Detecting Liquidity Traders

By

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Abstract

We present evidence consistent with the presence of liquidity traders who are willing to buy or sell at any price. Using the opening session of the Tel Aviv Stock Exchange we find that (1) a larger fraction of “market” buy (sell) orders of the total volume or/and (2) a demand curve that is steeper than the supply are negatively correlated with future return. Liquidity buyers (sellers) are likely to arrive together (commonality) and they are likely to appear again the following day (persistence). Also we find that liquidity pressure in one stock creates price noise in other stocks (contagion).

JEL Classification: G12 , G14

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Introduction

Liquidity traders are an integral part of modern microstructure theory. They are assumed to have totally inelastic demand and supply schedules – i.e., they are willing to buy or sell a given quantity at any market price. This assumption may be justified by their extreme impatience and/or by their naïve attitude that makes them “trust” the market price. The motivation for their trade is not modeled. The potential existence of liquidity traders in the market is an unresolved empirical issue as even uninformed economic agents may obtain better trading results by conditioning their trades on prices. One wonders if there are investors whose liquidity needs are so intense that they adopt such a naïve trading strategy? In a market with continuous trading it is hard to detect willingness to buy or sell at any price since investors can trade against the quotes. Indeed Bloomfield, O’Hara and Saar (2004) find in lab experiments that liquidity traders as well as informed traders use both market and limit orders.¹ The trading environment that enables an empirical examination of this issue is a call auction. This is because sending a market order to the opening call session (the price of which will be determined only later) is a reasonable proxy for willingness to buy or sell at any price.

We derive empirical implications from a canonical model of call auctions that assumes the existence of liquidity traders willing to buy or sell a fixed amount at any price. The information structure of the other investors (whom we call “strategic”) is not modeled. The information structure can be asymmetric (as in the NREE models of Hellwig (1980) or Kyle (1989)) or it can be symmetric (as in Madhavan and Panchapagesan (2000), where the differences among the “strategic” investors arise

¹ See also Kaniel and Liu (2003) that analyze theoretically and empirically the order type placement decision of informed traders.
from differences in initial inventories). The relevant features of these models are liquidity demand/supply that is not conditioned on price and the linearity of the demand curves of the “strategic” investors.

The empirical implications are examined using a unique database we obtained from the Tel Aviv Stock Exchange (hereafter TASE). The database includes all orders submitted to the opening sessions at the TASE, which, like the opening at Tokyo, Paris, Milan, Madrid and many other exchanges, are conducted as call auctions where the public submits buy and sell orders between 8:30 and 10:00 a.m. At 10:00 a.m. 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 25th to September 28th 1998 (167 trading days).

The best description of a liquidity trader’s willingness to trade a given quantity at any price is a market order. Hence, we assume that liquidity traders submit market orders and strategic traders submit limit orders. With this interpretation, the implication of the model is that more “buy” market orders than “sell” market orders should be followed by negative returns. Consistent with the model, we find that the fraction of “buy” (“sell”) market orders in the total volume is a significant predictor of subsequent price decrease (increase).

The next empirical implication is derived by separating the excess demand of the strategic investors into demand and supply. This representation allows us to derive the relation between the relative slopes of the demand and the supply schedules in a call auction and the next period expected rate of return. The idea is very simple. The aggregate demand (supply) schedule of the strategic traders is the horizontal sum of the individual demand (supply) curves of this group. If more strategic traders are on the demand (supply) side, the aggregate demand curve of the strategic investors is
flatter than the aggregate supply (demand). To capture the asymmetric presence of the strategic investors in the market we construct a measure of the relative slopes (around the equilibrium price) of the demand and the supply schedule, $M$, as follows:

$$M = \frac{1/\text{demand curve's slope}}{1/\text{supply curve's slope} + 1/\text{demand curve's slope}}$$

At the extreme, when $M=1(0)$, all the strategic investors value the asset by more (less) than the price. Hence, when $M=1(0)$ all the strategic traders are on the buy (sell) side. An equal distribution of the strategic investors between the demand and the supply sides results in $M=0.5$. A state of fewer strategic traders on the buy (sell) side implies a relatively larger presence of liquidity buyers on that side of the market. Hence, while liquidity traders are assumed to be randomly divided on both sides of the market, our new measure, $M$, allows us to estimate their asymmetric presence. For example when $M=1$, all the sell orders are liquidity sells. In this case the asset is undervalued and we therefore expect a future price increase. In general, $M$ that is positively (negatively) correlated with the market sell (buy) orders is positively correlated with future price changes.

