocks.

n is the number of trades occurring during the price duration.

We notice that the use of MID price instead of the trading price allows us to avoid the bias introduced by the price rebound between bid and ask.

The VNET measure calls on different dimensions of liquidity, namely:

- Quantity dimension: since it is the sum of signed volume recorded during a price event;
- Temporal dimension when calculating the conditional expectation of the duration of each event;
- Price dimension: it is the basis for calculating the VNET variable.

2.1 Explanatory variables

The calculation of net directional volume is not sufficient to characterize the liquidity of a stock. In order to reflect its different features and be among the determinants of the trading process, it is necessary to express the extended VNET in function of the following variables:
Spread: the difference between the best bid and the best ask on percentage of the average price MID. It represents the distance between supply and demand curves.

Volume: the number of the traded securities during a price event. According to the asymmetric information theory, informed agents intervene through high volume periods to profit from their informational advantage before the price adjustment. Studying liquidity reaction to this variable will allow us to shed light on traders' behaviour during periods of asymmetric information.

The number of transactions recorded during the price event. This completes the previous variable to characterize the presence of asymmetric information. In fact, Chan and Fong (2000), Jones et al (1994) asserted that the number of transaction explains volatility better than the volume. They showed that returns increased more in response to the rise in the average trade size than the returns of the trading volume. However, this variable is related to the number of informational events which strengthen the positive relationship between volatility and volume.

The price change or price jump (Pjump below) represents the amplitude in absolute value of the event.

The variable "slope" is a representative of the pre-transaction limit order. Non informed traders monitor the order book variation since they update their beliefs according to the order flow evolution (see Foster and Viswanathan (1990), Madhavan (2000), Evans and Lyons (2000)). Indeed, the limit orders concentration creates a certain pressure on prices. This promotes its change in one direction rather than another (see Chordia et al., 2002). We define "Slope" as the ratio of bid pending number of stocks and the ask side quantities recorded during the event duration. When its value increases, the security becomes highly demanded. To calculate this variable, only the five best limits of the order book are taken into account as they have larger execution probability.

The time duration ("Pdur") between events represents the speed of the price adjustment process. In this respect, studying durations between events requires the use of specific models: ACD (autoregressive conditional duration) models initially proposed by Bauwens and Giot (2000). A particular empirical procedure was applied: first we estimated 12 ACD⁴ models, then we used Bauwens et al. (2004)'s procedure to choose the ACD model that efficiently suits the empirical properties of the data. Finally we extracted the conditional expected duration representing the anticipated time between price changes known as "Pdur".

2.2 Econometric model

In order to study the VNET dynamics, we have used an EGARCH model. Explicative variables related to the trading environment will be introduced in the variance equation.

⁴ Three formulations of ACD models were estimated: ACD simple model, Log-ACD1 and Log-ACD2. For each one we have used 4 empirical densities for standardized durations. Then twelve models were estimated.

In the light of this reasoning, the VNET variable could be expressed as follows:

$$VNET_t = C + \alpha_1 VNET_{t-1} + \varepsilon_t \quad (1)$$

The volatility equation:

$$\ln(\sigma_t^2) = \theta_0 + \theta_1 \frac{|\varepsilon_{t-1}|}{|\sigma_{t-1}|} + \theta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \theta_3 \ln(\sigma_{t-1}^2) + \sum_{i=1}^6 \beta_i \gamma_{i,t-1} \quad (2)$$

Where $\frac{\varepsilon_i}{\sigma_{t-1}} \sim N(0, \sigma_t^2)$

$\gamma_{i,t-1}$ the delay value relative to the variable

i ($i = 1, \dots, 6$) of the trading characteristics vector calculated pre-and post-transaction.

Variables other than “Pdur” can be directly calculated from the order book reconstitution. As detailed above, conditional durations require the implementation of an ACD (autoregressive conditional duration) model that best fits the characteristics of the data. After applying Bauwens et al. (2004)’s procedure, we selected the GGLACD1(1,1).

