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HOW DOES LIQUIDITY BEHAVE?

A MULTIDIMENSIONAL ANALYSIS OF NYSE STOCKS

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Abstract

In a continuous trading market, taking efficiency as given, variations in liquidity can be measured by simultaneous changes in both immediacy costs and depth. Past theoretical and empirical microstructure literature is, however, one-dimensional. Only a reduced number of empirical studies consider immediacy costs and depth proxies together. Using intraday data from the NYSE, this paper deals with how liquidity regularly behaves and how it reacts to changing market conditions by concurrently analyzing intraday regular patterns of alternative immediacy costs and depth measures. A new liquidity measure called BLM is introduced that captures simultaneous changes in both liquidity dimensions. It is evidenced that intraday patterns in market making costs can (at least partially) explain the regular changes in liquidity and that only volatility changes have an unambiguous effect on liquidity. In this way, this study looks in greater depth into, and is able to give more general conclusions about, the general behavior and the determinants of liquidity at the NYSE.

Keywords: Liquidity, market making costs, price impact of trades.

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1. - Introduction.

Liquidity is probably one of the most widely used terms in finance and it has given rise to an important theoretical and empirical research effort. Microstructure researchers have evidenced that liquidity matters as far as asset pricing (e.g., Amihud and Mendelson, 1986; Eleswarapu and Reinganum, 1993; Brennan and Subrahmanyam, 1996) and market competitiveness (e.g., Huang and Stoll, 1996; Blume and Goldstein, 1997) are involved. However, there is neither a common understanding of what liquidity means nor a general consensus as to how to measure it. O'Hara (1995, pg. 215) remarked that 'liquidity, like pornography, is easily recognized but no so easily defined [...]'. This apparent paradox might be explained by the inherent multidimensionality of the concept (e.g., Grossman and Miller, 1988). Drawing on the definitions by Black (1971) and Kyle (1985), a market for a given stock is liquid if: (a) it is always possible immediately to buy or sell small quantities of stock. (b) Investors can, in absence of private information, buy or sell large amounts of the stock over a long period of time without expecting significant changes in prices. Moreover, investors can immediately buy or sell large blocks of stock, though they will face proportional premiums or discounts. Finally, time that is required for price adjustment after a random and uninformative shock (resiliency) is short. (c) The difference between the best bid and offer price is small (tightness). (d) Depth, the minimum trading volume needed to change prices, is large. Therefore, liquidity requires trading to be continuous, and prices to fully reflect relevant information and to quickly adjust to new information. Moreover, the lower the immediacy costs and the larger the depth the more liquid a given stock will be. In other words, if we consider a stock market with a continuous trading system and take the level of market efficiency as given, liquidity could be measured by simultaneously considering both immediacy costs and depth.

Despite this apparent bidimensionality, microstructure theory has mainly focused on immediacy costs. The analysis of the theoretical determinants of the quoted bid-ask spread (e.g., Ho and Stoll, 1981; Copeland and Galai, 1983; Glosten and Milgrom, 1985; Huang and Stoll, 1997), and the relative magnitude of the cost-components of market making (e.g., Stoll, 1989; George et al., 1991) were widely considered topics. In these models, however, depth was avoided by assuming that trades were of constant size. The depth dimension has also been modeled (e.g., Kyle 1985 & 1989; Subrahmanyam, 1991). Nonetheless, in these cases immediacy costs were not considered since market makers set a single liquidation price conditional on the available information. Moreover, alternative measures have been supplied to approximate either of these two liquidity dimensions. Relative spread (e.g., McInish and

Wood, 1992), effective spread (e.g., Petersen and Fialkowski, 1993), realized spread (e.g., Huang and Stoll, 1996), and implicit spread (e.g., Roll, 1984) are frequent measures of immediacy costs. Quoted depth (e.g., Kavajecz, 1998), realized depth (e.g., Engle and Lange, 1997) and liquidity ratio (e.g., Kluger and Stephan, 1997) proxy for price sensitivity to order flow. These 'liquidity' measures have been applied to both cross-sectional and time series empirical analyses. Cross-sectional studies have dealt with topics such as illiquidity premiums in stock returns (e.g. Amihud and Mendelson, 1986), cost comparisons and integration between markets (e.g. Lee, 1993; Bessembinder and Kaufman, 1997), and evaluations of specialists' performance (e.g. Madhavan and Sofianos, 1998). Time series studies have covered event studies (e.g. Venkatesh and Chiang, 1986), regular patterns in immediacy costs (e.g. Wood et al., 1985) and liquidity determinants (e.g. McInish and Wood, 1992). As far as we know, however, empirical studies considering simultaneously immediacy costs and depth are scarce. Lee et al. (1993) is an important exception. For a sample of NYSE firms, they observed that liquidity providers used both spread and depth to actively manage changes in information asymmetry risks associated with earning announcements. With the same premise that motivated the Lee et al. (1993) paper, that is, assertions about changes in global liquidity can only be made when changes in both immediacy costs and depth are considered together, this paper offers a more general outline of how liquidity behaves.

Using intraday data for a sample of NYSE-listed common stocks, our study extends previous time series empirical analysis of liquidity by concurrently studying the most relevant measures of immediacy costs and price sensitivity to order flow. Additionally, with the intention of capturing simultaneous changes in both immediacy costs and depth, a new liquidity measure is introduced that we have called the Bidimensional Liquidity Measure (BLM). This simple and direct measure allows us to verify general intuitions about the global behavior of liquidity and opens up the possibility of extending prior time series and cross-sectional empirical work that has resorted to spread or depth alone to approximate liquidity. A comparative analysis of these alternative liquidity proxies is driven to the study of the existence of regular patterns in liquidity and to ascertain how liquidity reacts to alternative market scenarios.

Several papers have evidenced time regularities in immediacy costs in markets with distinct microstructures, usually consisting of U-shaped or reversed J-shaped intraday patterns and higher values on Mondays (e.g., McInish and Wood 1992, Foster and Viswanathan 1993, for the NYSE; Lehman and Modest 1994, for the Tokyo Stock Exchange; Rubio and Tapia 1996,

for the Spanish Stock Exchange). Lee et al. (1993) and Lehman and Modest (1994) also observed firm size effects on these regular patterns. Evidence concerning regular patterns in the other liquidity dimension is scarce (again, Lee et al., 1993, studied intraday regularities in quoted depth). Previous empirical studies, however, do not report evidence on why immediacy costs and depth experienced those regular patterns. This paper will show that liquidity experiences predictable intraday patterns that differ with the trading frequency of stocks. Moreover, it will be evidenced that regular patterns in liquidity can be explained (at least partially) by the intraday changes in market making costs.

Three main costs have been associated with market making: order-processing costs, inventory-holding costs and adverse selection costs. Order-processing costs reflect the nature of the trading mechanism (exchange fees, transfer taxes, etc.). They are usually considered as a constant part of the quoted spread (e.g., Stoll, 1989; Glosten and Harris, 1988). Inventory-holding costs arise from the suboptimal portfolio position the risk averse market maker is obliged to hold when providing dealer services (e.g., Amihud and Mendelsson, 1980; Ho and Stoll, 1981). Finally, adverse selection costs are faced because of trading with individuals who are better informed about the true value of the stock (e.g., Bagehot, 1971; Glosten and Milgrom, 1985). Liquidity providers are assumed to widen the quoted spread or reduce the quoted depth in order to compensate for or protect themselves from increases in the magnitude of these three cost-components. The relevance of each cost component on the magnitude of the quoted bid-ask spread has generated a lot of interest.[1] Little research effort, however, has been devoted to studying the time series regular patterns (exceptions are Foster and Viswanathan, 1993; Madhavan et al., 1996) and time series market determinants of the theoretical components of the bid-ask spread. In this paper we concentrate on the adverse selection costs, estimated as the revision in the expected true value of the stock after each trade (see Glosten and Milgrom, 1985; Glosten and Harris, 1988). This paper will show that information asymmetry risk is not uniformly distributed along the trading session. Expectations concerning when information asymmetries are larger or when informed trading is more probable may explain why similar market conditions cause different liquidity adjustments.

Activity, volatility, informed trading, off-competence and tick restriction are used to describe alternative market scenarios. Past theoretical and empirical microstructure literature is

[1] E.g. Glosten and Harris (1988); Stoll (1989); George et al. (1991); de Jong et al. (1996); Huang and Stoll (1996); Kim and Odgen (1996) and Huang and Stoll (1997).

sometimes unclear in predicting how liquidity should react to contemporaneous changes in these market conditions, either because the predicted changes in immediacy costs and depth are not compatible with an unambiguous variation in liquidity or simply because different models give rise to different predictions. This paper will show that liquidity adjusts to contemporaneous changes in market conditions and these adjustments are larger than expected by the predictable changes in the market variables. But, only changes in volatility will have an unambiguous effect on liquidity. Moreover, higher activity, unexpected trade size and volatility indicate higher informativeness of trades. However, more off-competence and more tick persistence signal lower informativeness of trades. Finally, this multivariate analysis allows other microstructure topics strongly linked to liquidity to be dealt with. The trade size effects (see Easley and O'Hara, 1987), the cream skimming effect on liquidity (e.g., Bessembinder and Kaufman, 1997), and the tick restriction effect on depth (e.g., Harris, 1994) are analyzed.

The paper proceeds as follows. Section 2 reviews the different immediacy costs and depth measures, and introduces the BLM. Section 3 presents data, sampling technique and some methodological aspects. Moreover, this section reports some descriptive statistics and studies independence of immediacy costs and depth. Section 4 reports empirical evidence about intraday and daily regular patterns in liquidity. Section 5 summarizes the main empirical findings about the contemporaneous adjustments of liquidity to changing market conditions. Finally, section 6 concludes.

2. - Measuring liquidity.

2.1. - Immediacy costs and adverse selection costs.

The quoted bid-ask spread is the measure which has been most commonly used to approach immediacy costs. It captures the costs of directly trading at the specialist's quoted prices instead of introducing a limit order. The economic value of such costs could be measured using the relative spread, which is simply the ratio of quoted spread to midpoint of the quoted spread (see equation 1). A first implicit assumption when quoted spread is employed as a measure of immediacy costs is that all trades are performed at the quoted bid or ask price. Empirical evidence has reported, however, that it is possible to trade at better prices than those quoted by the specialist (e.g., Lee and Ready, 1991). These price improvements may be due to stopped orders, hidden limit orders, crossing orders, and floor broker or specialist's own trades (see Hasbrouck et al., 1993). The effective spread (e.g., Petersen and Fialkowski, 1993) captures the notion that if a price improvement occurs immediacy costs will be lower

than those measured by the quoted spread (see equation 2, where P_t is the transaction price). A second implicit assumption of the quoted spread, and also of the effective spread, is that quotes do not change after a trade. Theoretical microstructure models (e.g., Glosten and Milgrom, 1985; Stoll, 1989) have shown, however, that trades convey information, modify specialists' expectations about the true value of the asset and induce changes in the quoted bid and ask prices. The realized spread (see equation 3, where $I(A)$ is 1 whenever A is true and zero otherwise, and $P_{t+\tau}$ is a proxy for the post-trade economic value of the stock) takes into account that, when quotes change after a trade, the specialist does not necessarily realize all the effective spread. In fact, after a trade at the posted ask or bid, quotes usually move against specialist interests (e.g., Hasbrouck, 1988; Huang and Stoll, 1996; Blume and Glostein, 1997).[2]

$$RS_t = \frac{(Ask_t - Bid_t)}{(Ask_t + Bid_t)/2} \tag{1}$$

$$EFS_t = 2\left|P_t - \frac{(Ask_t + Bid_t)}{2}\right| \tag{2}$$

$$RZDS_t = (P_{t+\tau} - P_t)I(P_t = Bid_t) - (P_{t+\tau} - P_t)I(P_t = Ask_t) \tag{3}$$