We predict the stock return from open to close by running a time-series regression for each stock on three explanatory variables: fraction of buy market orders out of the total volume (predicted to have a negative coefficient), fraction of sell market orders out of the total volume (predicted to have a positive coefficient) and $M$ (predicted to have a positive coefficient). The coefficients on each one of these variables are highly significant, and have the predicted sign. The average adjusted $R^2$ of the regressions is 0.162. Our measure of the relative presence of strategic traders, $M$, remains significant in explaining the next period return when the lag of return is
added as explanatory variable to the regression. Moreover, we find that the equally weighted average of the \( M \)'s of our sample stocks predicts the future return of the stock index. We document a correlation of 0.42 between the equally weighted average \( M \) and the stock index future return. In contrast we find no such predictive ability for the stock index lagged returns.

It would be interesting to know what triggers the appearance of liquidity buyers and sellers. Do they come to the market at the same time? If the answer is yes, what can we say about the factors that trigger their appearance? We measure commonality in the behavior of the liquidity traders. Our 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. Indeed the contemporaneous \( M \)'s of individual stocks are positively correlated.

In general liquidity traders seem to follow the trends. We find a positive (negative) correlation between the return from open to close at day \( t-1 \) and liquidity buys (sells) at day \( t \), indicating that liquidity traders are “trendists” or “momentum traders”. Furthermore, we document persistence in our measures of liquidity trades. Liquidity sells (buys) in stock \( i \) at time \( t \) are positively correlated with liquidity sell in stock \( i \) at time \( t-1 \).

Finally we find a contagion effect. The future returns of stock \( i \) is predicted by its \( M \) and by the equally weighted average of the \( M \)'s of all the other stocks. These relations remain statistically significant when adding lagged returns to the regression. It seems that investors derive information about the value of stock \( i \) by examining the

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2 Griffin, Harris and Topaloglu (2003) find contrarian investment by individual investors in NASDAQ 100 stocks. Kaniel, Saar and Titman (2004) find that in NYSE individuals are contrarians and that their buys are followed by positive returns. This means that in a rough classification of “individual” and “institutional” the latter seem to be the “liquidity traders”.

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prices of the other stocks (see the multi-asset NREE model of Admati (1985)). Even if the arrivals of liquidity buyers (sellers) are uncorrelated, the contagion effect can explain the documented commonality in liquidity measures. Contagion increases the price impact of stocks in days dominated by liquidity buyers (or sellers) and reduces it when the two types of traders appear evenly. This creates time-series similarities in the standard measures of liquidity of different stocks.

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 more elastic 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, Liaw, Liu and Wei (2000) find a positive correlation between demand elasticity and abnormal return in discriminatory IPO auctions in Taiwan. Madhavan and Panchapagesan (2000) investigate the opening sessions at the New York Stock Exchange, where the specialist may add orders after observing the book. In their model there are two sources of price noise: strategic 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 affects prices by pushing the market prices towards 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.

For evidence on commonality in liquidity measures see Chordia, Subrahmanyam and Roll (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001).
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 indicate that the limit order book contains valuable information, highlighting the importance of further investigating the effects of trading transparency. The potential importance of trading transparency 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 1 describes the empirical predictions. Section 2 describes the market structure of the TASE and the data. Section 3 presents the predictability of future returns based on our proxies for liquidity pressures. Section 4 investigates the commonality and persistence of liquidity. Section 5 concludes the paper.

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1. Empirical Implications

The construction of the variable that enables the detection of the presence of liquidity traders in the market uses the common assumption made in numerous models that their demand is not sensitive to the price. The same models assume that strategic traders (informed or traders influenced by inventory considerations) condition their demand on prices. This economy fits models of Noisy Rational Expectations Equilibrium such as Hellwig (1980) and Kyle (1989) as well as inventory models such as Madhavan and Panchapagesan(2000).\(^5\) Below we describe the ingredients of the call auction and derive our estimate of the presence of liquidity traders in it.

The value of the risky asset after the auction is \(\tilde{x}\). There are two types of traders: \(n\) strategic traders (denoted \(j = 1...n\)) and an unspecified number of liquidity traders. Each of the strategic traders has a demand function

\[
Q_j(p) = a_j[u_j - p]
\]

The expected value of each of the \(u_j\) is \(\tilde{x}\). Traders have different private information (or different initial inventory) and therefore have different \(u_j\).

As is typically the case, liquidity traders are assumed to base their trading decisions on factors (exogenous to the model) other than private information and/or market price. The total net supply of the liquidity traders is \(Z\) (a negative number denotes demanded quantity). It is natural to assume that the expected net supply of the liquidity traders, \(E\tilde{Z}\), equals zero. However, this assumption is not needed for the derivation of our estimate.

\(^5\) Hellwig’s 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, Grundy and McNichols (1989) and Brown and Jennings (1989) investigate the price revelation through time and Brennan and Cao (1996) analyze the economic value of having more frequent trading.
\[ p^* = \sum_{j=1}^{n} \frac{a_j - \bar{u}_j}{\sum_{i=1}^{n} d_i} - \frac{\bar{Z}}{\sum_{i=1}^{n} d_i} \]  

(1.2)

The equilibrium requires \( \sum_{j=1}^{n} Q_j(p^*) = Z \) and therefore the equilibrium price is \( p^* \).

