JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 44, No. 1, Feb. 2009, pp. 29–54

doi:10.1017/S0022109009090085

Detecting Liquidity Traders

Avner Kalay and Avi Wohl*

Abstract

We develop a measure (based on the relative slopes of the demand and supply schedules) quantifying the asymmetric presence of liquidity traders in the market: a steeper slope of the demand (supply) schedule indicates a concentration of liquidity traders on the demand (supply) side. Using the opening session of the Tel Aviv Stock Exchange, we demonstrate the predictive power of our measure. Consistent with theory, we find that the concentration of liquidity traders on the demand (supply) side is negatively (positively) correlated with future returns. We find that liquidity traders are likely to arrive at the market together (commonality).

I. Introduction

The interaction between providers of liquidity and liquidity traders is a central theme in market microstructure models. While there is no generally accepted definition for "liquidity traders," in many cases this term refers to investors that

*Kalay, kalay1@post.tau.ac.il, Tel Aviv University and University of Utah, Faculty of Management, Tel Aviv University, POB 39010, Tel Aviv 69978, Israel; Wohl, aviwohl@post.tau.ac.il, Tel Aviv University, Faculty of Management, POB 39010, Tel Aviv 69978, Israel. We thank the Tel Aviv Stock Exchange for providing us with the data. For very useful comments and suggestions, we thank Yakov Amihud, Doron Avramov, Shmuel Baruch, Jonathan Berk, Stephen Brown (the editor), Loran Chollete, Tarun Chordia, David Feldman, Thierry Foucault, Martin Hellwig, Eugene Kandel, Shmuel Kandel, Ron Kaniel, Pete Kyle, Spiros Martzoukos, Roni Michaely, Barbara Rindi, Gideon Saar (the referee), Orly Sade, Oded Sarig, Andrei Simonov, Pascal St-Amour, Richard Stanton, S. Viswanathan, Masahiro Watanabe, the participants in the seminars of Ben Gurion University, Duke University, the Federal Reserve Bank of Washington, Hebrew University, HEC Lausanne, Interdisciplinary Center Herzliya, New York University, Norwegian School of Management, the Securities and Exchange Commission, Tel Aviv University, University of Amsterdam, University of California at Berkeley, University of Copenhagen, University of Utah, University of Vienna, University of Zurich, and participants in the European Finance Association meetings 2002 in Berlin, the conference on capital markets at the University of Cyprus 2002, the MTS-CEPR conference in Toulouse 2003, the Israeli Economic Association 2004, the CEPR Symposium at Gerzensee 2004, Norges Bank/BI Conference on the Microstructure of Equity and Currency Markets 2005. Wohl thanks the David Orgler and Family Research Fund for Banking and Finance for partial financial support. A previous version of this paper was entitled, "The Information Content of the Demand and Supply Schedules of Stocks."

trade for reasons other than private information. As such, liquidity traders' market activity is assumed to push security prices temporarily away from their fundamental value. Providers of liquidity, on the other hand, are typically assumed to have a superior ability to absorb liquidity shocks or to have better information. In this paper we develop a measure of the liquidity pressure (buy or sell side) in call auctions. We demonstrate the predictive power of our measure using a unique database of all the orders submitted to the opening session at the Tel Aviv Stock Exchange (TASE).

The noisy rational expectations equilibrium (NREE) models of Hellwig (1980), Kyle (1989), Admati (1985), and Easley and O'Hara (2004) are suitable for analyzing call auctions. In these one-period models, investors having different information react to an exogenous demand/supply shock. The supply/demand shock in these models is usually viewed as a representation of the effects of the trading behavior of liquidity traders that do not condition their trades on market prices. In other words their demand and supply schedules are infinitely inelastic. In contrast, the informed traders submit a price-sensitive excess demand schedule.

As a prototype for these models, we examine Hellwig (1980). We separate the excess demand schedules into demand and supply curves and develop a measure of the asymmetric presence of informed traders around the equilibrium price:

$$M(p) = \frac{|D'(p)|}{S'(p) + |D'(p)|}.$$

The idea is very simple. By assumption, only the informed traders submit price-sensitive demand and/or supply schedules. The aggregate demand (supply) schedule of the informed traders is the horizontal sum of the individual demand (supply) curves of the group. If more informed traders are on the demand (supply) side, the aggregate demand curve of the informed investors is flatter than the aggregate supply (demand), resulting in a larger M. At the extreme, when $M = 1(0)$, all the informed investors value the asset by more (less) than the price. Hence, when $M = 1(0)$, all the informed traders are on the buy (sell) side. An equal distribution of the informed investors between the demand and supply sides results in $M = 0.5$. Clearly, while M represents the asymmetric presence of informed investors in the opening call, it reveals the inverse asymmetric presence of the liquidity traders as well. We estimate a linear transformation of M, BP $= 1 - 2M$. BP (buying pressure) measures the liquidity BP in the market. When BP = $1(-1)$, all the buyers (sellers) are liquidity traders. Based on the above models, we expect BP to be negatively correlated with future price changes.

It is important to emphasize that we can derive a similar measure in models, such as Madhavan and Panchapagesan (2000), with symmetric information among the informed traders, where the differences among them arise from differences in initial inventories. Therefore, the liquidity providers need not have private information. Our BP measure relies on the differences of demand elasticity between "liquidity traders" and the other traders. The "liquidity traders" are assumed to have inelastic demand/supply, while the other investors have elastic demand/supply. Though this dichotomy, of course, takes the differences between traders to the extreme, it is nevertheless reasonable to expect differences between price sensitivity of liquidity investors and other investors (as is assumed in many models). The difference in price sensitivity of demand/supply may arise from differences in information accuracy, risk aversion, or hedging possibilities. In many models, less information, more risk aversion, and less hedging possibilities are related to less price-sensitive demand.

To examine the predictive power of our measure, we use a unique database obtained from the TASE that includes all orders submitted to the opening sessions, which, like the opening at Tokyo, Euronext, and many other exchanges, are conducted as call auctions. Investors submit buy and sell orders to the opening call auction between 8:30 AM and 10:00 AM. At 10:00 AM the opening price is set at the intersection of the supply and demand schedules. Our sample consists of the 105 most active stocks on the TASE. The period investigated is January 25, 1998, to September 28, 1998 (167 trading days).

For each stock in our sample, we run a time-series regression of its return from open to close as a dependent variable on the stock's BP, estimated around the opening auction price. Consistent with our empirical implications, the coefficients of BP in each of the 105 regressions are negative. The t-statistic of the series of the BP coefficients is -26.74 and the average adjusted R^2 of the regressions is 0.112. Our measure of the liquidity BP remains significant in explaining the next period return when the lagged return (LR) is added to the regression as an explanatory variable. Moreover, we find that the equally weighted average of the BPs of our sample stocks predicts the future return of the stock index. We document a correlation of 0.42 between the equally weighted average BP and the stock index future return. In contrast, we find no such predictive ability for the stock index LRs. While many studies investigate return serial correlation, we use the call environment to investigate additional information: the slopes of the demand and supply curves. This is somewhat in the spirit of papers that use volume and return as predictors of future return (see, for example, Campbell, Grossman, and Wang (1993), Llorente, Michaely, Saar, and Wang (2002), and a literature survey there).

The assumption that liquidity traders do not condition their demand/supply on prices is not common to all the microstructure models. For example, in Glosten and Milgrom (1985), liquidity traders are given utility functions and can choose not to trade. Our data enable an empirical examination of this issue. A submission of a market order to an opening call auction is equivalent to having a completely inelastic demand/supply. If liquidity traders submit market orders to the call auction (i.e., have completely inelastic demand/supply), we expect a larger fraction of buy market orders than sell market orders to reveal the presence of liquidity traders on the demand side and to be followed by negative returns. Note that market orders play a completely different role in continuous trading.[1] In such a trading environment, market orders are executed immediately against the best bid or ask. Hence, submitting a market order in the continuous trading stage is not an indication of willingness to buy/sell at any price. In continuous trading, market orders are executed immediately against the best bid or ask and as such they

[1]See, among others, Kaniel and Liu (2006), who analyze theoretically and empirically the order type placement decision of informed traders, and Bloomfield, O'Hara, and Saar (2005), who find in lab experiments that liquidity traders as well as informed traders use both market and limit orders.

do not reveal the maximum (minimum) price the buyer (seller) is willing to pay (receive). In contrast, submitters of the largest possible limit order in call auctions (our estimate of a market order in such a trading environment) will trade at the unknown equilibrium price, and hence reveal their willingness to trade at any price up to the limit price.

To examine the effects of market orders submitted to a call auction, we run a time-series regression of the returns from the opening to the closing of the day as a dependent variable and the fraction of buy (Z_D) and sell (Z_S) market orders out of the total volume as an explanatory variable for each stock in the sample.[2] Consistent with the assumption of demand inelasticity of liquidity trades, we find significantly negative (positive) coefficients for Z_D (Z_S). The average adjusted R^2 of these regressions, however, is 0.065—lower than the 0.112 documented when BP is used as an explanatory variable.

Though the empirical evidence presented thus far indicates that liquidity traders use market orders in the opening call auction, to argue that they are completely insensitive to price, one needs to demonstrate that they use only market orders. To investigate this issue, we add the fraction of aggressive limit orders, with a limit price 5% to 9.5% different from the previous closing price, as an explanatory variable. We find that aggressive limit orders predict future returns just as well as market orders. Thus, our evidence indicates that liquidity traders should be modeled as somewhat price sensitive. The alternative assumptions concerning the price sensitivity of the liquidity traders do not affect our new measure, BP, however, as it is estimated around the equilibrium price.