The difference between the effective spread and the realized spread assesses the price impact of a trade. The magnitude of the price impact will positively depend on the probability of a trade being motivated by not-publicly-known information. The greater the price impact of a trade the greater the information this trade convey to the market. Therefore, the price impact of a trade captures market makers' losses with informed traders (e.g., Huang and Stoll, 1996). In periods when the specialist believes there is a higher probability of informed trading, any trade should have a larger impact on prices and, therefore, reduce the spread that the market maker finally realizes. Consequently, the realized spread represents market maker's compensation for order-processing costs and inventory-holding costs. Let us define the half-effective spread as in (4), where X_t equals 1 for buyer initiated orders and -1 for seller initiated orders, m_t is a proxy for the pre-trade true value of the stock and P_t is the price of a trade at t. Let us also define the half-realized spread as in (5), where $P_{t+\tau}$ is a proxy for the post-trade true value of the stock. The difference (see equation 6) will be our estimator of adverse

[2] Roll (1984) obtained an estimator on the quoted spread based on the negative correlation induced on prices by the bid-ask bounce effect. George et al. (1991) and Kim and Odgen (1996) have lately improved this implicit spread. Although this alternative measure of immediacy costs was also considered in the analysis, the results add nothing to the intuition obtained with the other immediacy costs proxies. Therefore, results for the implicit spread are not reported, though they are available upon request.

selection costs associated to a particular trade. Huang and Stoll (1996) and Bessembinder and Kaufman (1996) have also applied this procedure to cross-sectional studies. As far as we know, however, this is the first study that will consider the time series properties of this estimator.

$$(½)EFS_t = X_t(P_t - m_t) \quad (4)$$

$$(½)RZDS_t = X_t(P_t - P_{t+\tau}) \quad (5)$$

$$PI_t = X_t(P_{t+\tau} - m_t) \quad (6)$$

2.2. - Depth

Depth, or sensitivity of prices to order flow, is usually approximated by the total quoted size at the best bid and ask prices. It measures how many shares could be traded at the existing quoted prices. Although the specialist decides how much depth is to be offered, quoted depth may represent the specialist's own trading interest, the trading interest in the crowd, existing limit orders, or even any possible combination (e.g., Hasbrouck et al., 1993; Bessembinder and Kaufman, 1997). Therefore, quoted depth does not necessarily reflect the effective market depth (see Kavajecz, 1998). In the same way that the effective spread is lower than or equal to the quoted spread, the effective depth is larger than or equal to the quoted depth. Recently, Engle and Lange (1997) have introduced a new depth measure called VNET. It could be understood as a realized depth. VNET captures how much one-sided volume (excess of buyer or seller initiated trading volume) has been needed to change the midpoint of the quoted bid-ask spread, as an estimation of the slope of the specialist's supply curve (see equation 7, where X_g takes the value 1 for buyer initiated trades and -1 for seller initiated trades, and k is the number of trades between two different values of the midpoint of the quoted bid-ask spread). VNET is conceptually similar to the liquidity ratio of Kluger and Stephan (1997).[3]

$$VNET = \left| \sum_{g=1}^{k} X_g Vol_g \right| \quad (7)$$

2.3. – The Bidimensional Liquidity Measure.

This study's premise is that it is not possible to infer changes in global liquidity based solely

[3] The liquidity ratio (LR) is just the ratio of accumulated trading volume to accumulated change in prices during a given time interval. It ignores whether volume comes from buyer or seller initiated trades. The LR crucially depends on the magnitude of the change in prices: small changes in prices move the liquidity ratio to extremely high values. VNET, however, depends on the quantity that needs to be traded in order to move prices (no matter how much). In our opinion, sensitivity of prices to order flow is better captured using VNET than through the LR and it has better properties. This leads us to discard the latter measure in our analysis.

on immediacy costs or depth. Liquidity unambiguously changes whenever immediacy costs and depth move in the opposite direction, or one of them changes and the other one remains constant. From this point of view, it is not correct to assert that a narrower spread implies more liquidity without studying how depth has simultaneously evolved.[4] We introduce a simple direct measure of liquidity that captures simultaneous relative changes in both immediacy costs and depth. This measure is named the Bidimensional Liquidity Measure (BLM). When the change in liquidity is ambiguous, that is, when immediacy costs and depth move in the same direction, BLM will reflect which dimension of liquidity has experienced a relatively larger variation.

BLM consists of a corrected ratio of depth to immediacy costs for a given time interval. The general expression for BLM appears in equation 8, where D_t and IC_t represent some indicators of depth and immediacy costs, respectively, during a given time interval t. D_{t-k}^{t-1} and IC_{t-k}^{t-1} are some indicator of the past evolution of both liquidity dimensions. Therefore, an increase (decrease) in BLM is interpreted as a liquidity improvement (worsening). The direction of a change in BLM will depend on the relative magnitude of the changes in the relative depth and relative immediacy costs. Observe that, in some sense, BLM is a proxy of depth-immediacy costs elasticity.

$$BLM_t = \Delta Liquidity_t = \left(\frac{\dfrac{D_t}{D_{t-k}^{t-1}}}{\dfrac{IC_t}{IC_{t-k}^{t-1}}} \right) \qquad (8)$$

3. - Data, methodology and some descriptive statistics.

3.1. - Data, sample and methodology.

The transaction and quote data used in this study were obtained from the TAQ (*Trade and Quote*) Database corresponding to the full year 1996. Data consists of 150 common stocks, sampled from the population of 2574 NYSE-listed common stocks in January-1996 using Systematic Sampling based on market capitalization.[5] Stocks that experienced stock-splits, those that did not trade the full year and those without quotes and trades registers for more

[4] See Lee et al. (1993, pg. 49-51) for further discussion on this issue.

[5] With Systematic Sampling (SS), all stocks have the same probability of being finally chosen, as with Simple Random Sampling (SRS). However, the final SS-sample is more representative of the sample population than the SRS-sample. SS consists of generating a random number k between 1 and the nearest integer to 2574/150. Then, the sample population is sorted by market capitalization and the stocks selected are those in the positions rkth, where r=1,...,150. See Som (1996) pg. 81-90 for a more complete exposition.

than two consecutive trading days were eliminated. Finally, from the remainder firms, two subsamples were formed taking the 25 with the largest (MFTS) and lowest (LFTS) mean trade frequency respectively (listed in appendix 1). Trades not codified as 'regular trades' have been discarded. All quote registers previous to the opening quote, those with bid-ask spreads lower than or equal to zero or quoted depth equal to zero have also been discarded. When prices and quotes must be considered together, the so-called 'five seconds rule' (see Lee and Ready, 1991) has been used in order to assign to each trade its corresponding quotes.

All previously revised measures have been constructed in an hourly basis. The trading session has been divided in seven time intervals: [9:30-10:00h.), [10:00-11:00h.), [11:00-12:00h.), [12:00-13:00h.), [13:00-14:00h.), [14:00-15:00h.), and [15:00-closing]. Following Foster and Viswanathan (1993), volume and transactions corresponding to the first time interval have been multiplied by two, in order to have comparable magnitudes. All immediacy costs, adverse selection costs and depth measures analyzed are described in appendix B. In general terms, relative spread and quoted depth are weighted by time, and effective spread and price impact are weighted by trade volume. The midpoint of the quoted bid-ask spread assigned to the trade i is used as the pre-trade true value of the stock, and the mid-point of the quoted bid-ask spread associated with the first trade reported at least five minutes later is considered as the post-trade value of the stock.[6] VNET is weighted by the magnitude of the change in the mid-point of the quoted spread. BLM is computed as a corrected ratio of depth weighted by time to relative spread weighted by time for a given time interval. The concrete expression for BLM appears in equation 9. $MVol_{dh}$ is the mean volume per trade in hour h of trading day d (h={1,...,7}, d={1,...,5}). Defined in this way, immediacy costs and depth are expressed in relative terms to stock price and trading activity respectively. Finally, $MAj(x)$, a moving average of its n previous values, divides each component x.[7] Computed in this way, BLM captures relative changes in depth and relative spread without getting rid of the regular patterns of both components.

[6] The quoted spread and the quoted depth have also been computed using last quotes for each time interval. The effective spread and the price impact have been defined using an unweighted mean too. Price impact has been computed for different values of τ and using the trade price as a proxy for the post-trade true value. Results for these measures are not generally reported because of space limitations. However, if any remarkable difference does occur, it will be mentioned. Results are available upon request.

[7] The first moving mean for the BLM is obtained using as many observations as there were hourly trading intervals in January (n=154). Therefore, the BLM is computed only from February to December.

$$BLM_t^{(d,h)} = \frac{\left\{DWT_t^{(d,h)} / MVol_{(d,h)}\right\} / MA_{j=1}^{n}(DWT_{t-j}^{(i,k)} / MVol_{(i,k)})}{RSWT_t / MA_{j=1}^{n}(RSWT_{t-j})}, \qquad (9)$$

$$s.t.\ i \in \{1,...,5\}, k \in \{1,...,7\}$$

3.2. - Some descriptive statistics.

A preliminary analysis of data reveals some interesting descriptive statistics, summarized in Table 1. For both the MFTS and the LFTS, around 24% of trades were at prices inside the quoted bid-ask spread. Additionally, after a transaction made at the ask or bid price, quotes were revised about half of times. These revisions usually consisted of an increase (decrease) in the midpoint of the quoted bid-ask spread after a trade at the ask (bid) price.[8] These results are enough to justify the use of measures of immediacy costs other than the quoted bid-ask spread: all trades did not take place at the ask or bid price and quotes did not always remain constant after a trade at the ask or bid. Moreover, most of the time quotes gave rise to spreads equal to the tick or two times the tick.

The percentage of the quoted bid-ask spread attributable to adverse selection costs, computed using decomposition in (4)-(6), conforms with those obtained in Stoll (1989), Affleck-Graves et al. (1994), Huang and Stoll (1996) and Kim and Odgen (1996). These authors obtained that a large part of the quoted bid-ask spread was due to information asymmetry risk (Glosten and Harris, 1988, and George et al., 1991, however, obtained smaller percentages). In mean hourly terms, adverse selection costs for the LFTS represent a larger part of the quoted bid-ask spread than for the MFTS only when volume is not taken into account (see Table 1). When we control for volume per trade, the percentage of adverse selection costs increases for both subsamples. This result supports the intuition in Easley and O'Hara (1987) and Hasbrouck (1988) that larger trades convey more information.

[Insert Table 1 around here]

3.3. – Bidimensionality and dependence.

Lee et al. (1993) reported a negative relationship between quoted spread and quoted depth, in the sense that wide spreads tended to be related to low depths and narrow spreads tended to be associated with high depths. This section generalizes this result by showing that specialists combine immediacy costs and depth in order to manage liquidity, independently of the

[8] Notice that the larger importance of quote revisions for the LFTS is due to a larger percentage of simultaneous changes in both bid and ask.

proxies used. If specialists in particular, and liquidity providers in general, support costs associated with market-making, and the prices and quantities they quote are the tools available to manage such costs, it seems reasonable to expect some degree of dependence between the evolution of the two liquidity dimensions. Contingency tables are used to evaluate the mutual independence of immediacy costs and depth proxies. Each hourly observation is classified into one of four categories, comparing the value of each of the two variables with the respective median.[9] Table 2 reports the results of testing the null hypothesis of independence between each pair of measures considered for the MFTS. A relationship is taken as positive when variables are simultaneously above or below their respective medians with a higher frequency than would be expected under the null hypothesis of independence, and negative whenever the two variables move in opposite directions with a higher frequency than expected. In summary, depth measures are generally dependent and positively related. Relative spread and effective spread are found to be independent, which confirms the intuition that the consideration of price improvements introduces new dynamics in the immediacy costs dimension. More important, immediacy costs and sensitivity of prices to order flow are not independent dimensions, and their relationship is negative: high immediacy costs are usually associated with low depth (high sensitivity of prices) and low immediacy costs tend to be linked with high depths (low sensitivity of prices). Price impact is positively associated to immediacy costs measures and negatively related to quoted depth. However, it is also positively connected with the realized depth. Results for the LFTS sample are roughly the same. In general, Table 2 can be summarized by saying that liquidity providers usually combine the prices and quantities they offer for trading in order to manage liquidity and, therefore, changes in both variables are not taken as independent decisions. Contingency tables for BLM show that this measure is not only positively related to quoted depth and negatively related to the relative spread but is in general positively related to all depth proxies and negatively related to immediacy costs measures. This suggests that using alternative proxies for immediacy costs and depth in (9) should not significantly change the main results of this paper.