Hence, the price is the weighted average of the \( u \) (with an expected value of the true value \( \bar{x} \) and a perturbation caused by the net supply of liquidity traders).

The derivation of our estimate detecting the presence of liquidity traders requires a separation of the net demand functions into their components – demand and supply.

For every \( 1 \leq j \leq n \):

\[ Q_j(p) = D_j(p) - S_j(p) \]  

(1.3)

where

\[ D_j(p) = \text{Max}[0, Q_j(p)] \]  
\[ S_j(p) = \text{Max}[0, -Q_j(p)] \]  

(1.4)

We separate the net supply of the liquidity traders similarly:

\[ Z = Z_s - Z_d \]  

(1.5)

where \( Z_s (Z_d) \) is the liquidity traders’ supply (demand).

The following example illustrates the empirical implications. Suppose there are three strategic investors denoted 1, 2, 3 (Example 1). Their excess demand functions are

\[ Q_1 = 14 - p, \ Q_2 = 12 - p, \ Q_3 = 10 - p. \]

Figure 1-A 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 as prices are higher (lower) more investors sell (buy) and the supply (demand) curve becomes flatter. It can also be seen
that the equilibrium price is 12. At this price investor 1 buys a quantity of two units from investor 3.

Figure 1-B shows the curves where there is liquidity demand $Z_d = 2$ and liquidity supply $Z_s = 1$. In this case the price is pushed up to 12.33. At this price investor 1 buys and investors 2 and 3 sell. The fact that the supply curve is flatter than the demand curve indicates that there are more strategic traders on the sell side than on the buy side. Therefore, we define the measure

$$M = \frac{1}{\sup \text{slope demand curve}} \left( \frac{1}{\text{slope supply curve}} + 1 \right)$$

If the slopes of the individual curves $(a_j)$ are equal then $M$ is a measure of the proportion of strategic investors who value the risky asset at more than its price. If the slopes of the individual demand curves are not equal this measure weighs each of the strategic traders by $a_j$. For example, $M=1$ implies an equilibrium price smaller than the valuation of all the strategic traders $(u_1, \ldots, u_n)$. Therefore, at the equilibrium price all the strategic traders are buyers. This can happen as a result of the price pressure of a large net supply $(Z)$ from liquidity traders. Note that in general we expect $Z_d$ $(Z_s)$ to be negatively (positively) correlated with $M$.

Our example demonstrates that the gain from buying, $(\bar{x} - p^*)$, is positively (negatively) correlated with $Z_s$ $(Z_d)$ and positively correlated with $M$. Since the formal proof of this proposition is straightforward we do not include it in the paper.
2. Data and the Opening Stage at the TASE

2.1 The Opening Stage

Trading at the TASE is conducted in three stages: an opening stage (8:30 a.m. to 10:00 a.m.), a continuous bilateral trading system (10:00 a.m. to 3:30 p.m.), and a closing session in which transactions are executed at the closing price (3:30 p.m. to 3:45 p.m.). The trading system is a computerized limit order book as in the Paris Bourse and in many exchanges around the world. This paper uses data on the call auction conducted in the opening stage. During the opening session, investors submit limit and market orders. Orders can be canceled up to 9:45 a.m. During the last 15 minutes of the opening stage (from 9:45 a.m. to 10:00 a.m.) orders expected to be executed cannot be canceled. The opening price, determined by the intersection of the supply and demand curves, is set at 10:00 a.m. 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 $|10\%|$. 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

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6 See Kalay, Wei and Wohl (2002) for a detailed description of the TASE market structure during the sample period.
stage does not restrict the number of shares per order.

2.2 The Data

For reasons of data availability, the period investigated is January 25th to September 28th 1998 (167 trading days). Our sample includes all 105 stocks traded during the entire period by the system described in Section 2.1. Other stocks, which are less liquid, moved to the system during the sample period (see Kalay, Wei and Wohl (2002)). Our data include all the orders placed at the TASE during the opening session. For each order we have the stock ID, the date, the time, the limit price (or an indication of market order), the quantity ordered, buy / sell indication and an indication of cancellation (and its timing). With these data we can precisely construct the demand and the 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 15,449 transactions executed during the opening sessions (we omitted transactions where there were not at least two orders at each side and we omitted two observations where the 10% maximum change limit was binding). The time horizon we choose for the calculation of the future return is from the opening to the closing of the same day. The mean return is 0.70% and the standard deviation is 2.32%. On average there are 6.3 (7.5) executed buy (sell) orders for each stock in an opening session. For additional summary statistics of this sample see Kalay, Sade and Wohl (2002).
3. Predicting Future Return

3.1 Examination of Individual Stocks

A crucial assumption underlying our predictions is that orders come from two sources: strategic traders and liquidity traders. If one can estimate the current price change that is due to liquidity traders (“noise”), one can predict future returns. We expect excess demand by the liquidity traders to be associated with negative future returns. The exact opposite is true for excess supply by liquidity traders.