We document commonality in BP: the contemporaneous BPs of individual stocks are positively correlated. The evidence from our measurement of commonality in the behavior of the liquidity traders indicates that the presence of liquidity buyers (sellers) in some stocks is correlated with the contemporaneous appearance of liquidity buyers (sellers) in the other stocks.

Finally we find a contagion effect. The future return of stock i is predicted by the equally weighted average of the BPs of all the other stocks, in addition to its own BP. This relation is statistically significant, though it has a small effect on the explanatory power of the regression.

The empirical evidence on the information content of the demand curve is very limited. Kandel, Sarig, and Wohl (1999), in an analysis of 27 Israeli IPOs conducted by non-discriminatory auction, find that a flatter demand curve (revealed immediately after the auction) is associated with a subsequent price increase. Their interpretation of this finding is similar to ours. A flat (more elastic) demand curve conveys to market participants that the current price of the asset is based on more precise information. In the same spirit, Liu, Wei, and Liaw (2001) find a positive correlation between elasticity of demand and abnormal return in

[2]In our sample period, TASE limits the overnight return (from last closing) to $|10\%|$. Furthermore, a limit order with a price differing by $|10\%|$ from the previous close has priority over market orders. Since market orders during the opening sessions are dominated by such limit orders, we rarely observe them. Consequently, we classify a limit order at 9.5%–10% above or below the last closing as a market order. We include limit orders with a limit differing from the last closing by as little as 9.5% because the tick size can be as large as 0.5%.

discriminatory IPO auctions in Taiwan. Madhavan and Panchapagesan (2000) investigate the opening sessions at the New York Stock Exchange (NYSE), where the specialist may add orders after observing the book. In their model, there are two sources of price noise: informed investors' initial endowments and liquidity shocks of other investors. By assumption, liquidity traders use market orders. Therefore, by observing market orders, the specialist may detect price "noise" associated with liquidity traders. The empirical evidence indicates that specialist intervention in the market has the effect of pushing the market prices toward the expected future price (based on previous closing price and market order imbalance). This is consistent with the notion that demand and supply curves convey information about future prices. Cornelli and Goldreich (2001), investigating the book-building process in Britain, find that investors submitting limit orders tend to get more favorable stock allocations than those who submit market orders. This is consistent with the hypothesis that informed investors submit limit orders; they are induced to reveal their private information by the favorable allocation. Using the same database, Cornelli and Goldreich (2003) find that a concentration of orders around the equilibrium price (a more elastic demand) is positively correlated with aftermarket returns. Biais, Hillion, and Spatt (1999), investigating the opening sessions at the Paris Bourse, find that as the opening gets closer, the indicative prices become more informative. This is consistent with a learning process.

Our empirical findings highlight the importance of further investigating the effects of trading transparency,[3] the potential importance of which is also evidenced by the recent decision of the NYSE to sell the real-time book and by the willingness of market participants to purchase it.

The paper is organized as follows. Section II contains the theoretical background. Section III describes the market structure of the TASE and the data. Section IV presents the predictability of future returns based on our proxies for the asymmetric presence of liquidity traders in the market. Section V investigates the commonality of liquidity. Section VI concludes the paper.

II. Theoretical Background

This section restates Hellwig (1980) and derives testable empirical implications.[4] Hellwig's model describes equilibrium in a market where traders possess different pieces of information about a risky asset. There is a random component to the supply of this risky asset that induces "noise" in its price.

[3]See Rindi (2008) for a theoretical analysis of the implications of pre-trade transparency and see Boehmer, Saar, and Yu (2005) for an empirical analysis of the effects of making the NYSE limit order book publicly available in real time. For a survey on the issue of trading transparency, see Madhavan (2000).

[4]Hellwig's (1980) model has become a significant and integral part of financial economics and has been extended and modified in many papers. For example, Admati (1985) extends Hellwig's model to deal with multiple assets, Kyle (1989) extends it by relaxing the assumption of price taking and by adding uninformed speculators, and Grundy and McNichols (1989) investigate the price revelation through time.

The model assumes the existence of an infinite supply of a riskless asset that pays with certainty one unit. In addition, there is a risky asset that pays $\tilde{x}$. The time lapse between trading and asset payoff is negligible. There are two types of traders: n informed traders (denoted $j = 1, \ldots, n$) and an unspecified number of liquidity traders. Each informed trader observes a noisy signal of $\tilde{x}$:

(1) $$\tilde{y}_j = \tilde{x} + \tilde{\varepsilon}_j.$$

The initial endowment of each informed trader is W_{0j} of the riskless asset. Every informed trader's utility is based on W_j, the total wealth after trading,

(2) $$U(W_j) = -e^{-\rho W j},$$

where for simplicity we assume that ρ, the coefficient of risk aversion, is equal for all traders. The informed traders are "price takers."

The total net supply of the liquidity traders is Z (a negative number denotes demanded quantity). For simplicity, we assume that the expected net supply of the liquidity traders, $E\tilde{Z}$, equals zero.

The random vector $(\tilde{x}, \tilde{Z}, \tilde{\varepsilon}_1, \ldots, \tilde{\varepsilon}_n)$ has a normal distribution with mean $(\mu_x, 0, \ldots, 0)$ and a variance-covariance matrix $(\sigma^2,\ \Delta^2,\ S^2, \ldots, S^2)\, I_{n+2}$, where I_{n+2} is the $(n+2)$-dimensional identity matrix. For simplicity we assume that each of the informed traders receives an equally precise signal.

Each investor may submit an excess demand function, $Q_j(p)$, to the trading mechanism. The functions specify the supplied or demanded quantity for each possible price (negative numbers denote supplied quantities). By assumption, the liquidity traders send orders that are not conditioned on price. The equilibrium price, p^*, satisfies the condition of market clearing—total supply equals total demand. Hellwig's model does not provide the economic rationale behind the assumption of "noisy" supply. In this paper, we interpret "noise" as the random element added to the economy due to the supply/demand of liquidity traders.

A. The Equilibrium

The assumption of an exponential utility function creates linear net demand functions for the informed traders. The net demand function of each informed trader, j, is

(3) $$Q_j(p) = \frac{E(\tilde{x}|y_j, p) - p}{\rho \mathrm{VAR}(\tilde{x}|y_j, p)}.$$

The key point is that traders base their estimate of the value of the risky asset on their own private signal as well as on its market price. Hellwig (1980) shows that there is an equilibrium in which for every $1 \leq j \leq n$,

(4) $$Q_j(p) = K[(1-A)\ \mu_x + Ay_j - p)],$$

where A and K are parameters dependent on the values of n, ρ, σ, Δ, and s.[5] The equilibrium requires $\sum_{j=1}^{n} Q_j(p^*) = \tilde{Z}$, and therefore the equilibrium price is

$$p^* = (1-A)\mu_x + A\bar{\tilde{y}}_j - \frac{1}{nK}\tilde{Z}. \tag{5}$$

To understand the equilibrium equation, denote

$$u_j = (1-A)\ \mu_x\ +\ Ay_j. \tag{6}$$

This is a weighted average of the signal investor j received and the unconditional expected value of $\tilde{x}$, μ_x. We refer to this variable as the "valuation of investor j." Therefore, the net demand function may be represented as

$$Q_j(p)\ =\ K(u_j\ -\ p). \tag{7}$$

It can be shown that K, the slope of the function, is decreasing in the risk-aversion coefficient, ρ, and in the variance of x (conditional on trader signal and the price). The equilibrium price, p^*, is a weighted average between the unconditional expected value of the risky asset μ_x and the average of the private signals, minus the "noise" term associated with Z (the net supply of the liquidity traders):

$$p^*\ =\ \bar{u}_j - \frac{\tilde{Z}}{nk}. \tag{8}$$

The derivation of the empirical implications requires a separation of the net demand functions into their components—demand and supply. For every $1 \leq j \leq n$,

$$Q_j(p) = D_j(p) -\ S_j(p), \tag{9}$$

where

$$D_j(p)\ =\ \text{Max}\,[0,\ K(u_j - p)],\ S_j(p)\ =\ \text{Max}\,[0,\ K(p-u_j)]\,. \tag{10}$$

Lemma 1.

A. If $u_j > p$, then $D_j'(p) = -K$ and $S_j'(p) = 0$.
B. If $u_j = p$, then $D_j'(p)_- = -K$, $D_j'(p)_+ = 0$, $S_j'(p)_- = 0$, and $S_j'(p)_+ = K$.
C. If $u_j < p$, then $D_j'(p) = 0$ and $S_j'(p) = K$,

where $D_j'(p)$ and $S_j'(p)$ denote derivatives and $D_j'(p)_-$ and $S_j'(p)_-$ denote derivatives for price decrease and $D_j'(p)_+$ and $S_j'(p)_+$ denote derivatives for price increase.[6]

Proof. Directly from (10).

Similarly we separate the net supply of the liquidity traders:

$$Z\ =\ Z_S -\ Z_D, \tag{11}$$

where Z_S (Z_D) is the liquidity traders' supply (demand).