[Insert Table 2 around here]

4. - Intraday regular patterns in liquidity.

This section focuses on the regular behavior of liquidity. Given the evidence reported in

[9] Hourly intervals in which one of the variables is equal to the median have been discarded. This does not induce any bias in the results of the test because these cases are negligible.

previous subsection, regular patterns of immediacy costs and depth should move, in some way, in opposite direction. To study whether alternative measures experience similar intraday and daily regularities will allow the overall regular patterns of liquidity at the NYSE to be looked at in greater depth.

For each liquidity measure considered, equations (10.1)-(10.2) have been estimated using a pooled GLS estimation procedure, which is robust to the presence of general heteroskedasticity and autocorrelation within each cross-section and also controls for heteroskedasticity between cross-sections. i represents the stock (the cross-sectional unit) and t the hour (i=1,...,25; $t=1,2,...,1778$). y_{it} represents a concrete liquidity measure. DHs_t (for s=2 to 7) is a dummy variable that takes the value 1 for the sth hour of the session and zero otherwise. DDh_t (for h=2 to 5) is a dummy variable that takes the value 1 for the hth trading day of the week (Monday-Friday) and zero otherwise.[10] ε_{it} is the error term, such that $E[\varepsilon'\varepsilon]=\Omega$. We allow for an autoregressive structure of order z on residuals. The number z of autoregressive terms is determined from a general-to-particular strategy.[11] The objective is to control for autocorrelation in each cross-section and to concentrate on parameter estimates that capture only contemporaneous effects.

$$y_{it} = \alpha + \sum_{s=2}^{7} \beta_s DHs_t + \sum_{h=2}^{5} \delta_h DDh_t + u_{it} \qquad (10.1)$$

$$u_{it} = \sum_{k=1}^{z} \gamma_k u_{i(t-k)} + \varepsilon_{it} \qquad (10.2)$$

Parameters β_s and δ_h represent the mean coefficients for the 25 firms in each subsample when controlling for the dynamic time series features of each stock's liquidity measure. Equations (10.1)-(10.2) are estimated with a two-stage procedure. In the first stage, the system of equations is estimated by Pooled Ordinary Least Squares (OLS). The variance for each cross-section and White's heteroskedasticity consistent covariance estimates are then obtained from the OLS residuals. In the second stage, the GLS estimation of equation (10.1), using the variance-covariance matrix obtained in the first stage, is performed by iterating until convergence is reached. $\beta=(\beta_2,...,\beta_7)$, $\delta=(\delta_2,...,\delta_5)$ and α are the coefficients of the model (10.1). α captures the Monday and the first half-hour of the session effects. Empirical results are summarized in Table 3.

[10] Given the past empirical evidence about daily regular patterns in financial time series, we also introduce daily dummies in the regression equation, although hour analysis is focused on the intraday regularities.

[11] We start with a long autoregressive structure and progressively reduce the number of unnecessary autoregressive terms.

[Insert Table 3 around here]

The liquidity measures considered show significant intraday regularities. Immediacy costs measures exhibit the usual regular patterns. For the MFTS, the relative spread (RSWT) follows a reversed J-shaped intraday pattern, dropping to its minimum around the central hours of the session (see Figure 1a).[12] The effective spread (EFSWV) also tends to be greater at the initial and final periods of the session. This U-shaped pattern persists if we do not control for trading volume, though it is less pronounced. Given that more than 90% of trades that obtained price improvements had an effective spread equal to zero (the trade price was equal to the midpoint), Figure 1b suggests that the probability of observing a price improvement decreases with trade size. Therefore, large trades are normally associated with a larger effective spread. Table 4 reports the results of testing this hypothesis. Independently of the hour of the session or day of the week considered, the median volume for trades inside the quoted bid-ask spread is significantly lower than for trades at the quoted bid or ask. Moreover, the size of trades inside the quotes is not statistically different between hourly and daily intervals. Therefore, if informed traders are expected to participate in large volume trades (e.g. Easley and O'Hara, 1987), it should be concluded that either they do not generally obtain better prices than those quoted by the specialist or they prefer to submit 'at-the-quote' limit orders. Table 4 also shows that the median percentage of transactions inside the quoted bid-ask spread is greater at the extreme periods of the session, but it achieves its maximum at the beginning of the trading day. For the LFTS immediacy costs measures regularly decrease along the session except for the EFSWV.

[Insert Figure 1 and Table 4 around here]

Quoted depth (DWT) progressively increases from the beginning of the session till the last two trading hours and then smoothly decreases (see Figure 2a). We have observed that the final regular decrease in depth is mainly due to the bid side. In fact, depth at the ask achieves its highest regular value at the last trading hour.[13] WVNET also increases from the first trading hour, however, it begins to decrease earlier and finally jumps to higher levels in the last trading hour (see figure 2b). In general terms, these patterns show that the quantity that

[12] When the relative spread is not weighted by time but constructed using the last quoted prices for each trading hour, it shows a U-shaped pattern.

[13] Harris (1989) and McInish and Wood (1990a) reported an increase in the proportion of trades at the ask relative to trades at the bid. The above patterns seem to be consistent with their findings.

can be traded without altering the quoted prices is lower during the first trading hours than during the rest of the session. Additionally, if we consider the midpoint of the quoted bid-ask spread as a proxy for the underlying value of the stock, regular patterns for WVNET could give new insights about regular market expectations concerning the presence of information-motivated trades. Thus, the fact that WVNET is systematically larger during the last trading hour may indicate that trading activity during this interval is related more closely to other motivations than to informed trading, making it more difficult to observe changes in the quoted midpoint. During the first trading hours, however, the quoted midpoint is more sensitive to order flow, suggesting a higher expected information-motivated activity. A comparative study of the characteristics involving changes in midpoint shows some significant and interesting differences between the first and the last trading hour for both subsamples: (a) the magnitude of changes is larger, (b) time between consecutive changes is shorter, (c) the number of trades required to provoke a change is lower, and (d) the mean volume per trade is larger for the MFTS and no significantly different for the LFTS. For the LFTS quoted depth systematically increases towards the end of the day. As in the MFTS case, quoted depth at the ask and bid follow different regular patterns in the last trading hour.

Comparative analysis of the above patterns allows us to establish that the largest change in liquidity happens between the first and the second trading interval for both subsamples. For the MFTS liquidity improvement persists, at least, up to the 13:00-14:00 interval. Finally, quoted liquidity deteriorates towards the end of the session. BLM captures the pattern predicted above: liquidity increases along the session, achieving its maximum at the interval 14:00-15:00, and finally decreases but never below the initial values. For the LFTS, however, BLM unexpectedly declines towards the end of the trading session. Although quoted depth increases, once mean trade size is taken into account, the relative depth decreases for this subsample, indicating that the increase in depth does not offset the increase in activity during these last trading intervals. Figure 3 shows the intraday regular evolution of the BLM. Observe that the difference between the first time interval and the rest of the session is larger for the MFTS. This could reflect a higher success rate of specialists in avoiding large changes in liquidity in thinly traded stocks (see Madhavan and Sofianos, 1998).[14]

[Insert Figure 3 around here]

[14] As regards daily regularities, Foster and Viswanathan (1993) for the NYSE, Lehman and Modest (1994) for the Tokyo Stock Exchange, and Rubio and Tapia (1996) for the Spanish Stock Exchange, among others, have reported larger immediacy costs in Mondays than in other days of the week. We only obtain evidence supporting this for the LFTS sample. In any case, daily regularities are no longer consistent when we control for firm size.

Two questions arise at this point: why does liquidity show the aforementioned regular behavior and why do we observe different regular patterns for MFTS and LFTS. Our intuition is that intraday fluctuations in market making costs might be behind the observed regular patterns in liquidity. The regular pattern reported for the price impact in Table 3 suggests that liquidity traders do not expect informed traders' activity to be uniformly distributed over the session both for MFTS and LFTS (as in Admati and Pfleiderer, 1988). New information accumulated during the overnight period and the short-lived advantage of informed traders, may increase the information asymmetry risk during the early hourly intervals. Therefore, for both MFTS and LFTS, the price impact of trades (PIWV) is greater during the first two intervals of the trading day than during the rest of the session and, hence, the mean profits of market making net of losses with informed traders are lowest. However, both price discovery process and the increased confidence on prior beliefs about the fundamental value of the stock should progressively reduce initial information asymmetries as the session advances (as in Foster and Viswanathan, 1990). Moreover, if new information is produced during trading periods, trades based on it may be delayed till the last trading hours because of the larger depth and, as we will see later on, the increased trading activity during these last trading periods. This would allow informed agents to trade more at the same price and to hide their trades among large liquidity-motivated trades. In addition, inventory costs should increase as we get close to the end of the session because of the risk of carrying undesired inventory overnight. Consistently, Table 5 -panel A- evidences that the highest adverse selection costs, computed as the ratio of the price impact to the half-effective spread for each trade, occur during the first two time intervals and decrease progressively towards the end of the trading day.[15] Moreover, the percentage of adverse selection costs is lower for the LFTS independently of the trading hour, which intuitively agrees with inventory holding costs being more important for those stocks that are less traded.

For the MFTS the price impact increases from the 13:00-14:00 time interval, but this upward trend is broken in the last trading hour. When volume per trade is not taken into account, however, this last jump disappears and the unweighted price impact follows a reversed J-shaped pattern (see Figure 4). Similar patterns arise when prices are used as post-trade values, also for the LFTS. Figure 4 shows that large trades have a larger price impact, but it also reveals that large trades in the last trading interval are less informative for the market than large trades in other time intervals. We have tested this hypothesis by grouping trades in five

[15] This result is independent of the proxy used for the post-trade theoretical value of the stock.

trade size-based quintiles.[16] Table 5 -panel B- shows first that there is generally an increasing trade-size effect independently of the trading hour considered. Paired tests (not reported) also display positive and significant differences between the largest and the smallest quintiles. Second, similar trades at different trading hours have significantly different effects on price, and this result is independent of the quintile considered. Finally, paired tests indicate that the price impact of any trade at the beginning of the trading day is significantly larger than that of a similar trade at the end of the trading day. Therefore, expectations about the informativeness of trades seem to move the market. Trades are expected to be more information motivated at the beginning of the trading day. This causes any trade to have a larger price impact than a similar trade towards the end of the session, independently of its size.

[Insert Figure 4 and Table 5 around here]

Summarizing, the evidence above seems to indicate that the reported intraday regular patterns in global liquidity may be explained (at least partially) by expectations about when informed trading is more intense or when information asymmetries are larger. These generally extended expectations determine the expected informativeness of trades and, in general, the sensitivity of the midpoint to the order flow. This argument also suggest that the market may interpret similar market conditions at different hourly intervals as being caused by distinct reasons. Market conditions are analyzed in the next section.

