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MEASURING, FORECASTING AND EXPLAINING TIME VARYING LIQUIDITY IN THE STOCK MARKET

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ABSTRACT

The paper proposes a new measure, VNET, of market liquidity which directly measures the depth of the market. The measure is constructed from the excess volume of buys or sells during a market event defined by a price movement. As this measure varies over time, it can be forecast and explained. Using TORQ data, it is found that market depth varies positively but less than proportionally with past volume and negatively with the number of transactions. Both findings suggest that over time high volumes are associated with an influx of informed traders and reduce market liquidity. High expected volatility as measured by the ACD model of Engle and Russell (1995) and wide spreads both reduce expected depth. If the asymmetric trades are transacted in shorter than expected times, the costs will be greater giving an estimate of the value of patience.

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1. Introduction

Heightened interest in the function and efficiency of financial markets has turned research on the price adjustment mechanism in stock exchanges sharply toward microstructure. Indeed, a good deal of evidence suggests that a familiarity with the particular trading processes and market procedures is not just helpful, but necessary for understanding the flow of information and prices. A well-grounded theory of equity markets must incorporate the market maker - trader interaction and its implications on liquidity. Of particular relevance is the heterogeneity of traders with respect to their information, and how the market maker forms expectations within this uncertainty. The composition of market participants ultimately determines liquidity, but the specialist is the vehicle though which liquidity is manifest.

With the number of major financial markets increasing world-wide, investors today have more choices of where to take their money. For this reason, market analysts have strong interest in determining the liquidity of various exchanges within this competitive arena. Inherent in the efficient market hypothesis is the stipulation that transaction costs are not large enough to prevent information from being incorporated into prices through trading activity. It follows that high long-run average market liquidity should attract investors seeking efficiently priced assets.

While trading costs and price movements are often aggregated and compared across assets or exchanges, abstracting from the underlying time series dynamics forfeits perhaps the most useful implications of modeling liquidity. Large, actively traded funds have much at stake each time they choose to adjust their portfolios. Market timing, not in the sense of predicting prices, but rather in predicting transaction costs, could prove quite valuable if a model of liquidity can be derived. If liquidity is endogenously determined by market activity, flowing up and down throughout the day, then forecasts of this process might help in developing optimal trading strategies.

Liquidity in a market has a variety of definitions and interpretations. Mostsimply, it is the ability to perform a transaction without cost. Kyle (1985) dissects liquidity into three components: tightness, depth, and resiliency. Tightness refers to the divergence of transaction prices from the efficient price. The market specialist sets the bid and ask quotes slightly below and above, respectively, the true equilibrium valuation of the asset. The magnitude of the spread between the quotes gives a measure of the total cost of an instantaneous round-trip transaction[1]. Or, assuming that the bid and ask quotes symmetrically straddle the true value of the stock, every unidirectional buy or sell order incurs a transaction cost equal to one half of the spread[2]. Perfect liquidity with respect to tightness is reached only when there is zero spread between quotes so that traders may buy and sell at the same price. In the picture below, tightness is graphically depicted by the vertical distance between the buy and sell curves which represents the price a buyer or seller can expect when trading various numbers of shares.

Market Reaction Curve

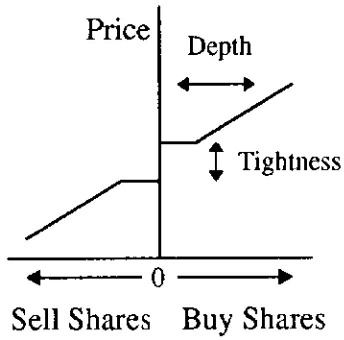


Figure 1. The price response of the market to net demand.

Another concept of liquidity is depth, which focuses on the volume which can be traded at the current price level. Again referring to the market reaction curve above, the horizontal distance between the vertical axis and the specialist's demand/supply response represents the depth of the market at a particular price. The short flat segment at the bid and ask prices is the posted quote depth and is guaranteed by the specialist. However, Glosten and Harris (1988) and others have documented a significant divergence between the quoted and effective bid-ask spreads. With effective spreads often smaller than quoted, effective depth may often be much greater than that guaranteed by the specialist.

The slope of the reaction function is pertinent to perspective large volume traders. Depth increases further from the quotes, reflecting the backlog of limit orders away from the market

[1] Effective spreads have been reported to be considerably smaller than posted spreads (Glosten and Harris (1988)).
[2] If inventory holding costs and adverse-selection risks are symmetric, the midpoint of the bid and ask quotes represents the expected equilibrium value.

price. A steeper curve entails a greater price impact for a fixed size transaction, revealing a lack of liquidity in the market. A precise knowledge of this function at a moment in time would obviously be quite useful for traders. However, one can not view the market reaction curve as simply reflecting the order book. While limit order submissions supplement liquidity, the specialist does not simply cross orders--he often will hold a position in the asset for the short or medium run in order to stabilize the market.

The specialist updates his price expectations according to external news as well as internal market behavior. For example, an imbalance in the number of buys versus sells has the obvious effect of displacing the specialist from his desired inventory position, but it may also indicate that some information has yet to become fully public and incorporated into prices, bringing informed traders to the market in search of profits. Eventually this information will be disseminated across the market and prices will move, but the amount of one-sided volume absorbed before prices are adjusted dictates the depth of liquidity in the market, and is driven by the specialist's perceived adverse selection risk.

The third component of liquidity, resiliency, considers the speed of return to the efficient price after a random deviation. If a large order or some other shock causes a jump in the price without affecting the underlying value of the stock, then the specialist should eventually move the quotes back to equilibrium. In a highly liquid market with respect to resiliency, prices bounce back immediately to their efficient level. This measure of liquidity obviously requires some estimate of the equilibrium price, a challenge made difficult by the continuous flow of new information into the market.