By assumption, 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 size-adjusted demand of the liquidity traders as

\[ Z_d = \frac{\text{(the quantities in buy “market orders”)}}{\text{(total volume)}}, \]

and the size-adjusted supply of the liquidity traders as

\[ Z_s = \frac{\text{(the quantities in sell “market orders”)}}{\text{(total volume)}}. \]

We find a mean \( Z_d \) of 0.123 and a mean \( Z_s \) of 0.232 for the 105 stocks,\(^8\) indicating that our sample is characterized by more liquidity-motivated sells than liquidity-

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\(^7\) In the few cases in which these variables are greater than 1 (in these cases there is partial execution in the opening price), we limit the values to be 1.
motivated buys. Our proxy of the future stock return (denoted $R$) is the realized return between the opening and the closing during the same trading day.

We expect a positive correlation between $M$ and future return because $M$ represents the proportion of strategic investors who value the stock more than its equilibrium price. We estimate $M$ by defining:

$$Dif_D = \text{the difference between the demanded quantity } \frac{1}{2}\% \text{ below the equilibrium and the demanded quantity } \frac{1}{2}\% \text{ above the equilibrium;}$$

$$Dif_S = \text{the difference between the supplied quantity } \frac{1}{2}\% \text{ above the equilibrium and the supplied quantity } \frac{1}{2}\% \text{ below the equilibrium.}$$

Thus,

$$M = \frac{Dif_D}{Dif_D + Dif_S}$$

Our a priori conjecture is symmetry between buyers and sellers, implying $M = 0.5$ on average. We find a mean $M$ of 0.55, showing an apparent tendency in our sample for the demand curve to be flatter than the supply curve. In 12.0% (16.7%) of the cases it has an extreme value: 0 (1).

We use an additional explanatory variable that has been shown to affect future returns – lag return, $LR$, namely, the return from the previous closing to the opening. Transitory price changes induce negative auto-correlation in returns because they tend to reverse (see among others Roll (1984) and Amihud and Mendelson (1987)). Consequently, $LR$ should predict the future return (with negative sign). For each stock in our sample we estimate six versions of the following time-series regression:

\[ \text{We replicate the experiment using non-standardized quantities of market orders. The results obtained are qualitatively similar.} \]
\[ \text{This evidence is consistent with the findings of Kalay, Sade and Wohl (2002).} \]
\[ \text{The results are qualitatively similar when we use returns measured from open to open.} \]
\[ \text{For each one on our 105 sample stocks we compute the correlation between } Z_d \text{ and } M \text{ as well as } Z_s \text{ and } M \text{ using the 167 trading days. As expected the average correlation between } Z_d \text{ and } M \text{ is negative (-0.263) with a t value of -25.5. Only 4 out of the 105 computed correlations are positive. The average correlation between } Z_s \text{ and } M \text{ is 0.335 with a t value of 31.18. One hundred and four of the 105 correlations are positive.} \]
\[ R_{it} = \alpha_i + \beta_{1i}Z_{d_{it}} + \beta_{2i}Z_{s_{it}} + \beta_{3i}M_{it} + \beta_{4i}LR_{it} + e_{it} \]  

(3.1)

where

\( i \) is stock \( i = 1, 2, \ldots, 105 \)

\( t \) is day \( t \).

The results are reported in Table 1. Regression 1 examines the effects of \( Z_d \) and \( Z_s \). Consistent with the model, we find a statistically significant negative coefficient for \( Z_d \) and a positive coefficient for \( Z_s \). Indeed it seems that market orders are more likely to represent liquidity traders than aggressive strategic traders. However, contrary to our model, the absolute values of the coefficients differ significantly. The average of \( \beta_{2i} \) is 1.569 and the average of \( \beta_{1i} \) is -0.966. To test whether these betas are significantly different, we construct 105 differences between \( \beta_{2i} \) and \( -1*\beta_{1i} \). The \( t \)-statistic is 4.00 and in 74 out of the 105 stocks the difference is positive (p-value less that 0.0001 in a binomial test). This evidence indicates that sell market orders are more likely motivated by liquidity traders than buy market orders.