5. - Market conditions and liquidity.

If liquidity providers were risk adverse agents, liquidity should be expected to deteriorate during periods of higher maker making costs. Because market conditions should be related to the magnitude of the different costs of market making, theoretical and empirical studies have pointed out that variables like activity, volatility, level of private information, off-competition and institutional restrictions are all influential in determining the quoted bid-ask spread (e.g., McInish and Wood, 1992). There is, however, little empirical evidence and few theoretical predictions about how changes in market conditions explain depth. The logical and usual claim is that, by extension, the effects on depth should be the opposite of those predicted on immediacy costs (e.g., Engle and Lange, 1997; Kavajecz, 1998).

The expected effect of activity on liquidity in a time series context is an open empirical question. Greater activity is associated with lower inventory-holding costs given that higher

[16] Each quintile has the same number of trades.

levels of activity should allow a faster return to desired optimal portfolios (e.g., Easley et al., 1996). On the one hand, as soon as there are economies of scale in order-processing costs, a higher level of activity will reduce immediacy costs (see Glosten and Harris 1988).[17] However, the effect of activity in adverse selection costs is uncertain. In Kyle (1985), Admati and Pfleiderer (1988) and Harris and Raviv (1993), periods of lower time between trades were due to liquidity motivated trade clustering. Furthermore, in Easley and O'Hara (1992) more time between trades was interpreted as a signal of no new information. Globally, volatility is expected to reduce liquidity. Because of greater uncertainty about the true value of stock, price volatility is positively related with holding risk and also with information asymmetry risk (e.g., Tinic and West, 1972; French and Roll, 1986). Consequently, the higher the volatility the greater the immediacy costs and the lower the depth (e.g., Cohen et al., 1981; Copeland and Galai, 1983; O'Hara and Oldfield, 1986; Foster and Viswanathan, 1990). Informed trading is expected to reduce liquidity due to both larger immediacy costs (e.g., Bagehot, 1971; Glosten y Milgrom, 1985) and smaller depth (e.g., Kyle, 1985; Engle and Lange, 1997; Kluger and Stephan., 1997). However, competition among informed traders may increase the informativeness of trades and finally increase depth (see Subrahmanyam 1991; Holden and Subrahmanyam 1992). The effect of off-competition in liquidity is doubtful. More intense external competition has been shown to bring about narrower quoted spreads (e.g., Copeland and Galai 1983; Ahn et al. 1995, and Madhavan and Sofianos 1998). However, the impact of external competition on depth has received little attention. Quoted depth may be lower during periods of more intense external competition simply because less trading is demanded from the NYSE (e.g., Harris, 1994). Moreover, competing through depth would only attract more informed trading due to the possibility of trading larger orders. Therefore we expect off-competition to reduce depth. Recently, it has also been shown that regional markets attract an important part of their trades not through better prices but through payment for order flow, and that there is a successful 'cream skimming' of uninformed orders by off-NYSE market makers (see Blume and Glostein, 1997; Bessembinder and Kaufman, 1997). If the cream skimming effect matters for liquidity, its effect will be negative. Finally, the minimum price variation or tick imposes a minimum value on the quoted bid-ask spread. If the quoted spread is larger than it would be in case of setting a smaller tick, market microstructure will be restricting liquidity (e.g., Ahn et al., 1995; Bessembinder, 1997). Harris (1994) suggested that when liquidity providers could not increase liquidity through a narrower spread because of the tick, liquidity would be improved through greater quoted depth. It is

[17] Economies of scale are possible given that, as we will see later on, high activity periods are strongly linked with larger trades. If, as hypothesized, order-processing costs are constant, this implies the possibility of sharing

therefore expected that quoted depth will increase in periods of high tick restriction.

Market determinants are defined in the following way: volume (VOL) and trading frequency (TFREC) are measured by the square root of the accumulated trading volume and the square root of mean time between transactions (in seconds) respectively.[18] Volatility (RISK) is defined as the deviation of the midpoint of the quoted bid-ask spread for each period t with respect to its median, weighted by time. Informed trading (INF) is approximated using an unexpected trade-size measure, defined as the standardized square root of the mean volume per transaction.[19] Standardization is performed by subtracting from each observation associated with a day $(d=1,...,5)$ and hour $(h=1,...,7)$ of the week, the median of all observations corresponding to this particular hour and day, and then dividing it by the standard deviation of this median (see Appendix B). Off-competition (COMP) is measured by the ratio of share volume traded at the regional markets and NASD to share volume traded at the NYSE. Finally, the tick restriction (TICK) is computed as the percentage of time that the quoted spread equals the tick ($1/8 for all firms in the sample).

5.1. - Intraday regularities in market conditions.

With the same methodology previously described for liquidity measures, we study regular intraday patterns in market variables and compare them with the regular patterns previously found for liquidity. Results are summarized in Table 6. VOL and RISK follow the familiar reversed J-shaped pattern that denotes larger levels of activity and volatility at the beginning and towards the end of sessions.[20] Regular patterns for TFREC show that time between trades is lower during the first two and the last two hours of the trading day. Moreover, mean volume per trade (not reported) is larger in the initial and final hourly time intervals. Therefore, although market conditions in terms of activity, volatility and trade size are more similar at the extreme periods of the trading session, there are large differences in liquidity behavior during these periods, which suggests that similar market conditions at different moments of the trading session may be assumed to be caused by different reasons.

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these fixed costs among a larger number of units of stock.

[18] These transformations are used to smooth the series and reduce the effect of outliers in the regressions.

[19] Informed traders are assumed to be impatient agents because their private information becomes less valuable over time. Therefore, they are expected to trade more aggressively (see Foster and Viswanathan, 1990) before their private information becomes publicly known. Unexpected trading volume could be used as a proxy for the intensity of informed trading (e.g., Black, 1971; Easley and O'Hara, 1987) because large trades 'convey more information than small trades' (Hasbrouck, 1988, pg. 229).

[20] Intraday patterns in volume and/or volatility were also evidenced by McInish and Wood (1985), Harris (1986), Jain and Joh (1988), McInish and Wood (1990), McInish and Wood (1992), Foster and Viswanathan (1993) and Lee et al. (1993) for the NYSE, McInish and Wood (1990b) for the Toronto Stock Exchange, Lehman and Modest (1994) for the Tokyo Stock Exchange and Biais et al. (1995) for the Paris Bourse, among others.

Nevertheless, these regularities are consistent with our previous intuition in the following sense: liquidity providers expect a higher probability of informed-motivated trading during the first hours of the session. The higher activity is thought to hide impatient informed traders, and the lower time between trades is also interpreted as a sign of new information arriving to the market (as in Easley and O'Hara, 1992). Uncertainty generated about the value of the stock is reflected in higher levels of volatility. As the session advances information asymmetry risk falls, prices stabilize, volume decreases, and the time between trades increases. As closing comes near, portfolio-adjustment needs increase volume and trading frequency. Higher inventory-holding risk makes liquidity providers reduce depth and increase immediacy costs again. Traders are disposed to trade larger amounts at any price, increasing volatility. In any case, the volume needed to move the midpoint is larger because of the lower expected probability of trading with better informed traders (notice the lowest regular patterns in INF during the last trading hour). Finally, if the cream skimming negatively affected liquidity, its effect would be regularly lower during the last trading hours. For the LFTS, the worsening of liquidity during the last trading hours seems coherent with market makers protecting themselves from higher inventory-holding risks.

[Insert Table 6 around here]

5.2. - Liquidity adjustments to changes in market conditions.

This section deals with the question of how liquidity behaves in alternative market scenarios, and investigates whether liquidity reactions to changing market conditions are only the consequence of automatic adjustments to the previously reported regular patterns in market indicators. Special attention is paid to the identification of those market variables that have an unambiguous effect on liquidity, in the sense that they are linked to immediacy costs and depth in opposite ways. Finally, studying their relationship with the mean price impact of trades identifies variables that indicate greater informational content of trades. As a first approximation, following Lee et al. (1993), each liquidity measure is regressed on each of our explanatory market variables, using the same pool generalized least square (GLS) regression procedure described in section 3, now applied to equation (11) (where x_t represents some market determinant). Table 7, panel A, reports the estimated β coefficients that were significant at the 5% level.

$$y_{it} = \alpha + \beta x_{it} + u_{it}$$
$$u_{it} = \sum_{i=1}^{z} \gamma_k u_{i(t-k)} + \varepsilon_{it} \qquad (11)$$

[Insert Table 7 around here]

Only volatility has an unambiguous effect on liquidity for both subsamples. High volatility periods are linked with high immediacy costs and reduced depth. Moreover, for the MFTS depth increases due to the impossibility of improving liquidity through narrower spreads, consistent with Harris (1994). For the LFTS, however, quoted depth decreases with TICK. In any case, tick restriction for the latter subsample is significantly lower (26% of time for the LFTS versus 69% for the MFTS in median terms). Consistent with adverse selection costs' arguments, immediacy costs grow with activity and with unexpected trade size. VOL and INF, however, are also significantly linked to larger quoted and realized depth.[21]Therefore, although specialists increase spreads in order to offset greater market making costs, at these worse quotes liquidity providers are willing to offer more quantity to be traded. Finally, although higher off-competition reduces immediacy costs, it also reduces depth (as expected). Hence, the effect of these last measures on liquidity is uncertain. These preliminary results also indicate that trades have a larger price impact during periods of higher activity (measured by either VOL or TFREC), higher volatility and larger unexpected trade-size. Hence, these market variables may indicate higher informational content of trades.

Results for BLM indicate that: (a) VOL and lower time between trades affect liquidity negatively. This result conforms to models that interpret higher activity as more adverse selection and inventory costs of market making (e.g., Foster and Viswanathan, 1993). Agreeing with Easley and O'Hara (1992) longer periods without trades are interpreted as no new information allowing liquidity providers to increase liquidity. (b) BLM decreases with RISK. Price uncertainty, because of either adverse selection costs (e.g. French and Roll, 1985) or inventory holding costs (e.g., O'Hara and Oldfield, 1986), leads risk averse liquidity providers to reduce liquidity. (c) Off-competition positively affects liquidity for MFTS. This result does not support the cream skimming effect as being relevant for liquidity. If this effect were important, days with greater competition from external markets should increase the risk of informed trading at the NYSE and greater price impact of trades should be expected. Recently, Battalio (1997) has shown, for a sample of NYSE-listed securities, that the adverse

[21] TFREC is also inversely related with WVNET

selection costs associated with the action of cream skimmers may be economically insignificant. Our results also suggest the possibility that informed traders adjust their trades to the lower liquidity-motivated trading volume during periods of higher off-competition in order to remain in hiding. (d) BLM is greater when TICK is larger. This result also supports the idea that lower minimum price variations would favor liquidity improvements (e.g., Harris, 1994). Finally, (e) our proxy for informed trading activity is positively related to BLM in both subsamples. During periods of large unexpected mean trade size the reported increase in depth is relatively larger than the corresponding change in immediacy costs.[22]

In order to analyze whether these relationships are mainly due to the regular patterns previously reported, we have estimated equation (11) for each liquidity measure and each market determinant but have added the dummy variables that control for trading hour and trading day. Those coefficients that are not longer significant at the 5% level are marked with an asterisk in Table 7, Panel A. Only one aspect is remarkable: when price improvements are considered, immediacy costs for the MFTS seems to automatically adjust to the predictable regular changes in activity. If these regular patterns are discounted, there is no additional relationship between activity and effective spread. Therefore, results show that liquidity adjusts to changes (either regular or irregular) in market conditions. However, only volatility is linked with opposite changes in immediacy costs and depth for both subsamples. Moreover, market activity and volatility provide signals about greater information asymmetry risk that increases the mean price impact of trades.