[5] A and K are obtained by solving the nonlinear equation set 7 in Hellwig's model.
[6] $D'(p)_+ = \lim_{h\to\infty,\ h>0} \frac{D(p+h)-D(p)}{h}$ and $D'(p)_- = \lim_{h\to\infty,\ h<0} \frac{D(p+h)-D(p)}{h}$.

https://doi.org/10.1017/S0022109009090085 Published online by Cambridge University Press

We demonstrate that the shape of the demand and supply schedules contains information about the true value of the asset, $\tilde{x}$. We focus on the holding period profit, $\tilde{x} - p^*$. From (5) and the definition of y_j (equation (1)), it can be shown that

$$\tilde{x} - p^* = (1 - A)(\tilde{x} - \mu_X) + A(\tilde{x} - \tilde{x} - \tilde{\bar{\varepsilon}}_j) + \frac{1}{nK}\tilde{Z}. \tag{12}$$

Since the expected value of $\varepsilon_j - s$ is zero, we get that

$$\mathrm{E}(\tilde{x} - p^* \,|Z) = \frac{1}{nK}Z = \frac{1}{nK}(Z_S - Z_D). \tag{13}$$

As $nK > 0$, the expected holding period return is increasing in the excess liquidity supply $Z = Z_S - Z_D$. Next we construct a variable that measures the relative number of informed traders on the "buy" side and does not require observing Z_D and Z_S directly.

Let us assume for simplicity and without loss of generality that

$$y_n > \cdots > y_1. \tag{14}$$

Let us define $D(p)$ and $S(p)$ as the aggregate demand and supply functions, respectively:

$$D(p) = Z_D + D_1(p) + \cdots + D_n(p) \tag{15}$$

and

$$S(p) = Z_S + S_1(p) + \cdots + S_n(p). \tag{16}$$

Lemma 2.

A. If $p > u_n$, then $D'(p) = 0$ and $S'(p) = nK$.
B. If $p < u_1$, then $D'(p) = -nK$ and $S'(p) = 0$.
C. If $u_j < p < u_{j+1}$, where $j = 1, \ldots, n-1$, then $D'(p) = -(n-j)K$ and $S'(p) = jK$.
D. If $p = u_j$, where $j = 1, \ldots, n$, then

$$D'(p)_- = -(n-j+1)K,\ D'(p)_+ = -(n-j)K \quad \text{and}$$

$$S'(p)_- = (j-1)K \quad \text{and} \quad S'(p)_+ = jK.$$

Proof. See Appendix.

We can now define a measure that we use later on in the empirical investigation:

$$M(p) = \frac{|D'(p)_+|}{S'(p)_- + |D'(p)_+|}, \tag{17}$$

where $D'(p)_+$ denotes a derivative for price increase and $S'(p)_-$ denotes a derivative for price decrease. These derivatives are well-defined. Lemma 2 presents their values.

Proposition 1.

A. If $p > u_n$, then $M(p) = 0$.
B. If $p < u_1$, then $M(p) = 1$.
C. If $u_j < p < u_{j+1}$, where $j = 1, \dots, n-1$, then $M(p) = (n-j)/n$.
D. If $p = u_j$, where $j = 1, \dots, n$, then $M(p) = (n-j)/(n-1)$.

Proof. The cases of Proposition 1 are the cases of Lemma 2. In each of the cases, plugging the derivative values into the formula of $M(p)$ (equation (17)) yields $M(p)$ values. □

Corollary 1. $M(p)$ is a step function decreasing in p.

Corollary 2. $M(p)$ represents the relative number of informed investors who value the risky asset at more than its price out of the number of investors with a valuation (u_j) that differs from the price.

The measure can be computed for any price level, but we are interested in M at the equilibrium price p^*. Let us denote

$$M^* = M(p^*). \tag{18}$$

For example, $M^* = 1$ implies an equilibrium price smaller than the valuation of all the informed traders $(u_1, \dots, u_n)$. This can happen as a result of the price pressure of a large net supply (Z) by liquidity traders. M^* is a function of the signals the informed investors get, y_j, and the net supply, Z.

Proposition 2.

A. If $\tilde{Z} < nK(\bar{u}_i - \tilde{u}_n)$, then $M^* = 0$ and $\mathrm{E}(\tilde{x} - p^*) < (\bar{u}_i - \tilde{u}_n)$.
B. If $\tilde{Z} > nK(\bar{u}_i - \tilde{u}_1)$, then $M^* = 1$ and $\mathrm{E}(\tilde{x} - p^*) > (\bar{u}_i - \tilde{u}_1)$.
C. If $nK(\bar{u}_i - \tilde{u}_{j+1}) < \tilde{Z} < nK(\bar{u}_i - \tilde{u}_j)$, where $j = 1, \dots, n-1$, then $M^* = (n-j)/n$ and $(\bar{u}_i - \tilde{u}_{j+1}) < \mathrm{E}(\tilde{x} - p^*) < (\bar{u}_i - \tilde{u}_j)$.
D. If $\tilde{Z} = nK(\bar{u}_i - \tilde{u}_j)$, where $j = 1, \dots, n$, then $M^* = (n-j)/(n-1)$ and $\mathrm{E}(\tilde{x} - p^*) = (\bar{u}_i - \tilde{u}_j)$.

Proof of Proposition 2. The claims regarding $\mathrm{E}(\tilde{x} - p^*)$ follow directly from (13). Let us prove the claims regarding M^*.

From (8), if $\tilde{Z} < nK(\bar{u}_i - \tilde{u}_n)$, then $p^* > \tilde{u}_n$ and according to Case A of Proposition 1, we get $M^* = 0$. In the same way, using (8) and the Cases B, C, and D of Proposition 1, we get Cases B, C, and D of Proposition 2. □

Corollary 3. M^* is weakly monotonically increasing in Z.

Corollary 4. M^* and $(\tilde{x} - p^*)$ are positively correlated.

In order to scale the measure such that it ranges in value between -1 and 1 and give it the interpretation of the liquidity BP, we define

$$\mathrm{BP} = 1 - 2M^*.$$

At the extreme, when $\mathrm{BP} = -1(1)$, the valuations of all the informed investors are higher (lower) than the equilibrium price.

The definition of BP and Corollary 4 yield Corollary 5.

https://doi.org/10.1017/S0022109009090085 Published online by Cambridge University Press

Corollary 5. BP and $(\tilde{x} - p^*)$ are negatively correlated.

Consequently, the model predicts a negative correlation between BP and the holding period profit $x - p^*$.

The following example helps to illustrate the intuition underlying our measures.

Example 1. Suppose there are three informed investors denoted 1, 2, and 3. Their excess demand functions are $Q_3 = 14 - p,\ Q_2 = 12 - p,$ and $Q_1 = 10 - p$. That is, $K = 1$ and $u_3 = 14$, $u_2 = 12$, and $u_1 = 10$.

Graph A of Figure 1 depicts the aggregate demand and supply schedules derived from these excess demand functions. It can be seen that the supply curve is concave and the demand curve is convex, the reason being that at higher (lower) prices, more investors sell (buy) and the supply (demand) curve becomes flatter. The equilibrium price in this example is 12. At this price, Investor 1 buys two units from Investor 3. Following Corollary 2, M^* quantifies the proportion of informed investors with a valuation that exceeds the equilibrium price. In this case, there are two investors with valuations that differ from the equilibrium price: Investor 3 values the asset more than its price and Investor 1 values the asset less than its price. Indeed,

$$M^* = M(p^*) = \frac{|D'(p^*)_+|}{S'(p^*)_- + |D'(p^*)_+|} = \frac{|-1|}{1 + |-1|} = \frac{1}{2}.$$

Graph B of Figure 1 shows the aggregate demand/supply schedules where liquidity demand $Z_D = 2$ and liquidity supply $Z_S = 1$ are added to the economy. In this case, the equilibrium price is pushed up to 12.33. At this price, Investor 1 buys 1.67 units from both Investors 2 and 3. Observing a less steep supply curve than the demand curve indicates that there are more informed traders on the sell side than on the buy side. Therefore, M^*, which represents the proportion of informed investors who value the risky asset at more than its price, is $|-1|/(2+|-1|) = 1/3$. $\mathrm{BP} = 1 - 2*(1/3) = 1/3$ indicates that there is liquidity BP.

Graph C of Figure 1 shows the case where $Z_D = 8$ and $Z_S = 1$. In this case, the equilibrium price is 14.3333,