This paper focuses on a new direct measure of market depth, called VNET. This is an estimate of the excess of buyer or seller initiated transactions associated with a particular price movement. If a price increase occurs with only a small excess of buyers then the market is illiquid, but if the same price increase is associated with a large excess of buyers then the depth is great. As VNET is measured in shares per price change, it has a direct interpretation of how much one sided volume can be transacted without driving prices more than this amount. It is an estimate of the slope of the market reaction function show in Figure 1 for the larger volumes.

The time dimension of Figure 1 is, however, unclear. Is the slope the same regardless of whether the transaction takes one minute or is spread out over a trading day? One would expect the slope to be steeper if the transaction demands immediacy; this is the price of impatience. A careful analysis of the time for these transactions leads to estimates of the slope as a function of the time for the trade.

The VNET measure varies over time and over stocks. Motivated by the models of asymmetric information in market microstructure, the determinants of VNET are examined for 17 stocks from the TORQ data set. These give quantitative estimates of the market depth as a function of predetermined variables and the speed of the trades.

The remainder of the paper is organized as follows. Section 2 will review the progress to date in the fields of liquidity and market microstructure, both theoretically and empirically. Section 3 will then describe the data and statistics used in this study. Section 4 discusses the results of our empirical estimations, with conclusions and remarks made in section 5.

2. Background

Two primary microstructure models of equity market price behavior have emerged in the past two decades. Early research viewed the specialist as an agent concerned with inventory management [see Garman (1976), Ho and Stoll (1981) and O'Hara and Oldfield (1986)]. A trade will lead to adjustment of the bid and ask quotes simply to restore inventories to some desired, balanced level. While this model explains the empirically documented link between buys (sells) and price increases (decreases), it can offer no explanation for the daily or hourly fluctuations in depth or the bid-ask spread. In a pure inventory world, processing and inventory holding costs cause the specialist to set a positive spread between his bid and ask quotes, but these factors alone can not explain the size and volatility of spreads or price adjustments.

More recent work stems from the asymmetric information models described byCopeland and Galai (1983), Glosten and Milgrom (1985), Glosten and Harris (1988) and Hasbrouck (1988). These models posit financial markets to be comprised of three types of agents: informed traders, uninformed traders, and a single, risk-neutral specialist.[3] Uninformed, or liquidity traders, are in the market simply for portfolio adjustment relating to lifetime consumption stream

[3] Although the NYSE gives specialists a monopoly on a number of stocks, rules implemented by the board restrain destructive, non-competitive behavior. Glosten and Milgrom (1985) show that perfect competition among market-makers is sufficiently imposed by assuming quotes are set to yield zero profits.

optimization. However, informed traders are speculative, entering the market because they have information on the future value of the asset which is not yet public.

Under the premise that a portion of the net demand in the market is related to informed traders, trading activity will hold some informational content as to future prices. This endogeneity of trading to the determination of prices is the critical link between market activity and liquidity. Because the specialist is among the uninformed and is unable to distinguish profit-seeking informed traders from the routine liquidity traders, the volume of one-sided trading necessary to push prices may fluctuate from moment to moment, depending on the specialist's conjectured probability of the trader having superior information. In a pure inventory world, depth is simply a function of the specialist's holding costs, and thus should be constant over time. However, when agents are heterogeneously informed, liquidity may move cyclically with the distribution of information in the market.

The inventory control and asymmetric information models introduced above are similar in their short-run predictions of the price impact of a trade. Whether it is to balance inventories, or because expectations of future prices have increased, a buy (sell) will incline the specialist to raise (lower) existing quotes. However, the long-run impact of trades distinguishes these two models. Inventory control effects can only explain transitory price movements; once inventory is balanced, the midpoint of the quotes should revert to the true equilibrium value. However, Hasbrouck (1988) finds evidence of persistent price impacts of trades, especially large orders in active stocks, supporting the asymmetric information view of securities exchanges. Price impact relates closely but not precisely to the liquidity concept of depth. While traders are interested in the implications of individual trades, a more common concern rests on the sheer volume that can be transacted without initiating a preemptory shift in quotes.

Along with an increased propensity to adjust prices, specialists respond to the existence of informed traders by widening their bid-ask quotes. Spreads exist to compensate the specialist for processing fees, inventory holding costs, and in the face of asymmetric information, the risks of encountering a better informed trader. Stoll (1989) reports that a larger portion of the bid-ask spread is to protect against this adverse selection risk than is to cover processing or inventory holding costs. Given this, it follows that the size of the spread gives an indication of the proportion of non-liquidity traders in the market, at least according to the specialist's speculation.

So small spreads between bid and ask quotes, earlier referred to as the tightness component, are a straight-forward and well-documented indication of stock market liquidity.

Obviously, liquidity traders would like to identify themselves in order to avoid the additional costs stemming from asymmetric information, while informed traders strive to remain anonymous. In the absence of a separating equilibrium, the true nature of the trader can only be imperfectly inferred from their trading behavior. Easley and O'Hara (1987) and Hasbrouck (1988) find a positive correlation between trade size and price impact, with the implication that informed market participants trade more heavily in order to take advantage of their fleeting informational advantage. McInish and Wood (1992) reveal an association between trade size and the bid-ask spread. If informed traders do tend to transact greater quantities in order to maximize profits from their advance information, then the specialist will react more guardedly with quotes, leading to wider bid-ask spreads, when confronting large orders.

Other studies investigate how the specialist derives information from the overall market environment. The thickness of trading in a particular asset, defined by either the number of shares or the number of transactions per time, may be a function the asymmetry of information. While Admati and Pfleiderer (1988) posit liquidity trader clustering, the empirical evidence does not support this view. Instead, it seems that the price impact of trades along with the bid-ask spread, which both reflect a lack of liquidity, are positively related to market intensity. Foster and Viswanathan (1993) suggest that an influx of informed traders, not liquidity traders, is behind temporary periods of above average market thickness (i.e. more transactions per time).