This model expresses the conditional expected duration φ_i as a function of the lagged duration x_i on logarithm:

$$x_i = e^{\varphi_i \varepsilon_i} \quad (3)$$

$$\varphi_i = \omega + \alpha \ln(x_i) + \beta(\varphi_{i-1}) \quad (4)$$

x_i : the intraday duration at the time i ;

φ_i : the conditional expected duration;

ε_i : the random variable called standardized duration following a generalized gamma law.

To save space we will not expose the empirical results of this model.

3. Empirical Results

The Tunis Stock exchange is an emergent market from the MENA region that has received less interest from microstructure studies although it is considered as a favourable field for such studies to be carried out. As an order driven market it disseminates, at real time, all information relative to the trading process thanks to an acceptable transparency degree.

Among the fourteen stocks quoting at the continuous session all along the year 2006 and with reference to the restrictive criteria⁵ we selected the following sample:

- The three most liquid stocks (STB, STPIL and SFBT);
- The three stocks among the least liquid ones (UIB, MG, and BIAT).
- An intermediate stock moderately liquid: Sotetel.

Furthermore, we have deseasonalized all the series of the above mentioned variables. Intraday seasonality introduces an autocorrelation which is related to the time interval at which the observation was recorded not to the empirical properties of the time series. Thus, this stylized fact typical for intraday data could lead to biased results. The seasonal adjustment is then necessary.

After expressing the VNET variable depending on its lagged value, we performed an ARCH test based on the squared residues that have been conclusive. The presence of heteroscedasticity errors was confirmed for all the stocks in the sample.

We have chosen an EGARCH (1,1) specification which is valid for all the stocks in the sample. This specification allows for asymmetric responses to shocks on the variance (see Nelson (1991)). The parameters θ_1 and θ_2 measure the impact of innovations on the volatility of liquidity (measured by VNET) at time t .

The first term θ_1 measures the absolute impact of innovations in $t-1$ on the volatility at time t . The second θ_2 is the asymmetry parameter. It represents the asymmetric response of the conditional variance to innovations of different signs. If it is negative (positive): negative shocks on average

⁵ We classified the 14 stocks traded in continuous session according to the daily number of trades, daily traded volume, quotation frequency, time duration between successive trades and daily price variation. The first (second) half the total number of stocks represents the most (less) liquid ones. The intermediate one is in the middle of this ranking. Less liquid ones are in the bottom of it.

generate more (less) volatility than positive ones (negative). A null value of this parameter implies the absence of leverage.

Table 1. Estimation results for the pre-transaction variables

		SFBT	STPIL	STB	SOTET	MG	UIB	BIAT
Observations	n	3668	2563	1547	1549	1302	1065	831
Mean equation	c	–	0.0031 (0.198)	–	0.279 (0.000)	–	0.897 (0.000)	0.983 (0.000)
	α_1	0.452 (0.000)	0.046 (0.000)	0.812* (0.008)	-0.531 (0.000)	0.231 (0.000)	0.096 (0.000)	0.138 (0.000)
Volatility equation	θ_0	0.027* (0.032)	2.232 (0.000)	0.152 (0.000)	0.301 (0.000)	-7.405 (0.000)	0.092 (0.001)	0.088 (0.000)
	θ_1	0.192 (0.000)	0.135*** (0.134)	0.271 (0.000)	0.489 (0.000)	0.522 (0.000)	0.034*** (0.122)	0.113 (0.000)
	θ_2	-0.022** (0.093)	-0.023 (0.000)	0.219* (0.055)	0.457 (0.000)	-0.070 (0.000)	0.057 (0.000)	0.084 (0.001)
	θ_3	0.719 (0.002)	0.396 (0.000)	0.670 (0.000)	0.566 (0.000)	0.632 (0.000)	0.813 (0.000)	0.756 (0.000)
	Spr_{t-1}	0.331* (0.045)	0.0902 (0.000)	0.136 (0.001)	-0.445 (0.198)	-0.132 (0.000)	-0.023 (0.000)	-0.135 (0.000)
	$Slope_{t-1}$	0.595* (0.045)	0.0807 (0.004)	0.745 (0.091)	0.253 (0.000)	-0.198 (0.000)	-0.577 (0.000)	-0.672 (0.000)
ARCH test:	Obs*R-squared	27.047 (0.000)	1978.59 (0.000)	31.175 (0.000)	99.148 (0.000)	19.361 (0.000)	18.443 (0.000)	14.343 (0.000)
Wald test statistic		76.430 (0.000)	13.715 (0.000)	141.985 (0.000)	26231.25 (0.000)	35.642 (0.000)	525.227 (0.000)	238.711 (0.000)
Ljung box statistics of the lagged standardized residuals, j=5, 10, 20		$Q_5=2.48$ $Q_{10}=6.09$ $Q_{20}=2.24$	$Q_5=5.143$ $Q_{10}=2.94$ $Q_{20}=6.68$	$Q_5=1.943$ $Q_{10}=2.252$ $Q_{20}=3.105$	$Q_5=4.756$ $Q_{10}=4.914$ $Q_{20}=4.527$	$Q_5=0.571$ $Q_{10}=0.701$ $Q_{20}=1.941$	$Q_5=2.564$ $Q_{10}=6.438$ $Q_{20}=5.934$	$Q_5=0.859$ $Q_{10}=11.285$ $Q_{20}=13.236$
Ljung box statistics of the lagged squared residuals, j=5, 10, 20		$Q_5=1.737$ $Q_{10}=2.32$ $Q_{20}=3.37$	$Q_5=1.627$ $Q_{10}=1.887$ $Q_{20}=3.43$	$Q_5=1.627$ $Q_{10}=1.887$ $Q_{20}=3.43$	$Q_5=3.464$ $Q_{10}=3.514$ $Q_{20}=3.597$	$Q_5=1.771$ $Q_{10}=2.481$ $Q_{20}=2.445$	$Q_5=5.673$ $Q_{10}=8.238$ $Q_{20}=5.234$	$Q_5=6.286$ $Q_{10}=7.639$ $Q_{20}=7.644$