It has already been shown that some market variables show similar regular patterns. Liquidity providers can also interpret many of these market indicators as a signal of informed trading activity. Moreover, there are high correlations between some of these variables, especially for the LFTS sample.[23] All this suggests that crossed effects due to other variables could bias previous simple regression results. Equation (12) is estimated, using again the pooled GLS regression procedure, to account for these crossed effects. Although the model is linear in the parameters, for some liquidity measures the functional form may differ. A preliminary analysis showed that some relationships were better captured by non-linear specifications. In some cases, however, non-linearities might be induced by the presence of outliers. Moreover, highest correlations between the explanatory variables might cause problems of

[22] For those market variables that, given their relationship with immediacy costs and depth, do not have an unequivocal effect on liquidity, BLM captures which liquidity dimension they are more strongly linked to. For example, for the MFTS sample, INF explains a larger part of the total variability of the quoted depth than that of the relative spread. The opposite happens with VOL and COMP.

multicollinearity. We have, therefore, analyzed several models, both linear and non-linear, concerned with the market variables. The paper reports the estimated model that was ultimately chosen.[24,25]

$$y_{it} = \alpha + \beta_1 VOL_{it} + \beta_2 TFREC_{it} + \beta_3 RISK_{it} + \beta_4 INF_{it} + \beta_5 TICK_{it} + \beta_6 COMP_{it} + u_{it}$$
$$u_{it} = \sum_{i=1}^{z} \gamma_k u_{i(t-k)} + \varepsilon_{it} \qquad (12)$$

Table 7, Panel B, summarizes the regression results for the variables that measure immediacy costs or depth. In all cases, the selected specifications were linear. Again, only volatility has opposite effect on immediacy costs and depth dimensions for both subsamples. Several joint effects between the explanatory variables were observed.[26] For the MFTS sample VOL and COMP do not explain immediacy costs and quoted depth anymore, the effective spread only depends on RISK and INF, and TFREC now has an unambiguous effect on depth. For the LFTS sample the main change is observed for TFREC, which seems to increase immediacy costs once the effect of other market indicators has been considered.[27] Equations (13) and (14) represent the pooled coefficient estimates for the price impact for both subsamples.[28] Adjusted-R^2 are 0.1988 and 0.5203 respectively. Once again volatility, activity and trade-size (when significant) are coupled with higher mean price impact of trades. Therefore, the market seems to interpret more active and volatile periods as times where there is more information arriving at the market. In contrast, stronger off-competition and high persistence of the minimum quoted spreads reduce the expected informational content of trades. Whether or not off-competition is based on payment for order flow, or whether or not the cream skimming effect exists, higher external competition does not increases the impact of trades.

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[23] Highest correlations are among VOL, TFREC and INF.

[24] Non-linear specifications are considered only when they provide a better interpretation of the estimated relationship. Therefore, whenever it is possible, we choose linear models.

[25] Results for the LFTS should be taken with care since missing observations are common for some liquidity measures and market indicators. Effective spread and price impact, for example, are not defined when there are no trades.

[26] In fact TFREC and VOL seem to capture the same aspect of market activity for these liquidity measures. When both market variables are considered together VOL is not significant. When only one of them is included in the regression, its coefficient is fully significant at the 5% level and, in both cases, it gives the same intuition about how activity influences on liquidity. This is a typical multicollinearity effect.

[27] Given that it is common for these LFTS to observe periods without trades, there is not reason to expect special behavior of liquidity around periods of scarce trading. Therefore, the rational in Easley and O'Hara (1992) may be not valid for these type of stocks, and we could be facing a spurious relationship. It is also possible that we are simply dealing with a scale factor since greater volume reduces liquidity but this effect is reduced when the volume is shared between a larger number of trades.

[28] Autoregressive terms have been omitted.

$$PIWV_{it}^{MFTS} = (.0269) + (3.14e^{-05})Vol_{it} - (5.87e^{-08})Vol_{it}^2 + (.2543)Risk_{it} + \\ + (.0029)Inf_{it} - (.0097)Tick_{it} - (.0032)Comp_{it} + u_{it} \quad (13)$$

$$PIWV_{it}^{LFTS} = (.0402) - (.0012)TFrec_{it} + (1.81e^{-05})TFrec_{it}^2 + (.4578)Risk_{it} + \\ + (.0027)Inf_{it} - (.0054)Tick_{it} - (.0007)Comp_{it} + u_{it} \quad (14)$$

Finally, equations (15) and (16) show the pooled estimates of the BLM model. Adjusted R^2 are 0.4346 and 0.5542 respectively. Observe that off-competition does not influence liquidity once the effect of other market indicators has been discounted. Mainly, three variables seem to influence BLM for both subsamples: VOL and RISK are linked to lower quoted liquidity, consistently with the simple regression results and with the previously reported regular patterns. The negative effect of VOL is due to the larger impact this variable has on immediacy costs than on quoted depth. TICK coexists with higher BLM values. For the MFTS, both quoted and realized depths grow during periods of high tick incidence. These results do not suffer significant changes once regular patterns are taken into account. Therefore, liquidity reacts to changes in market conditions more than is expected by automatic adjustments to the regular changes in the market conditions.

$$BLM_{it}^{MFTS} = (.6324) - (.00083)Vol_{it} - (.8302)Risk_{it} + (.1236)Inf_{it} + (1.0594)Tick_{it} + u_{it} \quad (15)$$

$$BLM_{it}^{LFTS} = (.9751) - (.0033)Vol_{it} - (.0006)TFrec_{it} - (1.3469)Risk_{it} + (.3969)Tick_{it} + u_{it} \quad (16)$$

In summary, liquidity adjusts to contemporaneous changes in market conditions. After controlling for the predictable changes in market variables, there is still a significant relationship between liquidity and market conditions. Activity and volatility tend to worsen quoted liquidity. For the MFTS, high tick persistence induces liquidity improvements through quoted and realized depth and off-competition does not affect liquidity once other market indicators are considered. When we study immediacy costs and depth separately, only volatility has an opposite effect on both liquidity dimensions for the two subsamples. For the other market variables, results for BLM indicate which liquidity dimension they are more strongly connected to (in terms of how much of the total variability of immediacy costs and depth they explain). Finally, more activity, unexpected trade size and volatility are signals of greater informational content of trades. More off-competition and persistence of the minimum quoted spreads reduce the impact of trades in prices.

6. - Summary and discussion.

Using intraday data from the NYSE, this paper has extended previous time series analysis of liquidity by a simultaneous analysis of immediacy costs and sensitivity of prices to order flow. As a first approximation to the multidimensional characterization of liquidity, a new and simple direct measure has been introduced, the Bidimensional Liquidity Measure (BLM), that captures simultaneous changes in both immediacy costs and depth. Significant intraday regular patterns for liquidity are obtained. These patterns suggest that liquidity progressively increases along the session and only deteriorates towards the end of the trading day. It is hypothesized that regularities in liquidity are mainly due to the intraday fluctuations in different market making costs. Using the price impact of trades as a proxy for adverse selection costs of market making, it is evidenced that liquidity traders do not expect informed traders' activity to be uniformly distributed throughout the session. Price impact of trades is systematically larger the first two trading hours. Significant differences between the first and the last trading hours are reported which suggest an increasing importance of inventory-holding costs towards the end of the session. Moreover, the percentage of the effective spread due to adverse selection costs declines over the day. In fact, although trade size is shown to matter, all trades at the beginning of the day and independently of their size have a higher probability of being considered as information motivated than similar trades during the rest of the session.

Liquidity is also shown to react to changing market conditions, and these adjustments are larger than expected from the predictable changes in market conditions. Only volatility, however, is shown to have an unambiguous effect on liquidity. Our Bidimensional Liquidity Measure indicates that higher activity and volatility reduce quoted liquidity. No significant effect due to off-competition is found after controlling for other market indicators. Therefore, if the cream skimming exists, it is irrelevant for liquidity. Finally, more activity, trade size and volatility are found to be indicators of new information arriving to the market, which increases the mean price impact of trades. In contrast, greater off-competition and more persistence of minimum quotable spreads are associated with lower informational content of trades.

These results suggest important lines for both theoretical and empirical future research. Liquidity at least requires a bidimensional characterization based on immediacy costs and depth. However, these two dimensions are not independent. Theoretical models that simultaneously analyze both dimensions of liquidity are required. The main problem of those models will be to set the main determinants of the depth dimension of liquidity. This paper

has shown that, although immediacy costs and depth are negatively related, only volatility seems to induce changes compatible with this negative relationship. Moreover, trading activity measured either by volume or trading frequency is found to better explain the evolution of immediacy costs than that of depth. Therefore, the identification of the main determinants of the sensitivity of prices to order flow requires further attention. In any case, the TAQ database does not allow us to distinguish between the part of the quoted depth that corresponds to the specialist and the part that reflects the limit order book. The motivations of the specialist may differ from those of other liquidity providers (e.g., Kavajecz, 1998). Future empirical studies are required to analyze how market conditions affect to that part of the quoted depth that corresponds to different liquidity providers.

A further relevant implication of this paper is that liquidity is also moved by expectations about the timing of the information arrivals at the market. Liquidity traders are expected to act with higher probability at the beginning of the trading day, and this increases adverse selection costs during these periods. However, although market conditions in terms of volume, volatility, trading frequency and trade size are similar, trades at the end of the day are considered as more likely to be caused by portfolio adjustments or other non information-motivated reasons. These elements will increase the relevance of inventory-holding costs during the last trading hours. Hence, the dynamics of liquidity and the reaction to changing market conditions are expected to differ at different trading hours. This paper evidences a mean relationship between market conditions and liquidity during the trading day that may differ at different moments of the session.

Finally, the use of multimensional liquidity measures may help to extend past time series and cross-sectional empirical analysis. Simple as it is, BLM gives some intuitions about the behavior of liquidity that cannot be captured studying immediacy costs and depth dimensions separately. Future research should provide alternative and better approximations to measuring liquidity.

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TABLE 1
Descriptive statistics

Means and standard deviations (in parentheses) of some statistics for both subsamples: the more frequently traded stocks (MFTS) and the less frequently traded stocks (LFTS).

General statistics			
Issue	**Details**	**MFTS**	**LFTS**
Daily trades		231.2 (199.6)	6.7 (2.6)
Daily share volume		594,846 (496,305)	12,356 (8,579)
Trades placement (%)	Inside quotes	24.4 (7.9)	24.6 (8.5)
	At the ask	38.4 (4.1)	35.7 (5.4)
	At the bid	36.1 (5.0)	37.5 (7.9)
	Not classified*	1.1 (0.4)	2.3 (1.6)
Tick restriction (%)	Spread=tick	61.9 (15.6)	42.5 (23.7)
	Spread=2*tick	33.2 (10.1)	41.4 (14.7)
	Spread>2*tick	4.9 (6.8)	16.1 (11.2)
Quote changes after a trade at the ask	Quotes revised	42.2 (15)	58.5 (9.4)
	(1) Ask rises	29 (8.6)	28.7 (8.4)
	(2) Bid rises	2.7 (1.6)	3.2 (1.5)
	(3) Ask and bid rise	7.5 (4.2)	23.2 (11.7)
	(4) Other	3.0 (1.6)	3.3 (1.5)
Quote changes after a trade at the bid	Quotes revised	44 (16)	56 (21.4)
	(1) Ask falls	3.2 (1.8)	3 (1.1)
	(2) Bid falls	30 (9.1)	27.2 (9.9)
	(3) Ask and bid fall	7.7 (4.7)	22.4 (12.2)
	(4) Other	3.1 (1.1)	3.5 (1.3)
Adverse selection cost-component (%) of the spread	Unweighted	53.1 (17.3)	62.1 (23.7)
	Weighted (volume)	74.8 (17.2)	65.3 (22.2)

Hourly statistics: one-dimensional liquidity measures and market variables		
Issue	**MFTS**	**LFTS**
Relative spread weighted by time	.0049 (.0031)	.0178 (.0151)
Effective spread weighted by volume	.1269 (.0462)	.1592 (.1055)
Price impact weighted by volume	.0526 (.0575)	.0495 (.0847)
Realized spread weighted by volume	.0111 (.0618)	.0504 (.1933)
Implicit spread	.0035 (.0023)	.0526 (.0341)
Quoted depth weighted by time	22,884 (24,340)	8,511 (13,240)
VNET	7,738 (17,016)	2,745 (6,750)
Share volume	95,591 (153,260)	1,998 (16,803)
Trading frequency (seconds between trades)	221.175 (381.279)	2,480 (12,714)
Volatility (quoted midpoint)	.0949 (.0984)	.0235 (.0461)
Volume per trade	2,155 (452)	299 (585)
Unexpected volume per trade	.15 (.9887)	.3131 (.9497)
Tick restriction (% of time)	.6388 (.2846)	.4099 (.4539)
Off-competition (% over NYSE volume)	.3844 (.3417)	.1047 (.4226)

* Trades not classified using the Lee and Ready (1991) 'five seconds rule'.