The inverse of market intensity is the time between trades. The models mentioned above assume fixed trade intervals, thus removing time from the equation. Easley and O'Hara (1992) make some progress into incorporating time by allowing traders the option of not trading. From this, a longer time between transactions indicates that market participants have abstained from trading. Since liquidity trader activity is a fairly steady process of portfolio adjustment, any non-active market players are likely to be informed agents without any new informational advantage. Again this supports the notion that high transactional intensity is related to greater information asymmetry, and low liquidity.

With the availability of transaction-by-transaction data for high frequency markets such as the NYSE, the time between trades has become another statistic for the empiricist. And on theoretical grounds, arguments can be made for the relevance of such issues. The proposition that a series of buys made 5 seconds apart would have a different impact on prices than if they were made 5 minutes apart seems reasonable. Engle and Russell (1995b) model the time durations between trades for IBM, revealing significant autocorrelation or clumping of orders. If the factors which determine the timing of trades or price changes are related to the distribution of information amongst market traders, then forecasts of the time between market events may give added insight into the behavior of liquidity. The relationship between trading activity, market volatility, and the costs of trading will be further explored in the empirical section.

3. Data

The data for this study is the TORQ (Trades, Orders, Reports, and Quotes) set, compiled by Joel Hasbrouck and the New York Stock Exchange. It contains transaction-by-transaction data for 144 stocks over the three month period, November 1, 1990 through January 31, 1991. Trade time, trade size, and the prevailing quotes are extracted for 17 of the more commonly traded stocks[4]. As will be described later, it is necessary to have a certain minimum level of trading activity in the stocks analyzed. This abstraction from extremely inactive stocks should not be completely ignored, but the topic of liquidity applies most readily to active investment assets.

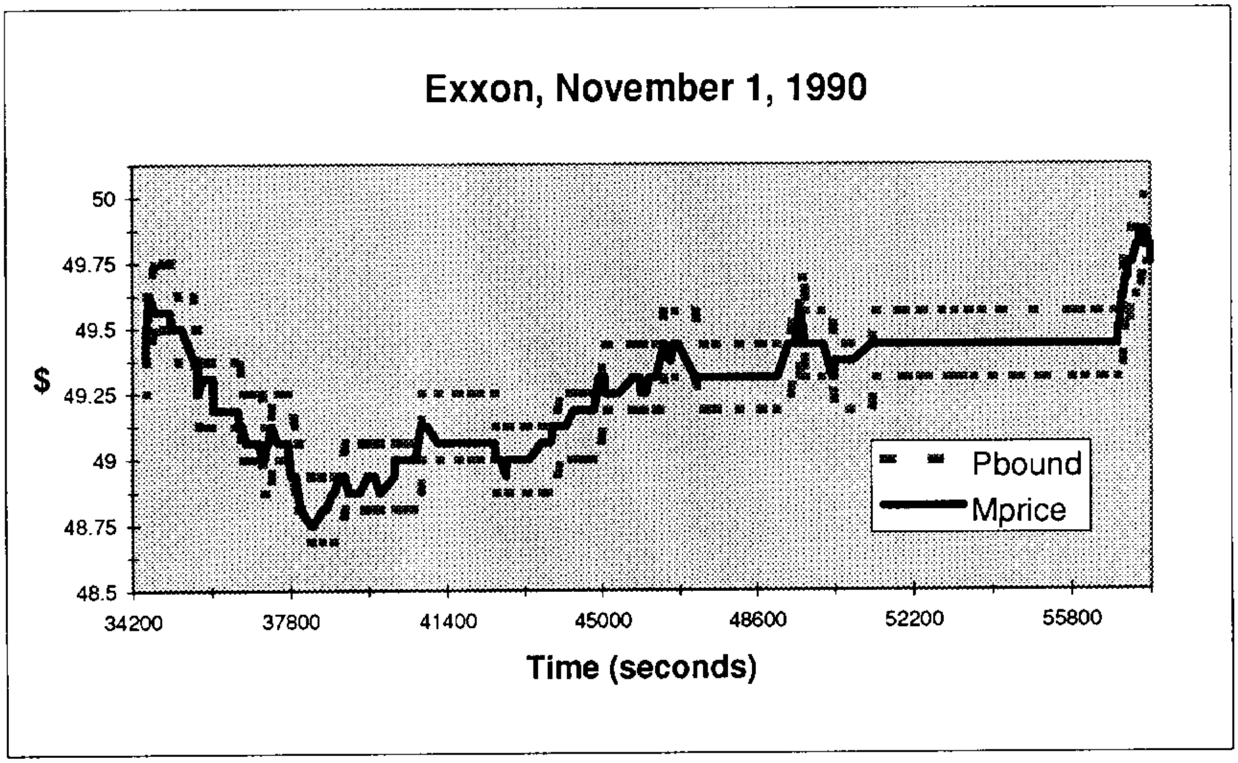
During these months, trading was halted or delayed on two occasions, November 23 (the Friday after Thanksgiving) and December 27. Omitting these two anomalous dates, data from 61 trading days is analyzed. In determining the prevailing quotes for a given transaction, Lee and Ready (1991) suggest the 'five second' rule. Because priority on the NYSE floor is given to posting new quotes over recording completed transactions, a quote revision will often precede the trade from which it was instigated. Matching transactions with quotes that are at least five seconds old removes the concern over mis-timed recordings.

Along with the prevailing quote, each trade is given a marker according to the side initiating (buyer or seller). Again following Lee and Ready, a modified 'midpoint' rule is used. If the transaction price is closer to the ask than the bid quote, then it is a buy, otherwise it is marked

[4] Only quotes and trades fully display their transaction plans, hope to alleviate any adverse selection concerns, and thus gain more favorable liquidity occurring in the New York market are included as regional exchanges can often diverge significantly. The 17 individual stocks were chosen according to the number of transactions on November1, 1990.

as a sell. However, if the transaction occurred precisely at the midpoint between the bid and the ask, then the 'tick' rule applies. Under this method, an up tick, meaning the current transaction price is greater than the previous price, implies that the trade must have been initiated by the buyer. Likewise, down ticks indicate sells. Lee and Ready found this process for distinguishing buys from sells to be the most accurate for a variety of simulated scenarios, and indeed a cursory examination of the TORQ data set corroborates their conclusions.