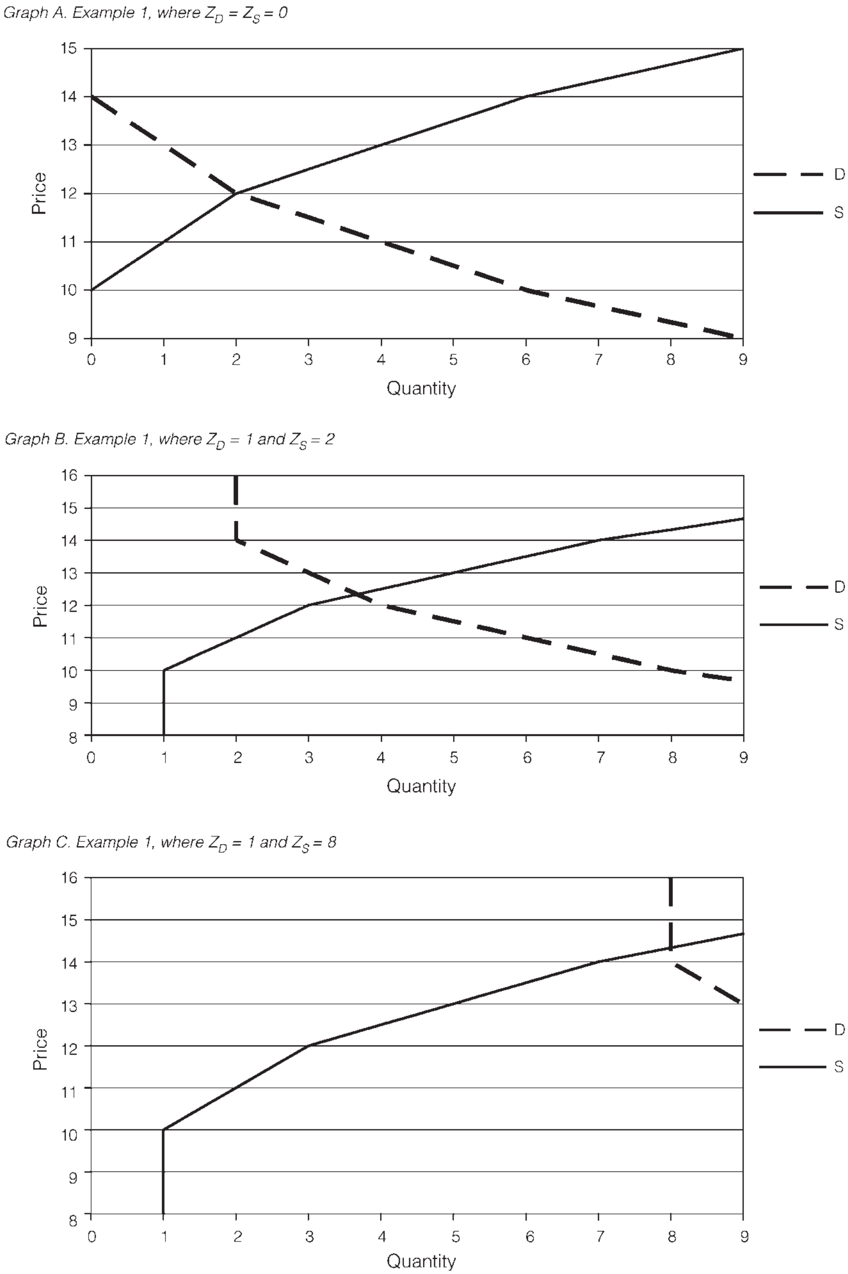
$$M^* = \frac{|D'(14.333)_+|}{S'(14.333)_- + |D'(14.333)_+|} = \frac{|0|}{3 + |0|} = 0,$$

and $\mathrm{BP} = 1$. In this case the buying liquidity pressure pushes the price higher than 14. At this level, only liquidity traders are willing to buy, and all the informed traders are on the sell side. Figure 2 presents the relation between the equilibrium price and M^*. The figure demonstrates the negative relation between the price and M^*.

B. Relaxing Some of the Simplifying Assumptions

We simplify Hellwig's model by assuming that $E\tilde{Z} = 0$ and that all informed traders have the same risk aversion and signal precision. Allowing for $E\tilde{Z} \neq 0$ adds a risk-premium term to the price of the risky asset. However, it does not

FIGURE 1
Demand and Supply Curve

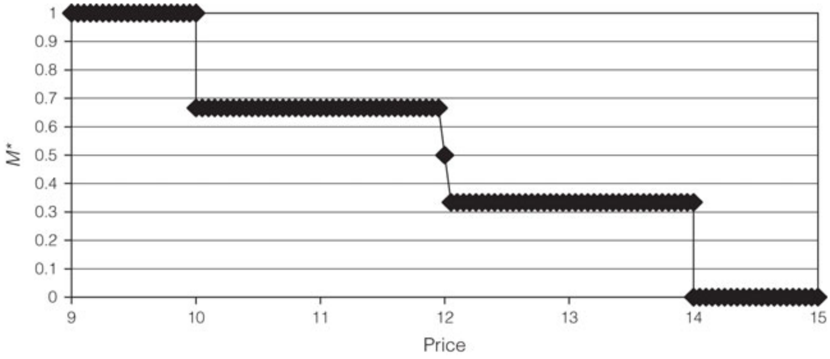


change the results concerning the information content of the demand and supply curves. If we allow for differences among investors in their risk aversion and their information precision, we lose the simple interpretation of $M(p)$. In the simple case, $M(p)$ measures the relative number of informed investors who value the

FIGURE 2

An Example of the Relation between the Price and M^*

Figure 2 is based on Example 1 and illustrates the relation between the possible prices and M^*.



risky asset by more than its price. In an economy with differential risk aversion and signal precision, $M(p)$ weighs each informed investor who values the risky asset by more than its price differently. The weight given to each informed investor is inversely related to her risk aversion and positively related to her information precision (i.e., $1/(\rho_j \mathrm{VAR}_j(\tilde{x}|y_j, p))$).

Kyle (1989) extends Hellwig's model by relaxing the assumption of price taking and adding uninformed speculators. The result is steeper excess demand curves and noisier price than in the competitive case. However, the linearity of the excess demand curves still holds. Therefore, we can relax the assumption that the informed traders are price takers without altering our results.

In Hellwig's model, there is information heterogeneity among informed investors. Information asymmetry is not necessary for deriving M. As stated in footnote 1, it is possible to use a model, such as Madhavan and Panchapagesan (2000), where the difference among informed investors is their initial endowments. The main ingredients needed for M to detect the asymmetric presence of liquidity traders in the market are liquidity demand/supply that is not conditioned on price and the linear excess demand curves of the other traders.

III. Data and the Opening Stage at the TASE

A. The Opening Stage

Trading at the TASE is conducted in three stages: an opening stage (8:30 AM–10:00 AM), a continuous bilateral trading system (10:00 AM–3:30 PM), and a closing session in which transactions are executed at the closing price (3:30 PM–3:45 PM). The trading system is a computerized limit order book as in the Paris Bourse and in many exchanges around the world.[7] This paper uses data on the call auction conducted in the opening stage. During the opening session, investors

[7]See Kalay, Wei, and Wohl (2002) for a detailed description of the TASE market structure during the sample period.

submit limit and market orders. Orders can be canceled until 9:45 AM. During the last 15 minutes of the opening stage (9:45 AM–10:00 AM) traders cannot cancel orders affecting the projected opening price. The opening price, determined by the intersection of the supply and demand curves, is set at 10:00 AM. If demand and supply intersect at more than one price, the exchange chooses the price closest to the previous day's closing price (base price). If at the opening price the quantity demanded does not equal the quantity supplied, execution is carried out by price and time priority. Price changes from closing to opening are limited to $|10\%|$.[8] Hence, a buy (sell) market order is similar to a limit order at 10% above (below) the base price. Market orders have lower execution priority than do limit orders. Therefore, submitting a buy limit order 10% above the base price dominates submitting a buy market order. Hence the use of market orders is rare. Orders not filled in the opening stage are automatically transferred to the continuous trading phase with the original time priority and price limit.

There are no hidden limit orders at the TASE, and the identity of the members submitting orders is unknown. Unlike the continuous trading session, the opening stage does not restrict the number of shares per order.

B. The Data

We have data for the period from January 25, 1998 to September 28, 1998 (167 trading days). Our sample includes all 105 stocks traded during the entire period by the system described in Section III.A. Our data include all the orders placed at the TASE during the opening session for these 105 stocks. For each order, we have the stock ID, date, time, limit price (or an indication of market order), quantity ordered, buy/sell indication, and an indication of cancellation (and its timing). With these data, we can precisely construct the demand and supply curves for each share in each opening session. In addition, we have information about opening volume, opening prices, and closing prices.

Our sample consists of 15,345 transactions executed during the opening sessions. The time horizon we choose for the calculation of the future return is from the opening to the closing of the same day. On average, there are 6.3 (7.5) executed buy (sell) orders for each stock in an opening session. The average volume in these 15,345 transactions is 167,240 Israeli Shekels per day-stock (in the sample period, $\$1 \approx 3.75$ Shekels), and the corresponding average all-day volume is 1,594,096 Israeli Shekels. Summary statistics of the variables used in our analysis are reported in Section IV. For additional summary statistics of this sample, see Kalay, Sade, and Wohl (2004).

IV. Predicting Future Return

A. Examination of Individual Stocks

As stated in Section II, a crucial assumption underlying our predictions is that orders come from two sources: liquidity traders and informed traders. Since

[8] In our sample this limit was binding in only two cases.

https://doi.org/10.1017/S0022109009090085 Published online by Cambridge University Press

markets must clear, when more liquidity traders are on the demand (supply) side, more informed traders are on the opposite side. Thus, determining the current net trading activity of the liquidity traders should help predict future returns. We expect excess demand by the liquidity traders to imply excess supply by the informed traders and to be associated with negative future returns. The exact opposite is true for excess supply by liquidity traders. Following the analysis of Section II, in this section we use the terminology "liquidity traders" and "informed trades." It should be noted, as in Section I, that it is possible to derive the same empirical implications in models where the liquidity providers do not possess private information.

We assume (see Section II) that liquidity traders' orders are not contingent on prices (market orders). The opening session during our sample period, however, limits the overnight return (from last closing) to $|10\%|$. Furthermore, a limit order with a price differing by $|10\%|$ from the previous close has priority over market orders. Since market orders during the opening sessions are dominated by such limit orders, we rarely observe them. Consequently, we classify a limit order at 9.5%–10% above or below the last closing as a market order. We include limit orders with a limit differing from the last closing by as little as 9.5% because the tick size can be as large as 0.5%. With a tick size of 0.5%, the highest limit a buy order can have is in the range 9.5%–10%.