Figures between parentheses are p-values of the estimate. * Significant at 5%, ** significant at 10%, *** significant at 15%. Statistics Ljung box are not significant at 5%.

Positive information occurred in t-1 ($\varepsilon_{t-1} > 0$) and has an impact value of amplitude $\theta_0 + \theta_2 \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ on volatility. Tables (1) and (2) show that coefficients α_1 are positive and statistically significant for all the stocks in the sample. Thus, VNET is autoregressive.

However, autoregressivity is not particular to average variables only, conditional volatility is also positively autoregressive. The coefficients θ_3 are positive and statistically significant for all the stocks. These two results indicate the concentration of trading activity over time: there occur periods of successive high volatility. Moreover, the stationary condition of the model is respected for all the stocks of the sample. θ_3 parameter values are all strictly less than the unity. Similarly and with reference to the Wald test, the impact pre and post- transaction variables is significant.

As a matter of fact and for the pre-trade variables, the coefficients θ_2 are negative and statistically significant for securities SFBT, STPIL and MG. For the post-trade equation, it is the case for the MG and the STB. Thus, we can speak of leverage for the MG. For the latter, the volatility of VNET is more important in response to negative shocks.

For the pre-trading variables, table (1) shows that orders' concentration on one side of the book ("slope" variable) and the spread have different impacts on the VNET measure depending on the liquidity degree. Apart from these signs, parameters significance shows that the agents are

attentive to the order book variation which represents a precious source of information necessary to update their beliefs and their expectations.

However, the ‘spr’ and ‘slope’ coefficients are positive (negative) and statistically significant for the most (least) liquid stocks. As for the ‘slope’, a heavy buy side leads to an increasing VNET volatility. Liquidity becomes more volatile in response to new information. This result is in accordance with that of Naes and Skeltorp and (2004) who found that depth has a positive impact on volatility. They asserted that it attracts transactions and promotes increased trading volume. The number of executed orders increases when the book is deep. On the other hand, they pointed out that the volume-volatility relationship depends on both the order flow structure and the state of the book.