From here, the data for each stock is filtered in order to identify the intraday price fluctuations. First, to avoid inconsistent trading patterns and procedures around the start of each day, the opening five minutes of trading is dropped. In addition, any stray recordings time-stamped after the close are included, but taken to be performed at 4:00pm. A price duration is the sequence of all transactions between a significant price movement, where price movements are specifically defined as changes in the midpoint of the specialist's quotes. Not only does this eliminate the problem of bid-ask bounce, it gives a more accurate indication of the true market value of the asset than transaction prices which may vary according to trade size.



The above graph displays a one day sample of the time paths of the quote midpoint (Mprice) and the constructed price barriers (Pbound) used to define price durations. A stock-specific threshold magnitude was used which would generate approximately 10 to 15 durations per day. Depending on the price level and volatility for each stock, the absolute price change needed to signal the end of a price duration ranged from 1/16 to 1/4 of a dollar. Overnight episodes are not analyzed, so duration starting values are reset each morning, with no durations recorded across days.

For each price duration, a variety of summary measures are compiled. Thenumber of trades, the total volume traded, the ending bid-ask spread, the actual amount prices moved, and the elapsed clock time (PTIME) are the fundamental statistics. Average trade size and the average time between trades, as well as interaction variables, are derived from these core marks.

The focal liquidity measure of this study is the amount of one-sided volume accumulated during a price-based duration, representing the depth of liquidity in the market. This statistic, labeled VNET, conveys the amount of excess demand which can be traded without causing the quotes to move beyond a specified threshold.

	MIN	MEAN	MAX
VNET	6,156	27,170	60,557
VOLUME	9,276	57,569	160,410
NUMBER	6	23	66
PTIME	1,333	1,843	2,509
Durations	459	668	970

Table 1. Duration statistics across the sample.

For the 17 stocks, the number of price durations identified over the 61 trading days ranged from 459 to 970, with the average price duration times ranging from 2,354 to 1,333 seconds (see Table 1). The average volume transacted during a price duration varied from 9,276 shares for CPC to 160,416 shares for IBM. The average number of trades per duration varies from 6 to 66, reflecting the technical diversity of the sample stocks. The amount by which the midpoint of the quotes must move to trigger a price duration varied from stock to stock, but because no direct, quantitative cross-stock comparisons are made, this non-uniform procedure should not present any practical concerns.

4. Empirical Models

The aim of this research is to develop a new statistic for the measurement of the depth of liquidity in financial markets. This study introduces price durations with inherent time sensitivity to document and explain intraday variability in liquidity for individual stocks. Because of the divergence between posted and realized quotes, the simple bid-ask depth does not provide an accurate measure of the true level of liquidity. Instead, the one-sided volume sustained before a subsequent move in the price level conveys the actual depth of the market. The dependent variable is defined as

$$VNET = \left| \sum_i (d_i \cdot vol_i) \right|$$

where d is the direction of trade indicator (buy = 1 and sell = -1) and vol is the number of shares traded. The summation is over all transactions within a given price duration.

4.1. PTIME

Underlying the topic of financial market liquidity are a variety of interesting timing issues. In developing a microstructure model, data must be viewed from the perspective of transaction to transaction, not minute to minute. As Joel Hasbrouck explains, 'for investigating causal relations (such as trade price impacts) that would be obscured by aggregation, the econometrician should lean toward modeling the data purely in event time[5]. Under this framework, most research abstracts from the clock time of trades or price changes. However, market information is conveyed by the decision of when to trade as well as by how much and at what price.

The autoregressive conditional duration (ACD) model posits the time between future events to be a function of the time between past events. The capabilities of these models to forecast time durations was introduced by Engle and Russell (1995a,b). In what can be thought of as an equivalent to an ARMA process for time durations, ACD models forecast the time between events conditioned on their history. These methods are employed to explicitly model PTIME for the series of price durations from each stock. Since much of the aforementioned theory behind liquidity refers to trading intensity, a more accurate estimate of the expected rate of time flow should improve the models.

[5] Hasbrouck (1995), p. 49-50.

First, PTIME is normalized by dividing by the unconditional mean to create a series with an expected value of unity. Unlike simple transaction time durations, the time between price changes do not display significant time-of-day patterns which would necessitate deseasonalizing by the hourly means. These normalized durations are examined for autocorrelations with 15 lagged values. The Ljung-Box statistics for the null of zero autocorrelation are greater than or equal to the 5% critical value for 12 of the 17 stocks examined, providing evidence of significant serial dependence in the timing of price changes. These results match the findings of Engle and Russell (1995b) for IBM.

Next, an appropriate ACD specification is chosen to model PTIME. The standardized duration times given by observed durations divided by forecast durations have standard deviations greater than the mean of 1, indicating that the underlying distribution of the hazard function may not be exponential. The sample statistic $\sqrt{N}(\hat{\sigma}_{\varepsilon}^2 - 1)/\sigma_v$ with a critical value of 1.645 is used for the one-tailed test (H_o: the sample variance, σ_{ε}^2, is equal to the mean of one). And indeed, an exponential ACD(2,2) model leaves 16 of the 17 standardized series with significant excess dispersion.