We denote the volume-adjusted demand of the liquidity traders as Z_D = (the quantities in buy "market orders")/(total volume), and the volume-adjusted supply of the liquidity traders as Z_S = (the quantities in sell "market orders")/(total volume).[9]

We find a mean Z_D of 0.123 and a mean Z_S of 0.232,[10] indicating that our sample is characterized by more liquidity-motivated sells than liquidity-motivated buys.[11] Our proxy of the future stock return (denoted R) is the realized return between the opening and the closing during the same trading day.[12]

We expect a negative correlation between BP and future return, as it represents the liquidity BP in the market. We estimate BP by defining DIF_D = the difference between the demanded quantity 0.5% below the equilibrium and the demanded quantity 0.5% above the equilibrium; and DIF_S = the difference between the supplied quantity 0.5% above the equilibrium and the supplied quantity 0.5% below the equilibrium. Thus, $\text{BP} = 1-2\times(\text{DIF}_D/(\text{DIF}_D+\text{DIF}_S))$.[13]

Our a priori conjecture is symmetry between buyers and sellers, implying BP = 0 on average. We find a mean BP of -0.108, which indicates that in our

[9]In the few cases in which these variables are greater than 1 (in which there is partial execution in the opening price), we limit the values to 1.

[10]We replicate the experiment using nonstandardized quantities of market orders. The results obtained are qualitatively similar.

[11]This evidence is consistent with the findings of Kalay et al. (2004).

[12]The results are qualitatively similar when we use returns measured from open to open and when we use longer horizons of two and three days.

[13]We use an interval of 0.5% so it includes at least one tick size from each size. We checked that the main results of the paper described in Table 1 do not change qualitatively where BP is computed using $\pm 1\%$ or $\pm 2\%$.

https://doi.org/10.1017/S0022109009090085 Published online by Cambridge University Press

sample the demand curves are flatter than the supply curves. In 12.0% (16.7%) of the cases, it has an extreme value: 1 (-1).[14]

We use an additional explanatory variable that has been shown to affect future returns, namely LR, the return from the previous closing to the opening. Transitory price changes induce negative autocorrelation in returns because they tend to reverse (see Grossman and Miller (1988) for a theoretical model that predicts negative return autocorrelation due to liquidity shocks and see among others Roll (1984) and Amihud and Mendelson (1987) for empirical evidence of negative autocorrelation in daily returns). Consequently, LR should predict the future return (with negative sign). Table 1 presents summary statistics on the variables and Table 2 presents simple correlations between the explanatory variables.

TABLE 1

Summary Statistics

Table 1 presents summary statistics of the dependent and explanatory variables of regressions (19) and (20). R is the percentage open-to-close return. LR is the percentage return from the previous closing price to the opening price. Z_D (Z_S) is the fraction of orders with price limits that are higher (lower) than the previous close by at least 9.5% out of the opening volume. AGGRESSIVE$_D$ (AGGRESSIVE$_S$) is the fraction of orders with price limits that are higher (lower) than the previous close by at least 5% and no more than 9.5% out of the opening volume. $X_D = Z_D$ + AGGRESSIVE$_D$, $X_S = Z_S$ + AGGRESSIVE$_S$. BP $= 1 - 2(\mathrm{DIF}_D/(\mathrm{DIF}_D + \mathrm{DIF}_S))$, where DIF$_D$ (DIF$_S$) is the difference between the quantity demanded (supplied) at a price 0.5% below the equilibrium and the quantity demanded at a price 0.5% above the equilibrium. Our sample consists of 15,435 observations. The sample period is 1/25/98–9/27/98 (a total of 166 days).

	Mean	Median	Std. Dev.
R	0.697	0.161	2.322
LR	−0.689	0	2.449
Z_D	0.123	0	0.240
Z_S	0.232	0.084	0.315
BP	−0.108	−0.171	0.712
AGGRESSIVE$_D$	0.057	0	0.175
AGGRESSIVE$_S$	0.089	0	0.214
X_D	0.180	0	0.293
X_S	0.321	0.169	0.360

For each stock in our sample, we estimate seven versions of the following time-series regression:

$$R_{it} = \alpha_i + \beta_{1i} Z_{Dit} + \beta_{2i} Z_{Sit} + \beta_{3i} \mathrm{BP}_{it} + \beta_{4i} \mathrm{LR}_{it} + \varepsilon_{it}, \tag{19}$$

where stock $i = 1, 2, \ldots, 105$ and t is day t.

Since Breusch-Godfrey tests show autocorrelated errors in some of the stocks, we estimate the model using maximum likelihood (Yule-Walker) with five lags.[15] The results are reported in Table 3.[16] Regression 1 tests the predictive power of BP.

[14]For each of our 105 sample stocks, we compute the correlation between Z_D and BP as well as Z_S and BP using the 166 trading days. As expected, the average correlation between Z_D and BP is negative (-0.263) with a t-value of -25.5. Only four out of the 105 computed correlations are positive. The average correlation between Z_S and BP is 0.335 with a t-value of 31.18. Out of the 105 correlations, 104 are positive.

[15]The results using regular OLS are qualitatively similar.

[16]While the returns of different stocks on each day are likely to be dependent, the coefficients estimated by a separate time-series regression for each stock are in all likelihood independent. As a robustness check, we examined a pooled regression with dummy variables for the days and dummy variables for the stocks (see Greene (1990) for a two-way fixed effects model). The results are qualitatively similar to those described in Table 1.

TABLE 2

The Correlation between the Explanatory Variables

For each of the 105 stocks in our sample, we calculate correlation coefficients between the explanatory variables of regressions (19) and (20). Table 2 presents the averages of these series. The number of positive coefficients (out of 105) appears below the average correlations in bold font. Critical values for the binomial sign test (positive vs. negative) are 41 and 64 (the p-value is 0.03 for the two-sided test). The t-statistics (not reported) are all greater in absolute value than 2, except for the correlation between Z_D and Z_S, which is −1.38. The sample period is 1/25/98–9/27/98 (a total of 166 days).

	Z_S	BP	LR	AGGRESSIVE$_D$	AGGRESSIVE$_S$
Z_D	−0.014 **41**	0.258 **101**	0.206 **100**	−0.018 **35**	−0.035 **31**
Z_S		−0.329 **1**	−0.319 **0**	−0.076 **14**	−0.096 **19**
BP			0.319 **103**	0.193 **104**	−0.154 **3**
LR				0.210 **103**	−0.199 **4**
AGGRESSIVE$_D$					−0.026 **30**

Consistent with the model, we find BP to be significantly negatively related to future returns. The mean beta is −1.07 with a t-statistic of −26.74. Moreover, all of the 105 estimated betas are negative.

TABLE 3

Predicting Future Returns

We estimate time-series regressions for each of the 105 stocks in our sample. The dependent variable is R_{it} = the return (in percentage) of stock i measured from the opening session of trading day t to its close. The explanatory variables are $Z_{Dit}, Z_{Sit}, \mathrm{BP}_{it}$, and LR_{it} (the lagged return). The estimation uses maximum likelihood (Yule-Walker) with five lags. The numbers presented are the average coefficients across the 105 time-series regressions. The t-statistics are presented below them in parentheses. The number of positive coefficients (out of 105) appears below the t-statistics. Critical values for the binomial sign test (positive vs. negative) are 41 and 64 (the p-value is 0.03 for the two-sided test). The significant values are in bold font. The sample period is 1/25/98–9/27/98 (a total of 166 days).

	1	2	3	4	5	6	7
Intercept	0.640 (13.50)	0.485 (12.18)	0.472 (11.61)	0.484 (15.96)	0.369 (11.27)	0.365 (10.59)	0.458 (13.93)
Z_D	—	−0.862 (−7.28) **15**	−0.196 (−1.79) **38**	—	−0.329 (−3.16) **36**	0.124 (1.25) 58	—
Z_S	—	1.497 (15.01) **100**	0.805 (8.23) **87**	—	0.802 (9.63) **85**	0.345 (3.93) **72**	—
BP	−1.070 (−26.74) **0**	—	−0.899 (−24.60) **1**	—	—	−0.700 (−19.05) **1**	−0.747 (−20.66) **3**
LR	—	—	—	−0.301 (−19.49) **2**	−0.261 (−17.51) **4**	−0.223 (−15.54) **4**	−0.231 (−15.20) **3**
R^2	0.119	0.079	0.152	0.145	0.173	0.222	0.205
Adjusted R^2	0.112	0.065	0.132	0.139	0.154	0.198	0.193

Regression 2 examines the effects of Z_D and Z_S. As expected, we find a statistically significant negative coefficient for Z_D and a positive coefficient for Z_S. The evidence indicates that market orders are more likely to be placed by liquidity traders than by aggressive informed traders. Indirect supportive evidence for this conclusion can be found in the order sizes. For each stock, we look at the average size of the "market" orders versus the average size of all executed orders. The average ratio is 0.59, and in only five out the 105 cases is the ratio greater than 1.