Similarly, for the most liquid stocks, the positive coefficient on the “spread” shows that liquidity is less volatile when it is cheap. A decrease in the trading cost stabilizes the market activity. However, this is not the case for less liquid stocks. Table (1) shows a negative relationship between pre-transaction variables and VNET volatility. Liquidity becomes less volatile when the spread is wider and the stock is demanded. The disparity of the result between the two sub-samples is related to the difference in perception of the order book variation and the trading incentives. In fact, for less liquid securities, we can say that traders act as market makers on dealers markets. When an imbalance occurs, they adjust prices and quantities propositions in order to stabilize the price trend (see Foster and Viswanathan (1990), Huang and Stoll (1994), Madhavan (1996)). According to Easley and O'Hara (1992), the market maker sets the bid-ask prices according to his anticipation of the order flow. Within the context of the present work, when new information intervenes, agents try to accommodate the flow in order to stabilize price variations and accordingly adjust proposed bid and ask prices and the relative quantities.

Meanwhile, the coefficients on trading volume are positive and statistically significant at 10% level for all stocks in the sample. By construction, the directional net volume is an increasing function of volume. When the latter increases, VNET becomes more volatile. The market becomes more active during periods of high volume transaction. Indeed, this result lends strong support to Harris (1994)'s one who argued that when the volume increases, the market becomes deeper and more liquid. According to Ahn et al. (2001), a strong market activity (measured by trading volume) leads to increasing depth. It encourages investors to provide liquidity.

For the most liquid stocks, the net volume necessary to cause five ticks price variation (upward or downward) decreases with the conditional expected durations. According to Admati and Pfleiderer (1988), a decrease in trade intensity announces the presence of information. For our study, we can say that this slowdown feeds VNET volatility. Prices become less sensitive to volume changes. With reference to the asymmetric information theory, traders interpret the absence of transaction as a signal of the introduction of new information. Diamond and Verrecchia (1987) associated long durations with the advent of bad information that causes sales orders sequences which contribute to the volatility increase. By contrast, Easley and O'Hara (1992) showed that in the absence of transactions, the volatility decreases. This is due to the fact that informed agents intervene only during periods of high volatility. In this respect, Admati and Pfleiderer (1988) asserted that the discretionary investors concentrate their transactions over time in order to reduce their adverse selection costs. The informed ones choose these periods to hide the information content of their trades. For less liquid securities, our results are well consistent with those of Diamond and Verrecchia (1987) who argued that the increase in duration makes more volatile liquidity.

According to Chan and Fong (2000), the number of trades explains volatility better than the volume. They showed that returns increases more in response to the number of medium size trades than the traded volume. For these authors, the number of trades is linked to the number of informational events which reinforces the positive dependence between volatility and volume. Chena and Wu (2008), on the other hand, found that the relationship between the two variables is unidirectional. Volume has a positive impact on the number of trades, the opposite is not checked. Hasbrouck (1991), however, showed that periods with low number of trades correspond to a narrow spread and more liquid market. As a matter of fact, the result of our study fits into this framework.

Table 2 shows a positive relationship between the number of trades and the volatility of liquidity for five stocks. As well as the volume, this variable can be considered as a signal of the presence of new information. The variable ‘p-jump’ measures the price change observed in the previous event. It has a positive and statistically significant impact on the variance of the net

directional volume for all stocks in the sample. As stated by French and Roll (1985), large trades are associated with significant price movements. Accordingly and within the present framework, significant changes in prices lead to an increase in the volatility of liquidity. Based on these empirical results we can say that liquidity as measured by VNET is a critical variable of the securities' behaviour.