Modeling the standardized durations ($\varepsilon = \mathbf{PTIME} / (\phi \cdot \psi)$) where ψ is the conditional expectation of PTIME, with a Weibull rather than an exponential distribution should generate a more realistic representation of the time between price changes. We expect to find γ (the Weibull parameter) to be less than one, implying a monotonically decreasing hazard function which accommodates the more extreme durations present in the data. With the Weibull ACD(2,2) model, the excess dispersion is dramatically reduced, with the null hypothesis of $\sigma_{\varepsilon}^2 = 1$ accepted for 12 of the 17 stocks. Specifically, a WACD(2,2) model with SPREAD as an exogenous variable for the conditional duration is used to estimate PTIME for each stock. This procedure appears to capture the autocorrelations present in the raw data as evidenced by Ljung-Box statistics for the conditional expectations below the 5% critical value for all 17 stocks examined.

In equation 1, ψ is the conditional expectation of PTIME. The WACD(2,2) formulation uses two lags of the conditional expectation and two lags of PTIME, along with the predetermined variable $SPREAD_{t-1}$ to forecast the time between price changes.

$$\psi_t = \omega + \alpha_1 PTIME_{t-1} + \alpha_x PTIME_{t-2} + \beta_1 \psi_{t-1} + B_2 \psi_{t-2} + \phi SPREAD_{t-1} \qquad (1)$$

Table 2 below lists the coefficient estimates for each of the 17 stocks in the sample. As can be seen in the last column, lagged SPREAD is highly significant in predicting the time between price changes. It's negative coefficient supports the theoretical implications that larger bid-ask spreads are indicative of less liquid, more volatile markets.

Eq 1: $\psi_t = \omega + \alpha_1 PTIME_{t-1} + \alpha_2 PTIME_{t-2} + \beta_1\psi_{t-1} + \beta_2\psi_{t-2} + \phi\, SPREAD_{t-1}$							
	ω	$\alpha 1$	$\alpha 2$	$\beta 1$	$\beta 2$	ϕ	$\gamma(H_0:\gamma=1)$
BA	0.41 (4.19)	0.236 (3.86)	-0.146 (-2.49)	0.534 (3.12)	0.241 (-2.49)	-1.426 (-4.34)	0.92 (-2.30)
CAL	1.45 (5.55)	0.096 (2.40)	0.049 (1.26)	0.005 (0.04)	0.156 (1.15)	-4.374 (-8.36)	0.92 (-2.24)
CL	0.28 (3.26)	0.076 (3.15)	0.091 (3.61)	-0.162 (-3.39)	0.798 (15.33)	-0.393 (-2.34)	0.92 (-3.46)
CPC	0.80 (4.30)	0.100 (2.73))	0.051 (1.22)	-0.140 (-0.95))	0.474 (3.59)	-1.200 (-3.36)	0.87 (-5.88)
DI	0.46 (2.22)	0.106 (2.43)	-0.085 (-2.19)	0.206 (1.19)	0.574 (4.54)	-1.184 (-2.42)	0.86 (-4.19)
FDX	0.26 (6.24)	0.069 (164.57)	0.068 (22.16)	-0.196 (-32.03)	0.837 (3109.6)	-0.273 (-2.10)	0.88 (-3.82)
FNM	0.51 (5.39)	0.145 (3.42))	0.023 (0.58))	0.138 (1.15)	0.499 (5.19)	-1.686 (-6.57)	0.96 (-0.93)
FPL	0.60 (9.54)	-0.043 (-2.45)	0.071 (2.56)	0.374 (3.64)	0.326 (2.75)	-1.967 (-13.24)	0.82 (-7.09)
GE	0.27 (5.96)	0.042 (2.98)	0.021 (1.34)	0.003 (0.11)	0.845 (25.32)	-0.952 (-7.48)	0.91 (-3.50)
GLX	0.01 (0.38)	0.010 (1.94)	-0.068 (-1.19)	0.748 (1.43)	0.193 (0.39)	0.080 (0.78)	0.91 (-2.67)
HAN	2.34 (9.50)	0.008 (0.40)	0.003 (0.15)	-0.814 (-5.89)	-0.320 (-2.34)	-2.526 (-10.84)	0.85 (-6.21)
IBM	0.66 (4.44)	0.276 (6.30)	0.138 (1.99)	-0.154 (-0.76)	0.257 (2.43)	-0.801 (-4.06)	0.98 (-1.05)
MO	0.84 (3.16)	0.151 (2.59)	-0.049 (-0.87)	0.263 (0.86)	0.124 (0.70)	-1.754 (-3.60)	0.98 (-0.56)
POM	1.72 (6.24)	-0.005 (-0.16)	0.109 (2.35)	-0.074 (-0.50)	-0.097 (-0.70)	-3.923 (-11.13)	0.91 (-2.65)
SLB	0.73 (3.02)	0.192 (3.91)	-0.033 (-0.50)	0.404 (1.60)	-0.029 (-0.28)	-0.921 (-2.86)	0.99 (-0.22)
T	0.53 (1.95)	0.157 (3.43)	0.002 (0.03)	-0.068 (-0.32)	0.513 (3.67)	-0.881 (-1.62)	0.87 (-4.03)
XON	0.63 (3.41)	0.214 (4.16)	0.202 (3.90)	-0.511 (-4.75)	0.484 (4.49)	-.309 (-0.80)	0.86 (-4.51)

Table 2. WACD(2,2) model coefficient estimates (T-statistics) for equation 1.

The output of these ACD estimates are conditional forecasts of PTIME which incorporate past information on PTIME and SPREAD. It is the unanticipated portion of PTIME which is of primary importance in modeling liquidity. PTIMEERR is defined as actual divided by expected PTIME and is the fraction of PTIME beyond what could be predicted by the WACD(2,2) model. While the forecast residuals should be orthogonal to our information set, there may remain some unidentifiable, systematic components to these errors which relate to the level of liquidity in the market. If the specialist detects an unexpected internal or external event, he may change prices sooner than expected with immediate ramifications on the realized depth of the market.

4.2. VNET (Depth)

This analysis of stock market depth relies on theoretical and empirical implications of prior research to provide the guidelines for our model setup. Although the definition utilized in this paper differs from past studies, within the general asymmetric information framework all of the components of liquidity should be related. The unifying feature is their link to informed trading in the market. This common undergirding allows us to view VNET and the bid-ask spread not as separate variables, but as separate vantage points from which to view liquidity.