A potential explanation for this asymmetry stems from limitations on short sells, which increase the cost of acting upon negative information over the cost of acting on positive information. Therefore, buy orders are more likely to be information motivated than sell orders.\(^{12}\)

Regression 2 tests the predictive power of \( M \). Consistent with the model, the coefficient is indeed positive and significant. Regression 3 looks at the three variables \( Z_d, Z_s \) and \( M \) together. All the coefficients are significant and with the right sign. In Regression 4 we test the explanatory power of lag return (\( LR \)), finding that it is indeed significantly negative. Regression 5 examines the effect of adding \( LR \) to \( Z_d \) and \( Z_s \). Regression 6 examines the effect of adding \( M \) to the model’s other explanatory variables (\( Z_d, Z_s \) and \( LR \)). \( LR \) and \( M \) are highly significant. However, \( Z_d \)

\(^{12}\) For the differences between buyers and sellers see Saar (2001). For related evidence and a discussion of this explanation see Kalay, Sade and Wohl (2002).
and $Z_s$ are not significant by binomial tests. Therefore, in Regression 7 we drop $Z_d$ and $Z_s$. Indeed, the mean adjusted $R^2$ is practically not affected, and it remains quite high (0.239 instead of 0.242).

For a more intuitive perspective on the predictive power of $M$ and $LR$, we lump the returns of all stocks in all days (15,449 observations) and divide the sample into four sub-samples according to $M$ (smaller or larger than median $M$) and $LR$ (smaller or larger than median $M$). Figure 2 depicts the percentage of returns in each sub-group that are greater than the median return (0.167%). The negative correlation of future returns with lag returns and the positive correlation of future returns with $M$ are apparent.

Dividing the stock sample into four sub-samples according to their average trading volume (in NIS), we obtain results that are qualitatively similar to those reported in Table 1 for each of the sub-samples. For the top quartile (the most liquid stocks) we find a somewhat lower explanatory power. For example, consistent with the findings reported in Table 1, in Regression 2, 26 of the 26 coefficients of $M$ are positive and their $t$-statistic is 14.0. However, the average adjusted $R^2$ is 14.7% and the average explained standard deviation is 0.663%.

The main assumption in the model is that liquidity traders do not condition their demand/supply on the price, that is, they submit market orders. As a result the market demand and supply are predictors of subsequent price decrease and increase, respectively. However, empirically, these variables when added to $M$ and $LR$ do not contribute to the explanatory power of the regression. A potential explanation of this phenomenon is that liquidity traders do indeed 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 size-adjusted “aggressive” demand as $AGGRESSIVE_d \left[ \text{(the quantities in “aggressive” buy orders) / (total volume)} \right]$, and the size-adjusted supply of the liquidity traders as $AGGRESSIVE_s \left[ \text{(the quantities in “aggressive” sell orders) / (total volume)} \right]$, we find a mean $AGGRESSIVE_d$ of 0.057 and a mean $AGGRESSIVE_s$ of 0.089 for the 105 stocks. For each stock in our sample we estimate the regression:

$$R_i = \alpha_i + \beta_1 Z_{d_{it}} + \beta_2 Z_{d_{si}} + \beta_3 Z_{s_{it}} + \beta_4 Z_{s_{si}} + \epsilon_{it} \quad (3.2)$$

where

- $i$ is stock $i = 1, 2, ..., 105$
- $t$ is day $t$.

The results are reported in Table 2. The means of the betas are (-0.946, -0.885, 1.645, 1.445), respectively. The $t$-statistics are (-8.07, -7.24, 14.41, 12.57), respectively and the numbers of positive coefficients are (14, 20, 100, 95). It can be seen that both $\beta_1$ and $\beta_2$ are significantly negative and both $\beta_3$ and $\beta_4$ are significantly positive. These results are consistent with the conjecture that liquidity traders use market orders in addition to aggressive limit orders. As expected, the average of $\beta_1$ ($\beta_3$) is more negative (positive) than the average of $\beta_2$ ($\beta_4$). However, only the difference between $\beta_3$ and $\beta_4$ is significant: the $t$-statistic of the series of differences is 1.56 and there are 64 positive numbers out of 105 ($p$-value $\approx 0.03$ in a two-sided binomial test). Perhaps one lesson to be learned from this is that the modeling of liquidity traders could allow for some demand/supply elasticity, however low. That being the case, our measure of the relative slopes of the demand and the supply schedules ($M$) which is measured around the equilibrium price is less sensitive to an

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13 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 be 1.
arbitrary cutoff between liquidity traders’ orders and orders placed by strategic traders.