Table 2. Estimation results for the pre-transaction variables

		SFBT	STPIL	STB	SOTET	MG	UIB	BIAT						
Mean equation	c	0.0134 (0.000)	0.099 (0.000)	-	0.132 (0.007)	-	-	0,22 (0.000)						
	α_1	0.315 (0.000)	0.51 (0.000)	0.054 (0.000)	0.129 (0.000)	0.278 (0.000)	0.473 (0.000)	0,367 (0.000)						
Volatility equation	θ_0	-0.096 (0.000)	0.854 (0.000)	-0.696 (0.000)	0.336 (0.000)	-6.749 (0.000)	-0.036 (0.000)	0,225 (0.000)						
	θ_1	0.174 (0.000)	0.040 (0.000)	0.108 (0.000)	0.481 (0.000)	0.683 (0.000)	0.159 (0.000)	0,096 (0.000)						
	θ_2	0.107 (0.000)	0.149 (0.000)	-0.249 (0.000)	0.211 (0.000)	-0.28 (0.000)	0.065 (0.018)*	0,489 (0.000)						
	θ_3	0.851 (0.000)	0.231 (0.000)	0.549 (0.000)	0.288 (0.000)	0.921 (0.000)	0.449 (0.000)	0,902 (0.000)						
	vol_{t-1}	0.866** (0.09)	0.299 (0.000)	0.387 (0.000)	0.248 (0.000)	0.11 (0.000)	0.240 (0.000)	0,22 (0.000)						
	num_{t-1}	0.113 (0.000)	0.140 (0.000)	0.218 (0.069)**	0.706 (0.000)	0.401 (0.000)	-0.031 (0.024)*	0,245 (0.000)						
	$pjump_{t-1}$	0.358 (0.000)	0.212 (0.000)	0.790 (0.000)	0.491 (0.000)	0.122 (0.000)	0.918 (0.015)*	0,303*** (0.114)						
	dur_{t-1}	-0.835 (0.000)	-0.131 (0.000)	-0.232 (0.000)	0.223 (0.000)	0.165 (0.000)	0.602 (0.091)**	0,089 (0.000)						
Wald test statistic	1476.57 (0.000)	5375.166 (0.000)	418385 (0.000)	85226 (0.000)	118622.3 (0.000)	661.699 (0.000)	476.57 (0.000)							
ljung box statistics of the lagged standardized residuals, j=5, 10, 20	Q_5	=0,217	Q_5	=5.199	Q_5	=7.979	Q_5	=0.135	Q_5	=2.598	Q_5	=2.662	Q_5	=2.453
	Q_{10}	=0,377	Q_{10}	=6.205	Q_{10}	=7.787	Q_{10}	=0.313	Q_{10}	=3.976	Q_{10}	=2.739	Q_{10}	=2.502
	Q_{20}	=0,731	Q_{20}	=6.68	Q_{20}	=7.894	Q_{20}	=1.265	Q_{20}	=7.564	Q_{20}	=2.892	Q_{20}	=2.54
ljung box statistics of the lagged squared residuals, j=5, 10, 20	Q_5	=0,115	Q_5	=0.409	Q_5	=1.476	Q_5	=0.275	Q_5	=1.315	Q_5	=2.547	Q_5	=1.647
	Q_{10}	=0,294	Q_{10}	=0.623	Q_{10}	=1.825	Q_{10}	=0.503	Q_{10}	=2.022	Q_{10}	=2.885	Q_{10}	=1.695
	Q_{20}	=0,596	Q_{20}	=0.142	Q_{20}	=1.896	Q_{20}	=0.969	Q_{20}	=2.337	Q_{20}	=2.908	Q_{20}	=1.796

Figures between parentheses are p-values of the estimate. * Significant at 5%, ** significant at 10%, *** significant at 15%.

4. Conclusion

This paper's aim is to locate liquidity among the main indicators of a stock intraday activity. To this end, we first measured liquidity. Given its multi-facets, it was difficult to consider a single variable. We have chosen the VNET measure: directional net volume necessary to vary the price of a number of ticks, ie event. Considering the duration of each event, this variable contains the main dimensions of liquidity (price, quantity and time). To take into account the variability of the trading process, we expressed the VNET volatility on the basis of the representative variables of the information sets available: pre-and post-transactions. Our results indicate the presence of a concentration of the transaction activity. There occur successive periods of high volatility.

Meanwhile our results show that due to the increased volume traded, liquidity becomes more volatile. Similarly, separating the analysis for two subsamples of securities classified according to their degree of liquidity, we found a difference in the behaviour of agents in response to changes in the order flow and spread. The most liquid stocks are able to absorb the imbalance of orders since the volatility of VNET is positively related to the variable "slope". During periods of asymmetric information, the liquidity of these securities becomes more volatile. For less liquid stocks, an order flow imbalance reduces liquidity. The agents act as "market makers" in a price-driven market. They

derive the information from the order flow. Order book imbalance signals the presence of new information thus market makers increase the "spread" and reduce their liquidity offers.

This paper reviews the determinants of liquidity and its main features. It emphasizes the inseparable characteristics of its multi-facets. It also highlights the main theories of the microstructure to explain the behaviour of the liquidity components of the price range.

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