In developing a model for liquidity, theoretical work proposes a wide variety of statistics as potential explanatory variables. From the discussion in section 2, two candidates are immediately obvious. First, the number of shares in a given transaction is presumably larger for informed traders; therefore, average trade size should be negatively correlated with liquidity [Easley and O'Hara (1987) and Hasbrouck (1988)]. Second, the intensity of trading, thought to result from the presence of informed traders, should also be negatively related to liquidity. Trading activity can be measured as either the number of trades or the volume traded. Both definitions, as well as volume and number per time are examined.

As proposed by Hasbrouck (1991), the interaction between trade activity and SPREAD may also be relevant to the analysis. If informed traders are more willing to accept high transaction costs in route to realizing profits from their information, then trades occurring while the bid-ask spread is wide may be linked to low liquidity. In the regressions this implies that the interactions between the spread and trading activity should be negatively related to liquidity. We define VOLSPR and NUMSPR as the number of shares and the number of trades, respectively, transacted throughout the price duration at non-minimum spreads.[6]

The magnitude of price jumps, beyond the fixed amount necessary to end a price duration, may provide an added indication of current volatility for the stock. While price durations in this study are marked by movements of a certain, preset magnitude in the midpoint of the bid-ask spread, there is no real limit as to how much the quotes can change between successive trades. If

[6] The minimum spread is one tick, or $1/8^{th}$ of dollar. Nearly half of the transactions occurred at minimum spreads.

prices jump beyond the threshold value, the residual magnitude should somewhat reflect the market' s price instability. Since price volatility is associated with illiquid markets, the absolute price jump last period should be negatively correlated with liquidity.

Along with these summary marks, the model of VNET incorporates the time forecasts of the ACD model from equation 1. The Autoregressive Conditional Duration formulation of PTIME in the previous section can be interpreted as a model of volatility. Expected PTIME provides an ex ante view of volatility since its reciprocal is proportional to the expected price change per unit time in a sense made precise by Engle and Russell (1995a,b).

One-step forecast errors, defined as the actual divided by the predicted PTIME, portray the fraction of the time between price changes which is beyond the explanatory power of the right-hand side variables in equation 1, which includes lagged SPREAD. While some of this ex post volatility could simply be noise attributable to unanticipated price shocks, a portion of the divergence may be dependent on trader behavior, or consciously initiated by the specialist in response to market conditions, though these factors are unobservable to the econometrician. In effect, the estimation errors represent a sooner than expected price adjustment by the specialist, stemming from either unanticipated trading or public news. To test this hypothesis, the conditional forecast errors, PTIMEERR, from equation 1 will be included in the VNET model.

A number of different specifications were examined, witlthe search algorithm working from general down to more specific models. The explanatory variables tested in the various formulations for VNET are:

SPREAD = (ASK-BID) / ((ASK+BID)/2) at the final trade of the price duration
NUMBER = the number of trades during the price duration
VOLUME = the total volume traded during the price duration
NUMSPR = the number of trades occurring at large spreads [7]
VOLSPR = the aggregate volume transacted at large spreads
PJUMP = the absolute price change over the duratio n
EPTIME = the conditional expectation of PTIME [8]
PTIMEERR = (PTIME / EPTIME)

[7] Large spreads are any bid-ask deviation greater than the minimal one eighth. Minimal spreads are present in nearly half of all transactions for most stocks.
[8] Expected PTIME is the one-step forecast taken from the WACD(2,2) model.

The most general formulation tested on each of the 17 stocks is included in Appendix A. The set of regressors which display statistical significance in the determination of VNET for a majority of the stocks turns out to be fairly concise. Equation 2 below (with all variables in logs) is the favored model of our search:

$$VNET = \beta_0 + \beta_1 SPREAD(-1) + \beta_2 VOLUME(-1) + \beta_3 NUMBER(-1) + \beta_4 EPTIME + \beta_5 PTIMEERR \qquad (2)$$

The lagged dependent variable no longer appears in this final formulation because it is typically insignificant. Estimation of an AR(1) model of VNET for each of the stocks found all to have positive autocorrelations, with 13 of the 17 statistically significant. The vanishing significance of lagged VNET in equation 2 implies that the right-hand side variables adequately represent the past depth of liquidity

Looking at the regression results in Table 3 below, the coefficients on SPREAD(-1) appear to qualitatively support the postulated model. The bid-ask spread immediately preceding the price duration is negatively related to VNET for 13 of the 17 stocks, although the confidence level for the estimates is above 95% for only 6. The spread also impacts VNET indirectly through the expected time in the ACD model. The effect is again generally negative. Since the spread and the depth are simply two aspects of market liquidity, it is not surprising that they are at least partially correlated.

According to equation 2, the number of trades appears to be the pertinent measure of trading intensity. If trade clustering is due to a rush of informed traders into the market, the asymmetric information models would predict a negative coefficient for NUMBER. Indeed, the number of trades in the prior price duration is negative for all but one stock, with 8 of these statistically significant.

While VOLUME is another indication of trading intensity, it also provides a perspective of the relative amount of one-sided trading implied by a given level of VNET. Since VNET is an absolute measure of one-sided trading, higher VOLUME in equation 2 implies a smaller percentage imbalance in orders because the coefficients are uniformly less than one. Thus increasing volume predicts a less than proportional increase in market depth, again presumably because the new volume is associated with increased risk of adverse selection.