That is, "market orders" tend to be "small orders." Interestingly, liquidity traders seem to constitute a larger fraction of those placing sell market orders than buys. We find the absolute values of the coefficients on Z_D and Z_S to differ significantly. The mean β_{2i} is 1.497, while the mean β_{1i} is only -0.862.[17] Limitations on short sales can explain the observed asymmetry. The higher costs of short sales make it more difficult to act on negative information. Therefore, buy market orders are more likely to be information-motivated than sell orders.[18]

Regression 3 examines the effects of the three variables (Z_D, Z_S, and BP) together. Similarly to the previous regressions, the coefficient of Z_S is significantly positive and the coefficients of Z_D and BP are significantly negative (Z_D is marginally significant using a t-test, but the p-value of a double sided binomial test is 0.6%). In Regression 4, we test the explanatory power of LR, finding (as in previous studies) that it is significantly negative. Regression 5 examines the effect of adding LR to Z_D and Z_S. Regression 6 examines the effect of adding BP to the model's other explanatory variables (Z_D, Z_S, and LR). LR, BP, and Z_S remain highly significant, while Z_D does not. Eliminating Z_D and Z_S (Regression 7) has a trivial effect on the mean adjusted R^2 (0.193 instead of 0.198). Adding the average LR of all the other stocks to BP and LR as an additional explanatory variable has almost no effect on the estimated coefficients and the regression's adjusted R^2.

For a more intuitive perspective on the predictive power of BP and LR, we divide our sample of 15,345 (future) returns measured from the open to the close into four subsamples. We separate the observations based on their magnitude being smaller or larger than the median BP estimated at the open, and based on LR being smaller or larger than the median LR. Figure 3 depicts the fraction of the returns in each subgroup that are larger than the median return of the total sample (0.161%). The negative correlations of future returns with LRs and with BP are apparent.

Dividing the stock sample into four subsamples according to their average trading volume (in dollars), we obtain results that are qualitatively similar to those reported in Table 3 for each of the subsamples. We find a slightly lower explanatory power (R^2 is 9.8%) for the most liquid stocks (the top quartile).

We find that the fraction of market orders (buys and sells), when added to BP and LR, results in a very modest increase in the explanatory power of the regression. Perhaps liquidity traders tend to submit aggressive orders, but not necessarily market orders.

To test this hypothesis, we classify a buy (sell) limit order, in the range of 5%–9.5% above (below) the previous closing price, as "aggressive." Denoting the volume-adjusted "aggressive" demand as AGGRESSIVE$_D$ [(the quantities in "aggressive" buy orders)/(total volume)], and the volume-adjusted supply of

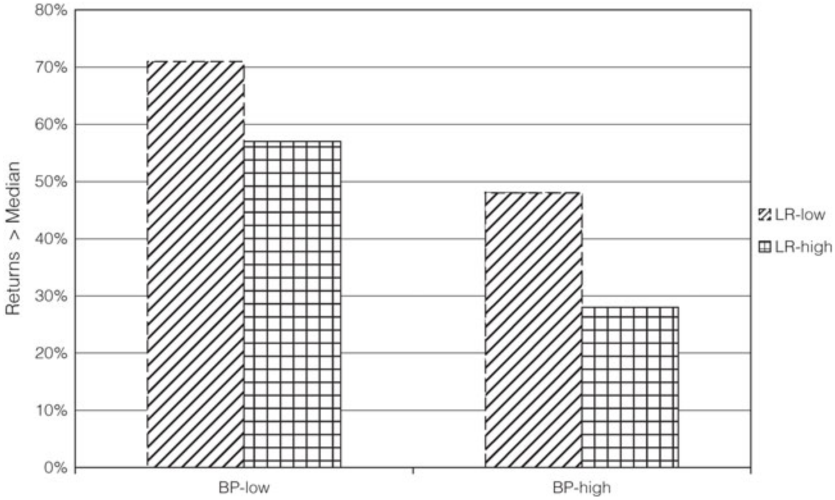
[17]To test whether these betas are significantly different,we construct 105 differences between β_{2i} and $-1*\beta_{1i}$. The t-statistic is 4.34, and in 69 out of the 105 stocks the difference is positive (p-value of 0.0017 in a binomial test). In 14 out of these 69 stocks, the F-test for equality of coefficients is rejected at the 0.05 significance level.

[18]For the differences between buyers and sellers, see Saar (2001). For related evidence and a discussion of this explanation, see Kalay et al. (2004).

FIGURE 3

The Effects of BP and LR on Returns

Figure 3 show the percentage of returns higher than their median (0.161%) conditional on buying pressure (BP) and lag of return (LR) being below or above their median.



the liquidity traders as AGGRESSIVE$_S$ [(the quantities in "aggressive" sell orders)/(total volume)], we find a mean AGGRESSIVE$_D$ of 0.057 and a mean AGGRESSIVE$_S$ of 0.089 for the 105 stocks.[19] For each stock in our sample, we estimate the regression:

$$(20)\quad R_{it} = \alpha_i + \beta_{1i} Z_{Dit} + \beta_{2i} \text{AGGRESSIVE}_{Dit} + \beta_{3i} Z_{Sit} + \beta_{4i} \text{AGGRESSIVE}_{Sit} + \varepsilon_{it},$$

where stock $i = 1, 2, \ldots, 105$ and t is day t.

The results, reported in Table 4, are inconsistent with the hypothesis that liquidity traders use only market orders. The mean betas are (−0.854, −0.847, 1.560, and 1.253) for betas 1 to 4, with t-statistics (−7.20, −7.05, 14.961, and 10.96), respectively. There are 15 positive β_1s, 18 positive β_2s, 100 positive β_3s, and 90 positive β_4s. β_1 and β_2 are significantly negative, and β_3 and β_4 are significantly positive. These results indicate that liquidity traders use aggressive limit orders in addition to market orders. If anything, liquidity traders tend to use market orders more than they use aggressive limit orders. The average of β_1 (β_3) is more negative (positive) than the average of β_2 (β_4), but the differences are small.[20]

The evidence suggests that liquidity traders use both market orders and aggressive limit orders. Perhaps one lesson to be learned from this is that the modeling of liquidity traders should allow for some demand/supply elasticity.

[19]In the few cases in which these variables are greater than 1 (when there is partial execution in the opening price), we limit the values to 1.

[20]The difference between β_3 and β_4 is significant: The t-statistic of the series of differences is 2.38, and there are 62 positive numbers out of 105 (p-value $\approx$ 0.08 in a two-sided binomial test). However, only in 5 out of these 62 stocks is the F-test for equality of coefficients rejected at the 0.05 significance level.

TABLE 4

Predicting Future Returns with Market Orders and Aggressive Limit Orders

We estimate time-series regressions for each of the 105 stocks in our sample. The dependent variable is R_{it} = the return (in percentage) of stock i measured from the opening session of trading day t to its close. The explanatory variables are Z_{Dit}, Z_{Sit}, AGGRESSIVE$_{Dit}$, and AGGRESSIVE$_{Sit}$. The estimation uses maximum likelihood (Yule-Walker) with five lags. The numbers presented are the average coefficients across the 105 time-series regressions. The t-statistics are presented below them in parentheses. The number of positive coefficients (out of 105) appears below the t-statistics in bold font. Critical values for the binomial sign test (positive vs. negative) are 41 and 64 (the p-value is 0.03 for the two-sided test). The significant values are in bold font. The sample period is 1/25/98–9/27/98 (a total of 166 days).

	1	2
Intercept	0.485	0.405
	(12.18)	(10.35)
Z_D	−0.862	−0.854
	(−7.28)	(−7.20)
	15	**15**
AGGRESSIVE$_D$		−0.847
		(−7.05)
		18
Z_S	1.497	1.560
	(15.01)	(14.96)
	100	**100**
AGGRESSIVE$_S$	—	1.253
		(10.96)
		90
R^2	0.079	0.114
Adjusted R^2	0.065	0.087

Aggressive orders, for example, in all likelihood are used by both liquidity traders and informed traders. This can result in the classification of orders submitted by informed traders as orders submitted by liquidity traders. The classification of orders as those placed by liquidity traders when submitted by informed traders (and vice versa) can reduce the explanatory power of Z_D, Z_S, AGGRESSIVE$_D$, and AGGRESSIVE$_S$. The reduction in the explanatory power of these variables is potentially the explanation for the superior predicting power of BP. BP is measured around the equilibrium price, and as such it is less sensitive to the classification of orders placed by the informed traders as orders placed by liquidity traders.

Including AGGRESSIVE$_D$ and AGGRESSIVE$_S$ in regressions that use BP does not contribute much to the explanatory power. We define $X_D = Z_D +$ AGGRESSIVE$_D$, $X_S = Z_S +$ AGGRESSIVE$_S$, and estimate the following regression for each stock:

$$R_{it} = \alpha_i + \beta_{1i} X_{Dit} + \beta_{2i} X_{Sit} + \beta_{3i} \mathrm{BP}_{it} + \beta_{4i} \mathrm{LR}_{it} + \varepsilon_{it}. \tag{21}$$

Indeed, the averages of R^2 and adjusted R^2 (0.222 and 0.198, respectively) are not materially different from the R^2 and adjusted R^2 documented in regressions that use only BP and LR (0.205 and 0.193, respectively). In order to obtain an estimate of the sensitivity of the return to the explanatory variables, we run regression (21) with standardized variables (each variable is divided by its estimated standard deviation). The averages of the estimates of the betas are 0.045, 0.127, −0.490, and −0.602.

B. Predicting Portfolio Returns

The prediction of portfolio returns demonstrates the power of using our measures of liquidity trading (BP, Z_D, and Z_S). According to Amihud and Mendelson

(1989), two effects can affect the serial autocorrelation of returns: i) the potential partial adjustment to new information (caused by information asymmetry, gradual reaction to information, etc.) induces positive autocorrelation; and ii) price noises (caused by temporal liquidity pressures, random errors, etc.) induce negative autocorrelation. Consequently, assuming that price noises are not correlated across stocks, the noise diminishes at the portfolio level, increasing the potential importance of the partial adjustment to new information.