3.2 Predicting Index Returns

The prediction of index returns demonstrates the power of using our measures for liquidity trading $M$, $Z_d$ and $Z_s$. As pointed out in Amihud and Mendelson(1989), two effects can affect the serial auto-correlation of returns: (1) the potential partial adjustment to new information (caused by information asymmetry, gradual reaction to information, etc.) induces positive auto-correlation; (2) price noises (caused by liquidity trading, random errors, etc.) induce negative auto-correlation. As we find in our sample, random pricing errors and the effects of liquidity traders are almost uncorrelated (in Section 4 we report low commonality of liquidity pressures). Hence the noise tends to vanish at the index level, resulting in a more positive auto-correlation at the index level than the individual stock autocorrelations. Thus, in Table 1 (Regression 4) we find that the autocorrelation of individual stocks is indeed negative (an average $R^2$ of 0.185), and as shown in Table 3, current daily returns of a stock index (computed only for the stocks that have positive volume at the opening), is not correlated with its lagged returns, $L\bar{R}$. The average $M$, however, is positively correlated with the next period stock index returns and the relation is economically significant (an average $R^2$-adj of 0.174). Moreover, as expected, when lagged returns, $L\bar{R}$, is added to $\bar{M}$ as an explanatory variable in a cross-sectional regression it has a significantly positive effect. This is expected as $M$ captures the effects of the noise associated with the liquidity traders, and the lagged returns measure the effects of the partial adjustment to new information.
4. Commonality and Persistence in the Arrival of Liquidity Traders

Thus far this paper has provided estimates of the effects of liquidity traders in the market: large $Z_s$ ($Z_d$) and large (small) $M$ are related to liquidity sell (buy) pressures. One wonders if liquidity traders exhibit herding behavior. Do they come to the market at the same time? In other words is there commonality in the behavior of liquidity traders? If there is, what triggers the common appearance of the liquidity traders? To test if there is a commonality in the behavior of liquidity traders, we estimate for each stock the following regressions:

$$Zd_{it} = \alpha_i + \beta_{1i}\bar{Zd}_{-t}^{-1} + \beta_{2i}\bar{Zs}_{-t}^{-1} + \epsilon_{it}$$  (4.1)

$$Zs_{it} = \alpha_i + \beta_{1i}\bar{Zd}_{-t}^{-1} + \beta_{2i}\bar{Zs}_{-t}^{-1} + \epsilon_{it}$$  (4.2)

$$M_{it} = \alpha_i + \beta_{1i}\bar{M}_{-t}^{-1} + \epsilon_{it}$$  (4.3)

where $\bar{Zd}_{-t}^{-1}$, $\bar{Zs}_{-t}^{-1}$, $\bar{M}_{-t}^{-1}$ are averages excluding stock $i$.

The results in Table 4 indicate significant commonality: the $Z_d$’s ($Z_s$’s) are positively correlated with the $Z_d$’s ($Z_s$’s) in the other stocks and negatively correlated with the $Z_s$’s ($Z_d$’s). The $M$’s of the individual stocks are also correlated with each other. The adjusted $R^2$ of these regressions is, however, modest: the averages are around 0.035.

Next, we examine what triggers the common appearance of the liquidity traders? The evidence documented in this paper indicates that liquidity traders follow the trend. We calculate the correlation between the return from open to close on day $t-1$ and $Z_d$ ($Z_s$) for each one of our 105 sample stocks. The average correlation with $Z_d$ is 0.04 with a $t$ value of 4.88. There are 66 positive correlations out of the 105 computed. The average correlation of $Z_s$ with yesterday’s return is -0.031 with a $t$ value of -2.26. Only 39 correlations are positive. Finally, the average correlation of
M at day t with the return at day t-1 is -0.069 with a t value of -7.91. We measure only 21 positive correlations out of the 105 computed. The evidence indicates that liquidity buyers come to the market after a day of positive returns and the sellers follow a day of stock price declines.

The next step is to investigate the persistence of liquidity pressures. For each stock we estimated the following regressions:

\[
Zd_{it} = a_i + \beta_1 \text{Lag}(Zd_{it}) + \beta_2 \text{Lag}(Zs_{it}) + \epsilon_{it} \quad (4.4)
\]

\[
Zs_{it} = a_i + \beta_1 \text{Lag}(Zd_{it}) + \beta_2 \text{Lag}(Zs_{it}) + \epsilon_{it} \quad (4.5)
\]

\[
M_{it} = a_i + \beta_1 \text{Lag}(M_{it}) + \epsilon_{it} \quad (4.6)
\]

The results are reported in Table 5. The conclusion from the findings is that there is significant persistence of liquidity pressures: liquidity buys (sells) are positively correlated with the previous day’s liquidity pressures. The adjusted $R^2$ of these regressions is, however, small: the averages are around 0.02.

4.1 The Contagion Effect of Liquidity Trading

Liquidity pressure in one stock may have an indirect effect on other stocks. An intuitive explanation of this effect is that investors derive information about each stock value from the price of other stocks (see the multi-asset NREE model of Admati (1985)). Therefore noise would appear to have a contagion effect. To test this hypothesis we estimate four versions of the following time-series regression:
\[ R_{it} = \alpha_i + \beta_{1i}M_{it} + \beta_{2i}M_{i-1} + \beta_{3i}LR_{it} + \epsilon_{it} \quad (4.7) \]

where

\( i \) is stock \( i = 1, 2, \ldots, 105 \)

\( t \) is day \( t \).