Eq. 2: $VNET = \beta_0+\beta_1 SPREAD(-1)+\beta_2 VOLUME(-1)+\beta_3 NUMBER(-1)+\beta_4 EPTIME+\beta_5 PTIMEERR$

	SPREAD(-1)	VOLUME(-1)	NUMBER(-1)	EPTIME	PTIMEERR
BA	0.021 (.89)	**0.232 (.003)**	-0.148 (.17)	0.058 (.78)	**0.334 (.0001)**
CAL	0.156 (.27)	**0.187 (.02)**	**-0.246 (.01)**	0.234 (.09)	**0.447 (.0001)**
CL	**-0.345 (.002)**	0.041 (.41)	-0.007 (.93)	0.203 (.20)	**0.295 (.0001)**
CPC	**-0.543 (.001)**	**0.213 (.0001)**	**-0.205 (.01)**	0.248 (.39)	**0.327 (.0001)**
DI	-0.127 (.58)	**0.289 (.0001)**	**-0.214 (.02)**	0.140 (.59)	**0.487 (.0001)**
FDX	-0.278 (.07)	**0.209 (.001)**	**-0.303 (.001)**	**0.520 (.02)**	**0.363 (.0001)**
FNM	-0.202 (.18)	**0.412 (.0001)**	**-0.219 (.04)**	-0.002 (.99)	**0.357 (.0001)**
FPL	**-0.834 (.0001)**	0.080 (.13)	-0.035 (.64)	**0.521 (.01)**	**0.596 (.0001)**
GE	-0.180 (.13)	**0.405 (.0001)**	**-0.220 (.01)**	**0.318 (.01)**	**0.333 (.0001)**
GLX	-0.188 (.23)	**0.235 (.0003)**	-0.153 (.08)	-0.639 (.08)	**0.474 (.0001)**
HAN	**-1.08 (.001)**	0.083 (.08)	-0.092 (.27)	**1.41 (.0001)**	**0.445 (.0001)**
IBM	-0.109 (.28)	**0.356 (.0001)**	**-0.337 (.001)**	0.161 (.21)	**0.327 (.0001)**
MO	**-0.568 (.01)**	**0.369 (.003)**	-0.076 (.59)	-0.614 (.20)	**0.318 (.0001)**
POM	-0.353 (.36)	0.034 (.55)	-0.043 (.64)	**0.835 (.03)**	**0.467 (.0001)**
SLB	-0.065 (.62)	**0.192 (.001)**	**-0.221 (.01)**	0.158 (.52)	**0.391 (.0001)**
T	0.009 (.96)	**0.300 (.0001)**	-0.168 (.06)	0.249 (.40)	**0.409 (.0001)**
XON	**0.309 (.03)**	-0.024 (.71)	0.044 (.59)	**0.419 (.04)**	**0.420 (.0001)**

Table 3. OLS regression coefficient estimates (p-values) for equation 2 (all variables are in log levels).

The error in forecasting the time length of a price duration, PTIMEERR, has an unambiguously significant impact for all stocks tested. When PTIME exceeds expectations, the market is less volatile than predicted by our ACD specification. Throughout the open trading hours the specialist expects a certain rate of information flow into the market which will dictate the movement of prices[9]. When a surprisingly small amount of new information has been revealed, there is less motivation for the specialist to adjust quotes and more time and incentive for new liquidity to be supplied. The market exhibits greater depth.

A trader can influence PTIMEERR by rapidly trading on one side of the market. In this sense, "impatience" of the trader is taken by the market as news the same way as any other new information. Thus the uniformly positive coefficient of time surprises indicates the cost associated

[9] This rate of information flow is partially achieved through transactions, and thus is endogenous to the microstructure model described in section 2.

with rapid trading. The market depth is reduced and the volume which can be traded with a particular price impact is reduced. From Table 3 it can be seen that this coefficient is about 0.4 so that a trader who spreads his trades over twice the expected time would face market depth 40% greater.

The anticipated duration, EPTIME, also enters positively in equation 2, but is only statistically significant for 6 stocks. The expected time for prices to move a fixed amount is simply the reciprocal of an expected volatility measure. Since the model is estimated in logs, the coefficient is interpreted as the negative of a volatility effect. It is therefore not surprising that increased volatility leads to decreased market depth since high volatility is associated with news flows and the potential for informed trading.

4.3. Pooled Estimates

The results across individual stocks are similar in character but not uniformly significant. This is unsurprising because the sample period is rather short and there are many obvious sources of noise in VNET which reduce the significance of results. To obtain estimates which summarize the behavior of VNET across these 17 stocks, a pooled regression is computed. As the typical volume and the threshold for price durations are different for each stock, it is important to allow individual specific effects so that the intercept is a set of 17 dummy variables.

The estimated pooled equation is

$$\begin{aligned} VNET &= \bar{\beta}_0 - 0.29(.04)\cdot SPREAD(-1) + 0.14(.02)\cdot VOLUME(-1) - 0.15(.02)\cdot NUMBER(-1) \\ &+ 0.48(.05)\cdot EPTIME + 0.39(.01)\cdot PTIMEERR \end{aligned} \quad \textbf{(3)}$$

All regressors now show extreme significance (greater than 99.9% confidence levels), which is to be expected as we increase the sample size. The signs and the magnitudes are similar to the individual regressions and support our earlier conclusions. An F-Test of the restrictions has a value of 803.6 which easily confirms their significance at 99% confidence.

5. Conclusions

This paper examines the topic of stock market liquidity from a variety of perspectives. The TORQ data set containing transactions and quotes for the New York Stock Exchange from November 1990 through January 1991 is used to identify, measure, and model intraday variations in the level of liquidity. While various market traits and characteristics naturally differ across the sample of 17 stocks, several common relationships and behavioral links appear to exist. The success of these models suggests that this duration-based microstructure approach may be a useful approach toward a better understanding of the fundamental determinants of liquidity and volatility in equity exchange markets.