TABLE 2
Independence

Results of a non-parametric test of independence based on contingency tables. Each hourly interval is classified into one of four categories depending on whether the value for each variable is higher or lower than its respective median. Observations in which any of the variables equals its median are not considered (they are, in any case, negligible). The contingency table for each pair of measures is reported. Values in parenthesis represent the expected numbers in each category, under the null hypothesis of independence. Categories are (from the upper-left cell to the lower-right cell): below-below, below-above, above-below and above-above. For each contingency table the value for the Pearson Chi-square test, the direction of the dependency, its significance level and the percentage of stocks for which independence is individually rejected, are also given. Direction of dependency is positive (+) when both measures are simultaneously above and below their respective medians on more occasions than expected. It is negative (-) when measures are in opposite categories on more occasions than expected. Results correspond to the more frequently traded stocks (MFTS) subsample.

	RSWT		EFSWV		PIWV		DWT		WVNET	
EFSWV	10227	10288								
	(10314)	(10253)								
	10914	10684								
	(10879)	(10719)								
	χ^2=.4352									
PIWV	12118	9708	11396	9779						
	(10909)	(10917)	(10406)	(10769)						
	9708	12134	9347	11627						
	(10917)	(10925)	(10337)	(10637)						
	χ^2=535.53 (+,***,80)		χ^2=371.96 (+,***,80)							
DWT	9955	12251	9973	11396	10060	11784				
	(11108)	(11098)	(10746)	(10623)	(10924)	(10920)				
	12263	9945	11220	9591	11790	10058				
	(11110)	(11098)	(10337)	(10364)	(10926)	(10922)				
	χ^2=479.32 (-,***,80)		χ^2=226.91 (-,***,72)		χ^2=273.36 (-,***,76)					
WVNET	9645	10530	9688	10308	10492	9672	13646	6530		
	(10084)	(10091)	(9974)	(10022)	(10080)	(10084)	(10089)	(10087)		
	10519	9648	10267	9743	9664	10491	6526	13640		
	(10080)	(10087)	(9987)	(10029)	(10076)	(10079)	(10083)	(10083)		
	χ^2=76.43 (-,***,76)		χ^2=32.73 (-,***,36)		χ^2=67.27 (+,***,48)		χ^2=5019 (+,***,100)			
BLM	7237	13055	9329	10081	8998	10983	16917	3382	11837	6616
	(10150)	(10142)	(9973.7)	(9436.3)	(9989.5)	(9991.5)	(10151)	(10148)	(9226.5)	(9226.5)
	13060	7228	10026	8427	10979	8998	3381	16912	6615	11836
	(10147)	(10141)	(9381.3)	(9071.7)	(9987.5)	(9989.5)	(10147)	(10146)	(9225.5)	(9225.5)
	χ^2=3344.6 (-,***,96)		χ^2=175.81 (-,***,76)		χ^2= 393.64 (-,***,84)		χ^2=18047 (+,***,100)		χ^2=2954 (+,***,100)	

*** Significant at the 1% level.

TABLE 3

Liquidity measures. Intraday regular effects.

For each measure analyzed, equation (T1) has been estimated using Pooled GLS with White's standard errors (robust to general heteroskedasticity within each cross-section unit). We also control for different heteroskedasticity across cross-sections. In order to account for residual autocorrelation within cross-sections, an autoregressive structure is allowed on residuals.†

$$y_{it} = \alpha + \sum_{s=2}^{7} \beta_s DHs_t + \sum_{h=2}^{5} \delta_h DDh_t + u_{it} \qquad \text{(T1)}$$

$$u_{it} = \sum_{k=1}^{z} \gamma_k u_{i(t-k)} + \varepsilon_{it}$$

i represents the stock (the cross-sectional unit) and t the hour (i=1,...,25; t=1,2,...,1778). DHs_t (for s=2 to 7) are dummy variables that take the value 1 for the sth hour of the session and zero otherwise. DDh_t (for h = 2 to 5) are dummy variables that take the value 1 for the hth trading day of the week and zero otherwise. ε_{it} is the error term, such that $E[\varepsilon'\varepsilon]=\Omega$. $\beta' = (\beta_2,..., \beta_7)$, $\delta' = (\delta_2,..., \delta_5)$, $\gamma' = (\gamma_1,...,\gamma_z)$ and α are the coefficients of the model. α captures the Monday and the first half-hour of the session effects. The coefficients δ of the daily dummies and γ of the autoregressive terms are omitted.

MFTS = more frequently traded stocks, LFTS = less frequently traded stocks. For definitions of RSWT, EFSWV, PIWV, DWT, WVNET and BLM see appendix B and equation (9).

Panel A: MFTS

	Measure					
Coefficient	**RSWT**	**EFSWV**	**PIWV**	**DWT**	**WVNET**	**BLM**
Intercept	.003324*	.124236*	.050467*	6639.146*	3600.194*	.538485*
[10:00 11:00)	-.000296*	-.003018*	-.002065*	2588.952*	905.44*	.474850*
[11:00 12:00)	-.000390*	-.003463*	-.007639*	3924.257*	1289.834*	.695414*
[12:00 13:00)	-.000419*	-.005155*	-.011484*	4194.851*	1274.229*	.729171*
[13:00 14:00)	-.000427*	-.004569*	-.010650*	4459.658*	1178.221*	.750943*
[14:00 15:00)	-.000411*	-.003788*	-.008651*	4339.946*	883.7245*	.833397*
[15:00 16:00]	-.000368*	2.17e-05	-.010778*	4336.878*	1245.805*	.646383*
Adjusted R^2♣	.7973	.3792	.0081	.4833	.0844	.4453

Panel B: LFTS

	Measure					
Coefficient	**RSWT**	**EFSWV**	**PIWV**	**DWT**	**WVNET‡**	**BLM**
Intercept	.013667*	.135169*	.043297*	2000.341*	1063.215*	.824493*
[10:00 11:00)	-.000401*	-.002105	-.001746*	168.3277*	116.1631*	.086243*
[11:00 12:00)	-.000734*	-.006092*	-.002829*	275.1872*	102.4501*	.170664*
[12:00 13:00)	-.000932*	-.006267*	-.004717*	315.9793*	168.5231*	.34381*
[13:00 14:00)	-.001036*	-.007436*	-.004996*	345.7370*	141.5824*	.315164*
[14:00 15:00)	-.001119*	-.007236*	-.004311*	369.1960*	157.0588*	.239098*
[15:00 16:00]	-.001151*	-.006672*	-.003483*	385.773*	204.9638*	.149778*
Adjusted R^2♣	.6664	.3651	.4647	.7615	—	.5726

† The number of autoregressive terms has been selected after rejecting more complex specifications, starting with z=7.
‡ For this regression the R^2 is almost zero.
* Significant (at least) at the 5% level.
** Significant at the 10% level.
♣ These R^2 are mainly due to the autoregressive structure.

TABLE 4

Trades with prices inside the quoted bid-ask spread

Summary of the distribution of trades with prices inside the quoted bid-ask spread (the quoted spread is assigned to the trade using the Lee and Ready (1991) algorithm). This includes the median volume per inside-quote trade for each time interval considered. Finally, it also reports the difference with respect to the median volume per trade transacted for a trade with a price equal to the quoted bid or quoted ask. MFTS = more frequently traded stocks, LFTS = less frequently traded stocks.

	Median percentage[1] of inside-quote trades		Median volume[2] per trade		Difference in median volume per trade with trades at the quotes	
Period	MFTS	LFTS	MFTS	LFTS	MFTS	LFTS
[9:30 10:00)	.2188	.2493	1972.90	1141.18	-1075.25*	-451.68
[10:00 11:00)	.1792	.1383	1875.99	903.06	-497.93*	-374.01*
[11:00 12:00)	.1317	.1296	1780.76	930.23	-450.16*	-437.41*
[12:00 13:00)	.1040	.1047	1890.81	667.57	-463.78**	-326.72*
[13:00 14:00)	.0943	.0994	1785.71	814.29	-479.32*	-411.24*
[14:00 15:00)	.1165	.1111	1720.52	872.22	-469.61*	-363.89*
[15:00 16:00]	.1595	.1527	2030.31	842.86	-598.22*	-362.77*
Monday	.1792	.1992	1770.85	687.90	-538.75*	-488.27*
Tuesday	.2179	.2204	1980.61	968.18	-538.38*	-311.98**
Wednesday	.2106	.1968	1814.06	1053.68	-646.72*	-403.64**
Thursday	.1993	.1882	2052.12	921.43	-518.08*	-227.27**
Friday	.1928	.1975	1849.85	848.33	-590.88*	-440.67*

[1] Medians of MFTS and LFTS are statistically different at the 5% level, using the Krustal-Wallis test for equality of medians (both for hours and days).

[2] Medians of MFTS and LFTS are not statistically different at the 5% level, using the Krustal-Wallis test for equality of medians (both for hours and days).

* Significant at the 5% level, using the Mann-Whitney W test for the equality of medians of two samples (alternative hypothesis: median volume of inside-quote trades is lower than median of trades at quotes).

** Significant at the 10% level, using the Mann-Whitney W test for the equality of medians of two samples (alternative hypothesis: median volume of inside-quote trades is lower than median volume of trades at quotes).

TABLE 5

Adverse selection costs as a percentage of the effective spread.

For each trade, the percentage of immediacy costs due to adverse selection costs is estimated using the ratio of price impact to half-effective spread. Immediacy costs have been computed using both trade price and midpoint of the quoted bid-ask spread as proxies for the post-trade theoretical value of the stock. Only the results for the midpoint are reported. Panel A contains mean values per hour. Panel B summarizes the results of testing differences in price impact of trades of equal size at different trading periods. The Mann-Whitney (Wilcoxon) W test is used to contrast equality of medians between each pair of trading hours. Quintiles are sorted from the lowest to the larger trade size. MFTS = more frequently traded stocks, LFTS = less frequently traded stocks.