The results are reported in Table 6. The empirical evidence indicates (Regression 2) that the equally weighted average \( M \) of all the other stocks has a significant impact on the future return of stock \( i \). The effect of the \( M \)'s of all other stocks on the future return of stock \( i \) remain significant after controlling for its own stock’s \( M \) and \( LR \) (Regressions 2, 3 and 4). Noise in the price of stock A, affects the price impact of stock B. Thus contagion can explain the documented commonality in liquidity measures (see Chordia, Subrahmanyam and Roll (2000), Hasbrouck and Seppi (2001) and Huberman and Halka (2001)). To illustrate the net effect of contagion, assume that there is no commonality in the arrival of liquidity traders. In such an environment there will be days dominated by the arrival of liquidity buyers (sellers) and days during which both types are approximately equally represented. Contagion increases the price impact during days dominated by one type of liquidity traders (buyers or sellers) and reduces the price impact in periods where both types of traders are equally represented in the market. This creates commonality in the liquidity measure even without commonality in liquidity traders’ arrival. Commonality of liquidity traders’ arrival is of course another cause for commonality in liquidity measures.

5. Conclusions

This paper examines the information content of “market” buy (sell) orders in a call auction. As a large fraction of such orders leads to an inelastic demand (or supply) schedule around the equilibrium price, we also investigate the information content of the elasticity of the demand and the supply schedules. Our empirical
implications are suitable for a wide range of models that assume liquidity traders. We expect that buy (sell) market orders, representing the “noise traders”, lead to temporary price increases (decreases) and are thus negatively (positively) correlated with future returns. The paper introduces a new measure calculated around the equilibrium price:

\[ M = \frac{1}{\text{demand curve's slope}} \]

This measure ranges between 0 and 1 and it represents the relative number of strategic investors whose valuation is higher than the price \( p \). Therefore, at the equilibrium price, this measure is positively correlated with future return.

We use a unique database of all orders submitted during the opening sessions at the TASE. Overall we find strong evidence to support the model. As predicted, the quantity demanded (supplied) by market orders is significantly negatively (positively) correlated with future return. We also find a significant positive correlation between \( M \) and future returns. Contrary to “market” buys and sells, \( M \) remains significant after adding lag return to the regressions. The explanatory power of these two variables is quite high (an average adjusted \( R^2 \) of 0.24). We conclude that, consistent with the model, the shapes of the demand and the supply curves convey information about future returns. Therefore, this paper shows that the information content of the supply and demand curve is significant, thus highlighting the importance of theoretical and empirical investigation of pre-trade transparency.

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 \( M \) in all the other stocks is positively correlated with the contemporaneous \( M \) of stock \( i \). This evidence is consistent with
herd mentality of liquidity traders – they tend to arrive together and at the same side of the market. The evidence indicates persistence in the $M'$s of stock $i$ and in its $Z_i$'s and $Z_{d}'$s. In other words, days dominated by liquidity buyers (sellers) in the market for stock $i$ are followed by days dominated by the same type of liquidity traders.

Finally we document what we define as a contagion effect. The future returns of stock $i$ is predicted by $M$ and the equally weighted average of the $M'$s of all the other stocks. These relations remain statistically significant after controlling for the effects of lagged returns. It seems that investors derive some information about the value of stock $i$ by examining the price behavior of the other stocks. Interestingly, the contagion effect can explain the documented commonality in liquidity measures even in an economy in which there is no commonality in liquidity traders’ arrival.
References


Kalay, Avner, Li Wei and Avi Wohl, 2002, Continuous Trading or Call Auctions: Revealed Preferences of Investors at the TASE”, *Journal of Finance*, 57(1), 323-542.


Table 1 – Predicting Future Return

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 closing. The explanatory variables are $Z_{dit}$, $Z_{sit}$, $M_{it}$, and $LR_{it}$ (the lag of return). 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 the 105) appears below the $t$-statistics. Critical values for the binomial test are 41 and 64 (the p-value is 0.03 for the two-sided test). The significant values are in bold and red numbers. The sample period is 1/25/98 – 9/28/98, a total of 167 days.

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<td>0.189</td>
<td>0.242</td>
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Table 2 – Predicting Future Return with “Market Orders” and “Aggressive Orders”

We estimate time-series regressions for each of the 105 stocks in our sample. The dependent variable is $R_{it} = \text{the return (in percentage) of stock } i \text{ measured from the opening session of trading day } t \text{ to its closing}$. The explanatory variables are $Z_{dit}$, $Z_{sit}$, $AGGRESSIVE_{dit}$ and $AGGRESSIVE_{sit}$. 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 the 105) appears below the $t$-statistics. Critical values for the binomial test are 41 and 64 (the p-value is 0.03 for the two-sided test). The sample period is 1/25/98 – 9/28/98, a total of 167 days.