From the modeling of liquidity, evidence is found for the adverse selection / asymmetric information models. This empirical study explores the depth of financial markets, which is conceptually simple yet difficult to quantitatively define. By defining price durations as the time (and all transactions) between substantial movements in the midpoint of the quotes, a measure of one-sided trading is achieved. Appealing once again to the common microstructure theories, the specialist formulates expectations based in large part on the flow of trading activity. Contrary to a pure inventory control model, we find that the market maker's willingness to hold a position varies according to market conditions. In general, the market traits associated with a high propensity to adjust prices (small one-sided volume triggering a quote change) are similar to those corresponding with low liquidity as represented by wide bid-ask spreads. This result is important in that it unifies our definition of depth with more accepted views of liquidity.

Reviewing the results of the aggregated equation 3, the model proposes some strategies of how to trade large volume at the least cost. First, it may seem obvious that the greater the overall trading volume, the more of a nominal imbalance will be accepted by the market. However, one-sided volume (measured by VNET) per total volume is not a constant percentage over time. The greater the intensity of transactions appears to reduce the depth of the market. This supports the notion that insider trading clusters cause market thickness, but goes against the established view that informed traders transact larger average volume. One explanation for this contradiction may be the inclusion of block trades in our sample. Block trades are organized in the upstairs market and are generally thought to be mostly liquidity based; the trader's open intentions minimize their informational impact.

As discussed earlier, movements in VNET are negatively correlated with movements in the bid-ask spread. Along with providing evidence that this new statistic is a valid measure of liquidity, this relationship adds another trading strategy component, albeit an obvious one: when the market is illiquid in terms of tightness, it will also lack depth. In addition, the positive sign on expected duration time implies that when the market is volatile it will offer less depth. Any unanticipated increases in PTIME boost liquidity. With respect to the traders' order strategy, this result carries the implication that patience may greatly reduce transaction costs. Random public news can always add noise and uncertainty to these results, but our findings give some evidence that trading behavior may have the potential to endogenously shape the liquidity of the stock market.

Dependent variable: VNET

	VNET(-1)	SPREAD(-1)	VOLUME(-1)	VOLSPR(-1)	NUMBER(-1)	NUMSPR(-1)	PJUMP(-1)	EPTIME	PTIMEERR
BA	-0.062 (.45)	0.077 (.89)	-0.269 (.58)	0.632 (.19)	0.212 (.64)	-0.534 (.24)	-0.241 (.45)	0.290 (.24)	**0.344 (.0001)**
CAL	0.022 (.75)	-0.053 (.83)	1.28 (.06)	-1.15 (.09)	**-1.27 (.04)**	1.06 (.08)	-0.084 (.72)	0.239 (.09)	**0.424 (.0001)**
CL	0.089 (.15)	**-0.433 (.05)**	-0.059 (.81)	0.031 (.90)	0.328 (.32)	-0.368 (.27)	-0.008 (.95)	0.153 (.39)	**0.309 (.0001)**
CPC	-0.077 (.26)	**-1.27 (.0001)**	**0.911 (.001)**	**-0.655 (.01)**	-0.582 (.14)	0.385 (.33)	0.081 (.56)	-0.009 (.98)	**0.316 (.0001)**
DI	-0.028 (.76)	0.348 (.53)	0.073 (.74)	0.229 (.21)	0.085 (.80)	-0.321 (.34)	0.171 (.61)	0.287 (.32)	**0.500 (.0001)**
FDX	-0.007 (.93)	-0.550 (.07)	-0.132 (.63)	0.362 (.16)	-0.021 (.97)	-0.272 (.57)	-0.055 (.75)	**0.497 (.05)**	**0.346 (.0001)**
FNM	0.123 (.17)	0.465 (.43)	0.179 (.78)	-0.119 (.85)	-0.084 (.94)	0.075 (.94)	-0.509 (.32)	-0.018 (.94)	**0.326 (.0001)**
FPL	-0.093 (.32)	**1.49 (.02)**	-0.206 (.45)	0.337 (.18)	0.445 (.18)	-0.447 (.17)	0.412 (.16)	**0.798 (.001)**	**0.619 (.0001)**
GE	**0.119 (.03)**	-0.508 (.28)	0.973 (.10)	-0.741 (.21)	**-1.42 (.03)**	1.25 (.06)	0.006 (.99)	0.061 (.67)	**0.348 (.0001)**
GLX	0.028 (.82)	-0.603 (.31)	0.469 (.50)	-0.144 (.83)	-0.420 (.50)	0.153 (.81)	0.532 (.19)	-0.313 (.59)	**0.538 (.0001)**
HAN	0.240 (.13)	1.35 (.08)	-0.212 (.43)	0.023 (.93)	-0.028 (.95)	0.194 (.66)	0.155 (.72)	0.405 (.45)	**0.348 (.0001)**
IBM	0.057 (.21)	-0.397 (.14)	**-1.21 (.01)**	**1.47 (.002)**	0.614 (.20)	-0.878 (.06)	0.442 (.09)	0.122 (.39)	**0.322 (.0001)**
MO	0.050 (.51)	**-2.05 (.01)**	2.06 (.09)	-1.66 (.16)	-1.66 (.15)	1.60 (.16)	**1.33 (.05)**	-0.341 (.59)	**0.425 (.0001)**
POM	-0.133 (.46)	1.43 (.15)	0.019 (.97)	0.171 (.66)	0.099 (.84)	-0.142 (.77)	-0.315 (.54)	-0.531 (.37)	**0.279 (.002)**
SLB	0.039 (.46)	-0.090 (.69)	0.329 (.29)	-0.184 (.55)	-0.439 (.15)	0.205 (.49)	-0.121 (.53)	0.221 (.41)	**0.365 (.0001)**
T	0.079 (.36)	0.276 (.75)	0.252 (.35)	-0.052 (.83)	-0.259 (.43)	0.225 (.48)	0.252 (.65)	-0.094 (.81)	**0.372 (.0001)**
XON	0.038 (.61)	0.020 (.98)	-0.014 (.96)	-0.013 (.96)	-0.277 (.42)	0.324 (.33)	0.086 (.83)	0.306 (.23)	**0.342 (.0001)**

Appendix A. General model estimation results.

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