Panel A

MFTS*

Hour:	[9:30 10:00)	[10:00 11:00)	[11:00 12:00)	[12:00 13:00)	[13:00 14:00)	[14:00 15:00)	[15:00 16:00]
Adverse selection (%)	83.38	73.05	62.28	60.32	61.15	64.1	65.85

LFTS*

Hour:	[9:30 10:00)	[10:00 11:00)	[11:00 12:00)	[12:00 13:00)	[13:00 14:00)	[14:00 15:00)	[15:00 16:00]
Adverse selection (%)	64.91	61.74	55.29	54.11	53.48	53.72	50.42

Panel B

MFTS

Quintile	[9:30 10:00)	[10:00 11:00)	[11:00 12:00)	[12:00 13:00)	[13:00 14:00)	[14:00 15:00)	[15:00 16:00]	First – last	Total
First*	.0311065	.0212718	.0169762	.0155513	.0151677	.0164342	.0189206	.0121859‡	.0187178
Second*	.0399013	.0301375	.0234615	.0219143	.0235534	.0249796	.0279118	.0119895‡	.0269625
Third*	.0533153	.0421973	.0332363	.0315645	.0335155	.0354256	.0369167	.0163987‡	.0377163
Fourth*	.0651551	.0529607	.0421111	.042128	.0415075	.0448838	.047401	.0177541‡	.0477843
Fifth*	.0678754	.0621512	.0551779	.0536864	.0526831	.0549097	.0568394	.0110361‡	.0576417

LFTS

Quintile	[9:30 10:00)	[10:00 11:00)	[11:00 12:00)	[12:00 13:00)	[13:00 14:00)	[14:00 15:00)	[15:00 16:00]	First – last	Total
First*	.0442603	.0352504	.0262199	.0215188	.0271329	.0271043	.0213038	.0229566‡	.0297845
Second*	.0511807	.0425314	.0419551	.0305915	.0300812	.035627	.0290836	.0227571‡	.0383343
Third*	.0588025	.0590113	.0506039	.0517376	.0457608	.0500852	.043476	.0153265‡	.0521813
Fourth*	.0744488	.069582	.0657697	.0545522	.0563202	.061383	.0492463	.0252024‡	.062871
Fifth*	.0734204	.0749124	.0696968	.0687416	.06425	.0634322	.0590452	.0143752†	.068506

* Means at the individual level are significantly different at the 5% level. Paired test of medians show also significant differences between the first two, the last two and the three intermediate hour intervals.

† Against the alternative hypothesis that the mean of the first trading hour is larger than the mean of the last trading hour, equality of means is rejected at the 5% level.

‡ Against the alternative hypotheses that the mean and median of the first trading hour are larger than the mean and median of the last trading hour, respectively, equality of means and medians is rejected at the 5% level.

TABLE 6

Market determinants: Intraday regular patterns.

For each of the market determinants of liquidity considered, equation (T2) has been estimated using Pooled GLS with White's standard errors (robust to general heteroskedasticity within each cross-section unit). We also control for different heteroskedasticity across cross-sections. In order to control for autocorrelation within cross-sections, an autoregressive structure has been allowed on residuals.†

$$x_{it} = \alpha + \sum_{s=2}^{7} \beta_s DHs_t + \sum_{h=2}^{5} \delta_h DDh_t + u_{it} \qquad \text{(T2)}$$

$$u_{it} = \sum_{k=1}^{z} \gamma_k u_{i(t-z)} + \varepsilon_{it}$$

i represents the stock (the cross-sectional unit, i=1,...,25) and t the trading hour (t=1,2,...,1778). DHs_t (for s=2 to 7) are dummy variables that take the value 1 for the sth hour of the session and zero otherwise. DDh_t (for h = 2 to 5) are dummy variables that take the value 1 for the hth trading day of the week and zero otherwise. ε_{it} is the error term, such that $E[\varepsilon'\varepsilon]=\Omega$. $\beta' = (\beta_2,..., \beta_7)$, $\delta' = (\delta_2,..., \delta_5)$, $\gamma' = (\gamma_1,...,\gamma_z)$ and α are the coefficients of the model. α captures the Monday and the first half-hour of the session effects. We omit the δ and γ coefficients of the daily dummies and the autoregressive terms respectively.

Panel A: MFTS

	Market determinants§					
Coefficient	**VOL**	**TFREC**	**RISK**	**INF**	**TICK**	**COMP**
Intercept	260.0949*	11.41089*	.098972*	.1867*	.590032*	.379869*
[10:00 11:00)	-34.54917*	-0.059819	-.022591*	-.04217*	.100449*	-.008697*
[11:00 12:00)	-62.1541*	.938258*	-.039084*	-.026619	.134714*	.018293*
[12:00 13:00)	-83.21754*	2.234545*	-.04668*	-.01574	.149212*	-.009851*
[13:00 14:00)	-.92.09661*	2.883077*	-.04929*	-.008135	.150967*	.010336*
[14:00 15:00)	-75.40341*	1.85106*	-.043263*	-.056355*	.14886*	-.031220*
[15:00 16:00]	-25.02055*	0.013573	-.032694*	-.082906*	.130298*	-.038078*
Adjusted R^2	.3396	.4241	.1097	.0879	.7604	.1924

Panel B: LFTS

	Market determinants					
Coefficient	**VOL**	**TFREC**	**RISK**	**INF**	**TICK**	**COMP**(‡)
Intercept	24.15444*	44.62192*	.025815*	.314563*	.203957*	.013665*
[10:00 11:00)	-7.494064*	4.245457*	-.009963*	-.023699	.02888*	.004076*
[11:00 12:00)	-8.249633*	4.554323*	-.011716*	.017490	.056908*	.00136
[12:00 13:00)	-11.00520*	5.997681*	-.014689*	.087002*	.067366*	-.003898*
[13:00 14:00)	-11.02949*	6.158546*	-.014435*	.088439*	.071733*	-.000599
[14:00 15:00)	-8.170158*	4.669108*	-.013722*	.024792	.074117*	-.000813
[15:00 16:00]	-3.903045*	1.747851*	-.010848*	-.099497*	.073349*	.005961*
Adjusted R^2	.0666	.3048	.0515	.0397	.6298	-----

§ VOL = square root of the accumulated share volume. TFREC = square root of the mean time interval (in seconds) between trades. RISK = standard deviation of the midpoint of the bid-ask spread with respect to the median for each period. INF = standardized square root of the mean volume per transaction. TICK = percentage of time during which the quoted bid-ask spread equaled the tick ($1/8). COMP = ratio of share volume traded at the regional markets and NASD to volume traded at NYSE. MFTS = more frequently traded stocks, LFTS = less frequently traded stocks.

† The z autoregressive terms for each measure have been selected after rejecting more complex specifications, starting with $z = 7$.

‡ For this regression the Adjusted-R^2 is almost zero.

* Significant at the 5% level.

** Significant at the 10% level.

TABLE 7
Liquidity and market conditions.

Panel A: for each liquidity measure analyzed, equation (T3) has been estimated using Pooled GLS with White's standard errors (robust to general heteroskedasticity within each cross-section unit) and controlling for cross-sectional heteroskedasticity. We allow for an autoregressive structure on residuals in order to control for autocorrelation and also in order to isolate the contemporaneous effect of each of the explanatory variables.‡

$$y_{it} = \alpha + \beta x_{it} + u_{it} \qquad \text{(T3)}$$
$$u_{it} = \sum_{k=1}^{z} \gamma_k u_{i(t-k)} + \varepsilon_{it}$$

Panel B: equation (T4) has been estimated using the same Pooled GLS procedure as in Panel A.

$$y_{it} = \alpha + \beta_1 VOL_{it} + \beta_2 TFREC_{it} + \beta_3 RISK_{it} + \beta_4 INF_{it} + \beta_5 TICK_{it} + \beta_6 COMP_{it} + u_{it} \qquad \text{(T4)}$$
$$u_{it} = \sum_{k=1}^{z} \gamma_k u_{i(t-k)} + \varepsilon_{it}$$

i represents the stock (the cross-sectional unit, i=1,...,25) and t the hour (t=1,2,...,1778). ε_{it} is the error term, such that $E[\varepsilon'\varepsilon]=\Omega$. β', $\gamma'=(\gamma_1,...,\gamma_z)$, and α are the coefficients of the model. In the table, we omit the coefficient estimates of the autoregressive terms. This table only reports the estimated βs that are significant (at least) at the 5% level. Panel A also omits the constant term. x in (T3) is one of the following market variables: *VOL* = square root of the accumulated share volume, *TFREC* = square root of the mean time interval (in seconds) between trades, *RISK* = standard deviation of the midpoint of the bid-ask spread with respect to its median for each period t, *INF* = standardized square root of the mean volume per transaction, *TICK* = percentage of time during which the quoted bid-ask spread equaled the tick ($1/8) and *COMP* = ratio of share volume traded at the regional markets and NASD to volume traded at NYSE. MFTS = more frequently traded stocks, LFTS = less frequently traded stocks.

Panel A: simple regressions

MFTS	y_{it}					
x_{it}	RSWT	EFSWV	PIWV	DWT	WVNET	BLM
VOL	8.05e-07	4.26e-06†	4.03e-05	1.3805	23.8039	-.000572
TFREC	-5.91e-06	-.000112†	-.000811	40.95	-73.7785	.009727
RISK	.001052	.060877	.212739	-5005.058	-551.5066	-1.5532
INF	4.86e-05	.001403	.003334	502.09	3247.805	.020675
TICK	-.002645	-.008464	-.033568	4072.82	2618.872	1.152429
COMP	-.00011	-.002012	-.011559	-220.867	-3075.502	.049916
LFTS	y_{it}					
x_{it}	RSWT	EFSWV	PIWV	DWT	WVNET	BLM
VOL	1.02e-06	5.14e-05	.030323	1.14379	50.0707	-.001398
TFREC	_____	-.000647	-.000135	_____	-22.2253	.001848
RISK	.003332	.0564236	.424614	-458.5098	-1654.197	-1.95248
INF	_____	.005212	.003072	31.3259	1487.059	.001859†
TICK	-.007734	-.02131	-.009412	-250.276	1285.111	.416244
COMP	-.000113	-.001933	-.00117	_____	-135.0937	_____

Panel B: multivariate regression.

	y_{it}							
	MFTS				LFTS			
Variable	RSWT	EFSWV	DWT	VNET	RSWT	EFSWV	DWT	WVNET
CONS.	.0054*	.115826*	8152.809*	-1540.306*	.0162*	.089754*	2401.194*	-5383.723*
VOL	_____	_____	_____	15.8982*	3.39e-07*	_____	.90548*	76.62*
TFREC	-5.55e-06*	_____	31.1909*	119.5684*	4.42e-06*	.000878*	_____	111.6038*
RISK	.000326*	.072257*	-4347.401*	-5145.303*	.002218*	.588037*	-789.6174*	-2650.233*
INF	1.29e-05*	.000572*	650.1301*	2178.041*	_____	_____	29.4025*	_____
TICK	-.002709*	_____	3862.257*	3239.257*	-.007719*	-.004761*	-255.03*	_____
COMP	6.49e-06**	_____	_____	-270.8911*	-1.96e-05*	-.002601*	_____	-37.2656
Adj-R^2	.9669	.3712	.4696	.4368	.8978	.3353	.7623	.4562

† Not significant at the 5% level when regular intraday patterns are taken into account.