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<td>$Z_d$</td>
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<td>$Z_s$</td>
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<td>1.645</td>
</tr>
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<td>(14.41)</td>
</tr>
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<td>$AGGRESSIVE_{s}$</td>
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<td>95</td>
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<tr>
<td>$R^2$</td>
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</tr>
<tr>
<td>$R^2$-adj</td>
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Table 3 - Predicting Index Returns

For each of the trading days we form the averages of stock returns from open to close (including only stocks with opening volume), $\bar{R}_t$, and the corresponding averages of M and LR(lag of return). We estimate regressions where the dependent variable is $\bar{R}_t$ and the explanatory variables are $L\bar{R}$, and $\bar{M}_t$. The $t$-statistics are presented below them in parentheses. The sample period is 1/25/98 – 9/28/98, a total of 167 days.

<table>
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<td>intercept</td>
<td>0.703 (11.08)</td>
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<td>-1.836 (-4.64)</td>
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<td>$L\bar{R}$</td>
<td>0.016 (0.43)</td>
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<td>$\bar{M}$</td>
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<td>4.107 (6.01)</td>
<td>4.700 (6.49)</td>
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<td>$R^2$</td>
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<td>$R^2$-adj</td>
<td>-0.005</td>
<td>0.174</td>
<td>0.196</td>
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</table>
**Table 4 – Commonality of Liquidity Pressures**

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

\[
Z_{it} = \alpha_i + \beta_{1i} \bar{Z}_d^{-i} + \beta_{2i} \bar{Z}_s^{-i} + \epsilon_{it} \quad (4.1)
\]
\[
Z_{it} = \alpha_i + \beta_{1i} \bar{Z}_d^{-i} + \beta_{2i} \bar{Z}_s^{-i} + \epsilon_{it} \quad (4.2)
\]
\[
M_{it} = \alpha_i + \beta_{1i} \bar{M}^{-i} + \epsilon_{it} \quad (4.3)
\]

where \( \bar{Z}_d^{-i}, \bar{Z}_s^{-i}, \bar{M}^{-i} \) 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 the 105) appears below the \( t \)-statistics. Critical values for the binomial test are 41 and 64 (the p-value is 0.03 for the two-sided test). The sample period is 1/25/98 – 9/28/98, a total of 167 days.

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<th>Regression</th>
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<td>( \bar{Z}_s^{-i} )</td>
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<td>( \bar{M}^{-i} )</td>
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<td>( R^2\text{-adj} )</td>
<td>0.036</td>
<td>0.032</td>
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</table>
Table 5 – Persistence of Liquidity Pressures

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

\[
\begin{align*}
Zd_{it} &= \alpha_i + \beta_{1i}Lag(Zd_{it}) + \beta_{2i}Lag(Zs_{it}) + \varepsilon_{it} \quad (4.4) \\
Zs_{it} &= \alpha_i + \beta_{1i}Lag(Zd_{it}) + \beta_{2i}Lag(Zs_{it}) + \varepsilon_{it} \quad (4.5) \\
M_{it} &= \alpha_i + \beta_{1i}Lag(M_{it}) + \varepsilon_{it} \quad (4.6)
\end{align*}
\]

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 the 105) appears below the \(t\)-statistics. Critical values for the binomial test are 41 and 64 (the p-value is 0.03 for the two-sided test). The sample period is 1/25/98 – 9/28/98, a total of 167 days.

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<th>(Zs_{it} (4.5))</th>
<th>(M_{it} (4.6))</th>
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<td>(Lag(Zs_{it}))</td>
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<td>(R^2)-adj</td>
<td>0.003</td>
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### Table 6 – 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 closing. The explanatory variables are $M_{it}$, $\bar{M}^{-i}$ and $LR_{it}$ (the lag of return). 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 the 105) appears below the $t$-statistics. Critical values for the binomial test are 41 and 64 (the p-value is 0.03 for the two-sided test). The sample period is 1/25/98 – 9/28/98, a total of 167 days.

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<td></td>
</tr>
<tr>
<td>$\bar{M}^{-i}$</td>
<td>-----</td>
<td>3.585</td>
<td>1.940</td>
<td>1.169</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(12.01)</td>
<td>(6.80)</td>
<td>(4.48)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>94</td>
<td>83</td>
<td>76</td>
</tr>
<tr>
<td>$LR$</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-0.270</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-12.05)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>8</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.145</td>
<td>0.029</td>
<td>0.159</td>
<td>0.259</td>
</tr>
<tr>
<td>$R^2$-adj</td>
<td>0.139</td>
<td>0.022</td>
<td>0.147</td>
<td>0.243</td>
</tr>
</tbody>
</table>
Figure 1-A (related to Example 1)
Figure 1-B (related to Example 1)
Figure 2 - The effects of M and lag of return (LR) on the returns

- M-low
- M-high

Median

Returns greater than median

- LR-low
- LR-high

0% 10% 20% 30% 40% 50% 60% 70% 80%

M-low

M-high