Consistent with the effect of noise on individual stocks, in Table 3 (Regression 4) we report negative autocorrelations at the individual stock level. The effects of diversifying the noise are shown in Table 5. In Regression 1, we find that current portfolio daily returns (computed using only those stocks out of our sample of 105 that have a positive volume at the opening) are not correlated with the respective LRs, $\overline{\text{LR}}$. In contrast, the mean BP has predictive power. In Regression 2, we find that the mean BP is negatively correlated with the next period portfolio returns and the relation is economically significant (an average adjusted R^2 of 0.174). The two effects (noise and partial adjustment) are documented in Regression 3. When LRs, $\overline{\text{LR}}$, are added to the mean BP ($\overline{\text{BP}}$) as an explanatory variable, they have a significantly positive effect. BP seems to capture the effects of the noise associated with the liquidity pressures, and the LRs measure the effects of partial adjustment to new information.

TABLE 5

Predicting Portfolio Returns

For each of the trading days, we form the equally weighted averages of stock returns from open to close (including only stocks with opening volume in our sample of 105), $\overline{R}_t$, and the corresponding averages of BP and LR (lagged return). We estimate regressions where the dependent variable is $\overline{R}_t$ and the explanatory variables are $\overline{\text{LR}}_t$ and $\overline{\text{BP}}_t$. The t-statistics are presented below them in parentheses. The sample period is 1/25/98–9/27/98 (a total of 166 days).

	1	2	3
Intercept	0.677	0.468	0.481
	(10.86)	(7.27)	(7.57)
$\overline{\text{LR}}_t$	−0.016	—	0.089
	(−0.47)		(2.53)
$\overline{\text{BP}}$	—	−2.069	−2.518
		(−5.97)	(−6.55)
R^2	0.001	0.179	0.209
Adjusted R^2	−0.005	0.174	0.200

V. Commonality in the Arrival of Liquidity Traders

Thus far, the paper has provided estimates of the effects of liquidity traders in the market: Large Z_D, AGGRESSIVE$_D$, and BP (Z_S and AGGRESSIVE$_S$) are related to liquidity buy (sell) pressures. One may ask, then, if liquidity traders come to the market at the same time. In other words, is there a commonality in liquidity pressures? To test this, we estimate the following regressions for each stock:

$$X_{Dit} = \alpha_i + \beta_{1i}\bar{X}_{Dt}^{-i} + \beta_{2i}\bar{X}_{St}^{-i} + \varepsilon_{it}, \tag{22}$$

$$X_{Sit} = \alpha_i + \beta_{1i}\bar{X}_{Dt}^{-i} + \beta_{2i}\bar{X}_{St}^{-i} + \varepsilon_{it}, \tag{23}$$

$$\text{(24)} \qquad \mathrm{BP}_{it} = \alpha_i + \beta_{1i}\overline{\mathrm{BP}}_t^{-i} + \varepsilon_{it}, \qquad \text{and}$$

$$\text{(25)} \qquad (X_D - X_S)_{it} = \alpha_i + \beta_{1i}\overline{(X_D - X_S)}_t^{-i} + \varepsilon_{it},$$

where $\bar{X}_{Dt}^{-i}$, $\bar{X}_{St}^{-i}$, and $\overline{\mathrm{BP}}_t^{-i}$ are averages excluding stock i.

The results in Table 6 indicate significant commonality: The X_Ds (X_Ss) of each stock are positively correlated with the X_Ds (X_Ss) in the other stocks and negatively correlated with the other X_Ss (X_Ds). The BPs of the individual stocks are also correlated with each other. We find a positive contemporaneous correlation between the total liquidity trading in stock i and the total liquidity trading in other stocks. The mean adjusted R^2 of the regressions of $(X_D - X_S)$ is 0.09.

TABLE 6

Commonality of Liquidity Pressures

For each of the 105 stocks, we estimated the following regressions:

$$\text{(22)} \qquad X_{Dit} = \alpha_i + \beta_{1i}\bar{X}_{Dt}^{-i} + \beta_{2i}\bar{X}_{St}^{-i} + \varepsilon_{it},$$

$$\text{(23)} \qquad X_{Sit} = \alpha_i + \beta_{1i}\bar{X}_{Dt}^{-i} + \beta_{2i}\bar{X}_{St}^{-i} + \varepsilon_{it},$$

$$\text{(24)} \qquad \mathrm{BP}_{it} = \alpha_i + \beta_{1i}\overline{\mathrm{BP}}_t^{-i} + \varepsilon_{it}, \ \text{and}$$

$$\text{(25)} \qquad (X_D - X_S)_{it} = \alpha_i + \beta_{1i}\overline{(X_D - X_S)}_t^{-i} + \varepsilon_{it},$$

where $\bar{X}_{Dt}^{-i}$, $\bar{X}_{St}^{-i}$, and $\overline{BP}_t^{-i}$ are averages excluding stock i. The numbers presented are the average coefficients across the 105 time-series regressions. The t-statistics are presented below them in parentheses. The number of positive coefficients (out of 105) appears below the t-statistics. Critical values for the binomial sign test (positive vs. negative) are 41 and 64 (the p-value is 0.03 for the two-sided test). The significant values are in bold font. The sample period is 1/25/98–9/27/98 (a total of 166 days).

	Regression			
	(22) X_{Di}	(23) X_{Si}	(24) BP_i	(25) $(X_D - X_S)_i$
Intercept	0.055	0.078	−0.029	−0.022
$\bar{X}_D^{-i}$	0.795	−0.088	—	
	(15.99)	(−1.97)		
	95	**41**		
$\bar{X}_S^{-i}$	−0.061	0.817	—	
	(−2.11)	(20.91)		
	44	**100**		
$\overline{BP}^{-i}$	—	—	0.743	
			(15.87)	
			96	
$\overline{(X_D - X_S)}^{-i}$				0.881
				(28.8)
				104
R^2	0.079	0.071	0.040	0.097
Adjusted R^2	0.065	0.064	0.033	0.090

Examining the commonality of $(Z_D - Z_S)$ by principal component analysis we find that the cumulative proportions of explanation by the first five factors are 0.102, 0.148, 0.189, 0.226, and 0.259. It seems liquidity traders arrive at the market not completely independently of others.

A. The Contagion Effect of Liquidity Trading

Liquidity pressure in one stock may have an indirect effect on other stocks. This may happen for two reasons:

i) The substitution effect. If the price of a stock rises, then the demand for other stocks rises as well, resulting in an increase in their price.

ii) Prices of stocks convey information about their respective payoffs. Since stock payoffs are correlated, investors can derive information about the payoffs of stock i from the price of stock j (see the multi-asset NREE model of Admati (1985)).

The consequence of both effects is that liquidity pressure would appear to have a contagion effect. To test this hypothesis, we estimate three versions of the following time-series regression:

$$R_{it} = \alpha_i + \beta_{1i}\text{BP}_{it} + \beta_{2i}\overline{\text{BP}}_t^{-i} + \beta_{4i}\text{LR}_{it} + \varepsilon_{it}, \tag{26}$$

where stock $i = 1, 2, \ldots, 105$ and t is day t.

As in estimating (19), we estimate the model using maximum likelihood (Yule-Walker) with five lags.[21] The results are reported in Table 7. The empirical evidence (Regression 2) indicates that the equally weighted average BP of all the other stocks has a significant impact on the future return of stock i. The explanatory power is small, however. The effect of the BPs of all other stocks on the future return of stock i remains significant after controlling for its own stock's BP and LR (Regression 3).[22] That is, noise in the price of stock A affects the price of stock B. It should be noted that eliminating $\overline{\text{BP}}_t^{-i}$ from the regression has only trivial effect on the average adjusted R^2 (0.193 vs. 0.198).

Contagion can create commonality in liquidity measures even if the liquidity traders arrive at the market independently.[23] In periods where liquidity traders arrive mostly on one side of the market (BP in most of the stocks is either positive or negative), the price impact on each stock they trade is increased by the effect of the price impact on other stocks. The result is a larger price impact due to liquidity trading. In periods where liquidity traders arrive at the market on both sides (in about half of the stocks BP is positive and in about half it is negative), the price impacts of other stocks have a mitigating effect. The result is a lower price impact. Hence, contagion may create time variation in measures of liquidity such as price impact.

[21] The results using regular OLS are qualitatively similar.

[22] Adding the average LR of all the other stocks to BP and LR as an additional explanatory variable has almost no effect on the estimated coefficients and the regression's adjusted R^2.

[23] For evidence on commonality in liquidity measures, see Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001).

TABLE 7

The Contagion Effect

We estimate time-series regressions for each of the 105 stocks in our sample. The dependent variable is R_{it} = the return (in percentage) of stock i measured from the opening session of trading day t to its close. The explanatory variables are BP_{it}, $\overline{BP}^{-i}$, and LR_{it} (the lag of return). The estimation uses maximum likelihood (Yule-Walker) with five lags. The numbers presented are the average coefficients across the 105 time-series regressions. The t-statistics are presented below them in parentheses. The number of positive coefficients (out of 105) appears below the t-statistics. Critical values for the binomial sign test (positive vs. negative) are 41 and 64 (the p-value is 0.03 for the two-sided test). The significant values are in bold font. The sample period is 1/25/98–9/27/98 (a total of 166 days).