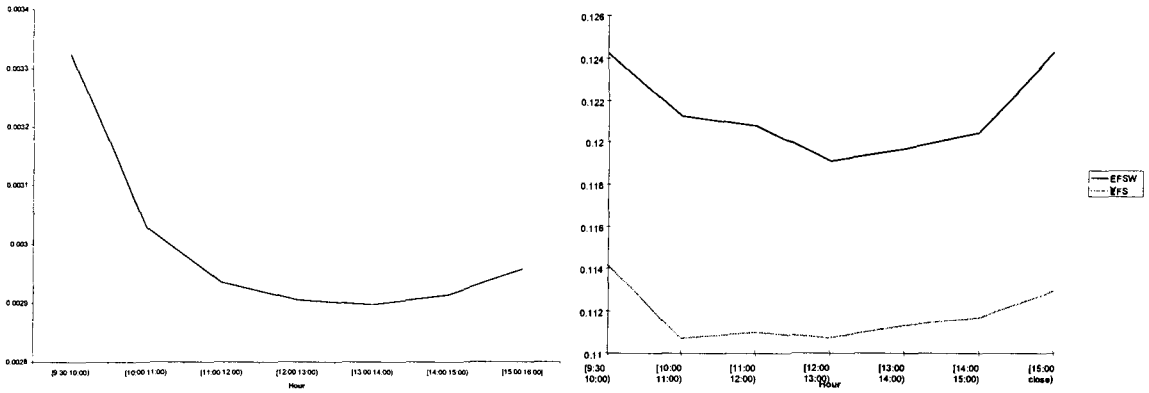
‡ The number of autoregressive terms has been selected after rejecting more complex specifications, starting with z=7.

* Significant at the 5% level.

** Significant at the 10% level.

FIGURE 1

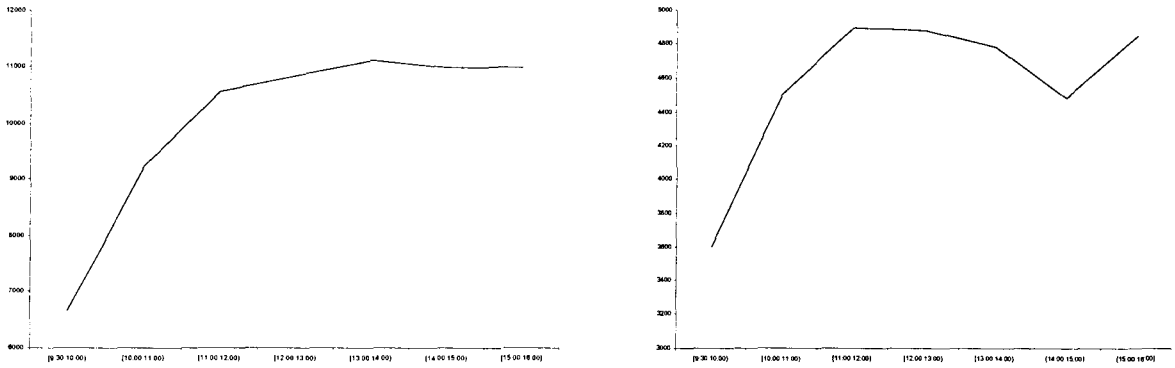
Intraday regular patterns.
Immediacy costs: relative spread, weighted and unweighted effective spread (MFTS).



(a) Relative Spread (b) Effective Spread

FIGURE 2

Depth: quoted and realized depth. Intraday regular effects (MFTS)



(a) Quoted depth (b) Realized depth (VNET)

FIGURE 3

BLM: Intraday regular effects

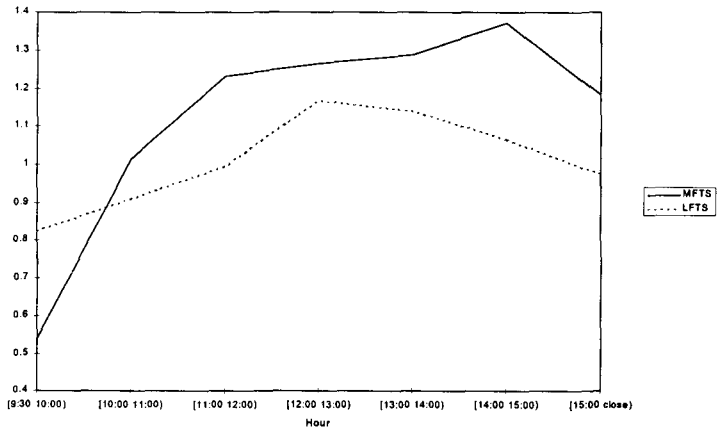
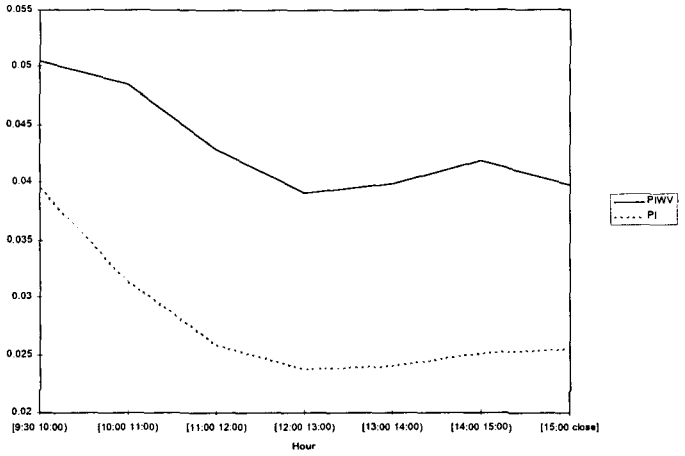


FIGURE 4

Price impact: intraday regular patterns (MFTS).



APPENDIX I

Sample

This sample consists of the 25 firms with the highest trading frequency (MFTS) and the 25 firms with the lowest trading frequency (LFTS) among 150 firms in a larger sample selected by Systematic Sampling. Firms are sorted by time between mean trades.

Order by capitalization	Symbol	Name	Time between trades	Time between changes in quotes[1]
		MFTS		
1	GE	GENERAL ELECTRIC CO	00:00:26	00:00:33
7	TXN	TEXAS INSTRUMENTS	00:00:39	00:00:56
6	CMB	CHASE MANHATTAN CO	00:00:43	00:00:35
2	GTE	GTE CORP	00:00:53	00:00:58
4	SLB	SCHLUMBERGER LTD	00:01:19	00:01:08
21	ELY	CALLAWAY GOLF CO	00:01:29	00:01:28
11	GP	GEORGIA-PACIFIC CORP	00:01:56	00:01:20
23	USS	U. S. SURGICAL CORP	00:02:01	00:01:30
5	GRN	GENERAL RE CORP	00:02:02	00:01:35
20	HM	HOMESTAKE MINING CO	00:02:14	00:01:56
8	HPC	HERCULES INC	00:02:20	00:02:43
3	K	KELLOG CO	00:02:22	00:01:17
22	GLM	GLOBAL MARINE INC	00:02:24	00:02:20
10	MAT	MATTEL INC	00:02:33	00:02:58
16	EC	ENGELHARD CO	00:02:32	00:01:56
12	NCC	NATIONAL CITY CORP	00:02:48	00:02:07
17	DDS	DILLARD DEPT STORES CL A	00:02:48	00:01:39
14	IR	INGERSOLL-RAND CO	00:02:51	00:01:49
24	RDC	ROWAN COMPANIES INC	00:03:13	00:02:40
9	AGC	AMER GEN CORP	00:03:34	00:02:19
27	ANN	ANNTAYLOR STORES CORP	00:03:45	00:02:33
19	RYC	RAYCHEM CORP	00:03:52	00:02:31
18	CEN	CERIDIAN CORP	00:03:58	00:02:46
15	OEC	OHIO EDISON CORP	00:04:09	00:02:58
13	ROH	ROHM AND HASS COMPANY	00:04:11	00:02:57
		LFTS		
29	MTS	MONTGOMERY STR INC. SECS	00:36:39	00:29:46
30	MMI	MMI COMPANIES INC	00:36:44	00:23:15
36	LXP	LEXINGTON CORP PROP. INC	00:37:44	00:22:42
41	KEF	KOREA EQUITY FUND INC	00:39:40	00:18:29
44	SNM	SINTER METALS INC	00:43:52	00:35:06
46	IF	INDONESIA FUND INC	00:43:59	00:24:37
42	UA	UNIONAMERICA HLDGS	00:45:56	00:29:32
33	SHD	SHERWOOD GROUP INC	00:46:10	00:29:56
32	PFM	PREFERRED I.M. FUND INC	00:46:14	00:25:01
28	GNC	GUARANTY NATIONAL CORP	00:49:21	00:24:31
25	JWA	WILEY JOHN SONS INC CL A	00:50:09	00:21:09
40	ODC	OIL-DRI CORP. OF AMERICA	00:53:58	00:27:37
31	WHT	WHITEHALL CORP	00:55:52	00:26:59
39	WTX	WORLDTEX INC	00:55:56	00:37:34
34	BAR	BANNER AEROSPACE INC	00:56:28	00:25:53
45	CAN	CONTINENTAL CAN CO INC	01:14:31	00:39:11
35	MYM	MUNIYIELD MICHIGAN FUND INC	01:14:31	00:39:50
49	BNG	BENETTON GROUP S.P.A.	01:26:24	00:50:16
48	VCO	VINA CONCHA Y TORO	01:27:05	00:40:43
47	BAS	BASS PUB LTD CO	01:31:16	00:54:02
26	NYM	NYMAGIC INC	01:31:26	00:45:24
43	UIF	USLIFE INCOME FUND INC	01:38:40	00:48:30
50	EEC	ENVIRONMENTAL ELEM. CORP	02:15:20	01:16:06
38	BPC	BANCO COMERCIAL PORTUGUES	02:40:19	00:51:24
37	TDI	TWIN DISC INCORPORATED	02:40:07	01:10:16

[1]Change in quoted ask, bid or depth.

APPENDIX B

Measures

Measure	Equation	Specifications
Relative spread weighted by time	$RSWT_t = \dfrac{\sum_{j=1}^{l}\left[\dfrac{Ask_j - Bid_j}{(Ask_j + Bid_j)/2}\right]T_t}{\sum_{j=1}^{l} T_j}$	l is the number of quotes registered during a given time interval. T_j represents the time elapsed (in seconds) till a new quote is observed.
Quoted depth weighted by time	$DWT_t = \dfrac{\sum_{j=1}^{l}(DepthAsk_j + DepthBid_j)T_j}{\sum_{j=1}^{l} T_j}$	Same specifications as for the relative spread.
Effective spread weighed by trade volume	$EFSWV_t = \dfrac{2\sum_{i=1}^{r}[X_i(P_i - m_i)]\times Vol_i}{\sum_{i=1}^{r} Vol_i}$	r is the number of trades in an hourly interval. Vol_i is the number of shares negotiated with the ith trade. X_t equals 1 for buyer initiated orders and -1 for seller initiated orders.
Price impact weighted by trade volume	$PIWV_t = \dfrac{\sum_{i=1}^{r}[X_i(P_{i+\tau} - m_i)]\times Vol_i}{\sum_{i=1}^{r} Vol_i}$	Same specifications as for the effective spread. m_t is the midpoint of the quoted bid-ask spread assigned to the trade i. $P_{t+\tau}$ is the midpoint associated with the first trade reported at least five minutes later. τ represents the time elapsed ($\tau \geq 5$ minutes).
VNET weighted by the change in the midpoint	$WVNET_t = \left(\sum_{w=1}^{p}\left\lvert\sum_{g=1}^{k} X_g Vol_g \Big/ \Delta m_w\right\rvert\right)\sum_{w=1}^{p}\lvert\Delta m_w\rvert$	p is the number of midpoint changes. Δm_w is the magnitude of the change. k is the number of trades between two different values of the midpoint. X_g takes the value 1 for buyer initiated trades and -1 for seller initiated trades.
Proxy for informed trading intensity	$INF_t^{(d,h)} = \dfrac{TVol_t^{1/2} - median\left[TVol_{(q,m)}^{1/2}\right]}{Std.Dev\left[median(TVol_{(q,m)}^{1/2})\right]}, \quad \forall(q,m)\ s.t.\ q=d,\ m=h$	$TVol_t$ represents the share volume per trade in hour t.