	1	2	3
Intercept	0.458	0.558	0.390
	(13.93)	(10.24)	(10.16)
BP	−0.747	—	−0.723
	(−20.66)		(−19.77)
	3		**2**
$\overline{BP}^{-i}$	—	−1.817	−0.680
		(−12.32)	(−5.00)
		11	**26**
LR	−0.231	—	−0.222
	(−15.20)		(−14.45)
	3		**5**
R^2	0.205	0.029	0.215
Adjusted R^2	0.193	0.022	0.198

VI. Conclusions

This paper constructs a new variable in the opening call auction, enabling the detection of the presence of liquidity traders in the demand or supply side of the market. The new measure is based on the key assumption made in some microstructure models that the demand and supply of liquidity traders is not sensitive to prices. The implication of this assumption is that in a call auction, liquidity traders use market orders. A large fraction of such orders (not contingent on prices) leads to a market demand (or supply) schedule with a more negative slope around the equilibrium price. A steeper supply (demand) curve at the opening represents a downward (upward) temporary price pressure that should be followed by a price increase (decrease). We show that the liquidity BP can be quantified by the following measure (calculated around the equilibrium price):

$$\mathrm{BP} = 1 - 2 * \frac{|D'(p^*)_+|}{S'(p^*)_- + |D'(p^*)_+|}.$$

In our model, when BP = $1(-1)$, only liquidity traders are willing to buy (sell). Therefore, this measure is negatively correlated with future returns.

We use a unique database of all orders submitted during the opening sessions at the TASE for the 105 most liquid stocks. Overall, we find strong evidence to support the model. As predicted, we find a significant negative correlation between BP and future returns that remains significant after adding LR as an additional explanatory variable to the regressions. The explanatory power of these two variables is quite high (an average adjusted R^2 of 0.193). We conclude that, consistent with the model, the shapes of the demand and the supply curves convey information about future returns. Thus, we show that the information content of the supply and demand curve is significant, highlighting the importance of theoretical and empirical investigation of pre-trade transparency.

Not all market microstructure models are based on the assumption that liquidity traders are totally price insensitive. In Glosten and Milgrom (1985), for example, liquidity traders have utility functions and based on maximizing behavior can choose not to trade. That is, they are not totally price insensitive. We find evidence consistent with the hypothesis that liquidity traders use aggressive limit orders as well as market orders. On the basis of the evidence we document, we conclude that liquidity traders have inelastic demand/supply but are somewhat price sensitive.

We find commonality in our measures of liquidity trades. Liquidity sells are positively (negatively) correlated with contemporaneous liquidity sells (buys) in other stocks. Similarly, the equally weighted average BP in all the other stocks is positively correlated with the contemporaneous BP of stock *i*. This evidence is consistent with the hypothesis that liquidity traders tend to arrive together and at the same side of the market.

Appendix

Proof of Lemma 2. From (15) and (16), we get that

(A-1) $$D'(p) = D_1'(p) + \cdots + D_n'(p),$$

(A-2) $$D'(p)_+ = D_1'(p)_+ + \cdots + D_n'(p)_+,$$

(A-3) $$D'(p)_- = D_1'(p)_- + \cdots + D_n'(p)_-,$$

(A-4) $$S'(p) = S_1'(p) + \cdots + S_n'(p),$$

(A-5) $$S'(p)_+ = S_1'(p)_+ + \cdots + S_n'(p)_+, \quad \text{and}$$

(A-6) $$S'(p)_- = S_1'(p)_- + \cdots + S_n'(p)_-.$$

Proof of Claim A. We assume without loss of generality

(14) $$y_n > \cdots > y_1.$$

From (14) and (6) it can be seen also that

(A-7) $$u_n > \cdots > u_1.$$

From (A-7) we get that if $p > u_n$, then for every $j = 1, \ldots, n,\ \ p > u_j$. Therefore from Claim C in Lemma 1 it can be seen that for every $j = 1, \ldots, n$,

$$D_j'(p) = 0 \text{ and } S_j'(p) = K.$$

Therefore from (A-1) it can be seen that $D'(p) = 0$ and from (A-4) it can be seen that $S'(p) = nK$.

Claims B and C of Lemma 2 can be shown in the same way.

Proof of Claim D. Let us recall (A-3):

$$D'(p)_- = D'_1(p)_- + \cdots + D'_n(p)_-.$$

Since $u_j = p$, then according to Claim B of Lemma 1, $D'_j(p)_- = -K$. From (A-7) we get that where $i > j$, $u_i > u_j = p$ and according to Claim A of Lemma 1, $D'_i(p)_- = -K$. Therefore for all $i = j, \ldots, n$, $D'_i(p)_- = -K$ and, therefore, $D'(p)_- = -(n-j+1)K$. In the same way it can be shown that

$$D'(p)_+ = -(n-j)K, \; S'(p)_- = (j-1)K, \text{ and } S'(p)_+ = jK. \qquad \square$$

References

Admati, A. R. "A Noisy Rational Expectations Equilibrium for Multi-Asset Securities Markets." *Econometrica*, 53 (1985), 629–657.

Amihud, Y., and H. Mendelson. "Trading Mechanisms and Stock Returns: An Empirical Investigation." *Journal of Finance,* 42 (1987), 533–553.

Amihud, Y., and H. Mendelson. "Index and Index-Futures Returns." *Journal of Accounting, Auditing and Finance*, 4 (1989), 415–431.

Biais, B.; P. Hillion; and C. Spatt. "Price Discovery and Learning during the Preopening Period in the Paris Bourse." *Journal of Political Economy*, 107 (1999), 1218–1248.

Bloomfield, R.; M. O'Hara; and G. Saar. "The 'Make or Take' Decision in an Electronic Market: Evidence on the Evolution of Liquidity." *Journal of Financial Economics*, 75 (2005), 165–199.

Boehmer, E.; G. Saar; and L. Yu. "Lifting the Veil: An Analysis of Pre-Trade Transparency at the NYSE." *Journal of Finance*, 60 (2005), 783–815.

Campbell, J. Y.; S. J. Grossman; and J. Wang. "Trading Volume and Serial Correlation in Stock Returns." *Quarterly Journal of Economics,* 108 (1993), 905–939.

Chordia, T.; R. Roll; and A. Subrahmanyam. "Commonality in Liquidity." *Journal of Financial Economics*, 56 (2000), 3–28.

Cornelli, F., and D. Goldreich. "Bookbuilding and Strategic Allocation." *Journal of Finance*, 56 (2001), 2337–2370.

Cornelli, F., and D. Goldreich. "Bookbuilding: How Informative is the Order Book?" *Journal of Finance*, 58 (2003), 1415–1444.

Easley, D., and M. O'Hara. "Information and the Cost of Capital." *Journal of Finance*, 59 (2004), 1553–1583.

Glosten, L., and P. Milgrom. "Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders." *Journal of Financial Economics*, 14 (1985), 71–100.

Greene, W. H. *Econometric Analysis*. New York, NY: Macmillan Publishing Company (1990).

Grundy, B. D., and M. McNichols. "Trade and the Revelation of Information through Prices and Direct Disclosure." *Review of Financial Studies*, 2 (1989), 495–526.

Hasbrouck, J., and D. J. Seppi. "Common Factors in Prices, Order Flows, and Liquidity." *Journal of Financial Economic*s, 59 (2001), 383–411.

Hellwig, M. F. "On the Aggregation of Information in Competitive Markets." *Journal of Economic Theory*, 22 (1980), 477–498.

Kalay, A.; L. Wei; and A. Wohl. "Continuous Trading or Call Auctions: Revealed Preferences of Investors at the Tel Aviv Stock Exchange." *Journal of Finance*, 57 (2002), 523–542.

Kalay, A.; O. Sade; and A. Wohl. "Measuring Stock Illiquidity: An Investigation of the Demand and Supply Schedules at the TASE." *Journal of Financial Economics*, 74 (2004), 461–486.

Kandel, S.; O. Sarig; and A. Wohl. "The Demand for Stocks: An Analysis of IPO Auctions." *Review of Financial Studies*, 12 (1999), 227–247.

Kaniel, R., and H. Liu. "So What Orders Do Informed Traders Use?" *Journal of Business*, 79 (2006), 1867–1913.

Kyle, A. S. "Informed Speculation with Imperfect Competition." *Review of Economic Studies*, 56 (1989), 317–355.

Liu, Y.; K. C. J. Wei; and G. Liaw. "On the Demand Elasticity of Initial Public Offerings: An Analysis of Discriminatory Auctions." *International Review of Finance,* 2 (2001), 151–178.

Llorente, G.; R. Michaely; G. Saar; and J. Wang. "Dynamic Volume-Return of Individual Stocks." *Review of Financial Studies*, 15 (2002), 1005–1047.

Madhavan, A. "Market Microstructure: A Survey." *Journal of Financial Markets*, 3 (2000), 205–258.

Madhavan, A., and V. Panchapagesan. “Price Discovery in Auction Markets: A Look Inside the Black Box.” *Review of Financial Studies*, 13 (2000), 627–658.

Rindi, B. “Informed Traders as Liquidity Providers: Anonymity, Liquidity and Price Formation.” *Review of Finance,* 12 (2008), 497–532.

Roll, R. “A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market.” *Journal of Finance*, 39 (1984), 1127–1139.

Saar, G. “Price Impact Asymmetry of Block Trades: An Institutional Trading Explanation.” *Review of Financial Studies*, 14 (2001), 1153–1181.