The Information Content of the Demand and Supply Schedules of Stocks

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Abstract

We restate Hellwig’s (1980) NREE model and derive empirical implications for call sessions: 1) A larger fraction of buy (sell) orders of the total volume submitted significantly above (below) the eventual equilibrium price predicts future price decreases (increases) 2) A demand curve that is steeper than the supply curve is associated with more liquidity buys than sells and a higher price. Hence, a steeper demand (supply) predicts negative (positive) future returns. 3) The supply curve is concave and the demand curve is convex. We present empirical evidence consistent with our predictions. Our study highlights the importance of pre-trade transparency.

JEL Classification: G12, G14

Keywords: return predictability, NREE, rational expectations, demand elasticity, liquidity traders, liquidity, transparency.
Introduction

What can investors induce from orders to buy (sell) at prices significantly higher (lower) than the last existing trading price? If a buyer is willing to pay 10% above the previous trading price, are potential market participants to conclude that she possesses positive private information concerning the “true value” of the asset? Or, as models of market microstructure typically assume, is this essentially a market order placed by a liquidity trader who has no private information? More generally, the question we address in this paper is: what is the information content of market demand and supply schedules? Is the observation of a steep demand curve evidence of the presence of liquidity buyers or does it provide information of a probable future price increase?

The trading environment that enables an empirical examination of these issues is a call auction. Having data on all orders submitted to the call auction, we can precisely construct the demand and the supply schedules. We can then examine, as detailed below, the information content of the elasticity of the demand and the supply schedules.1

Our paper adopts a Noisy Rational Expectation Equilibrium (NREE) model (Hellwig’s (1980)) and derives empirical implications concerning the information content of the demand and supply schedules.2 Hellwig’s model can be interpreted as follows. There are two types of traders: those who trade on the basis of information and condition their trades on the price (henceforth informed traders), and those who trade for other reasons and do not condition their trades on the price (henceforth

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1 During continuous trading there is an upper bound on the short-term trading price. Investors can get immediate execution by paying the ask or by selling at the bid.
2 We could have adopted other models (such as Kyle (1989)) to derive similar implications.
liquidity traders). Liquidity traders add “noise” to the economy and reduce the economic content of equilibrium prices.

Hellwig’s model predicts that informed traders have a linear excess demand curve for the only risky asset in the economy. In this paper we separate the excess demand of the informed investors into demand and supply. Furthermore, we separate liquidity buys from liquidity sells. This restatement of the model allows us to derive three empirical implications. First, a larger fraction of buy (sell) orders of the total volume submitted significantly above (below) the eventual equilibrium price in a call option predicts future price decreases (increases). The second empirical implication is the following. A demand curve that is steeper than the supply curve around the equilibrium price is associated with more liquidity buys than liquidity sells and therefore with a higher equilibrium price. Similarly, a steeper supply around the equilibrium price is associated with more liquidity sells than buys and a lower equilibrium price. Consequently, a relatively steeper demand (supply) curve is associated with future stock price decreases (increases).

From our restatement of Hellwig’s model we develop a variable, $M(p)$, quantifying the relative presence of informed buyers to informed sellers given that the stock price is $p$. We show that the fraction of informed traders with valuations above a given price is quantified by

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

(where $D(p)$ and $S(p)$ are the demand curve and the supply curves, respectively). This measure of the relative slopes of the demand and the supply curves ranges in value from 0 to 1. When $M(p) = 1(0)$ all the informed investors value the asset by more (less) than the price $p$. Hence, when $M(p)=1(0)$ all the informed traders are on the buy (sell) side. Fewer
informed traders on the buy (sell) side lead to a relatively larger presence of liquidity buyers. Hence, while liquidity traders are assumed to be randomly divided on both sides of the market, our new measure, $M(p)$ allows us to estimate their asymmetric presence in the market. For example, when $M(p) = 1$, all the sell orders are liquidity sells. In this case the asset is undervalued and we therefore expect future price increases. In general $M(p)$ (estimated at the equilibrium price) is positively correlated with future price changes.

The third empirical implication we derive is the following. The supply curve is concave, having a slope that is (weakly) decreasing. At higher prices more informed traders are willing to sell, and hence the aggregate supply curve becomes more elastic (or flatter). Above a high enough price all the informed investors are already selling and the slope of the supply curve becomes constant. Similarly, the demand curve is convex because at lower prices more informed investors are willing to buy.

These empirical implications are examined using a unique database we obtained from the Tel Aviv Stock Exchange (hereafter TASE). This database includes all orders submitted to the opening sessions at the TASE. These sessions (like the opening at the Paris Bourse 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 the 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).

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3 For ease of exposition, we assume that all informed investors in the economy are equally risk averse and have private information with the same precision. Relaxing these simplifications would lead to qualitatively similar results. See the end of Section 2.

4 The analysis examines price required as a function of quantity supplied.
Central to our interpretation of Hellwig’s model is the assumption that liquidity traders do not condition their demand on market prices, a position best described as a market order. Hence, we assume that liquidity traders submit market orders and informed 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 out of the volume is a significant predictor of subsequent price decrease (increase). It turns out that “buy” (“sell”) market orders, are not submitted by the better informed. Rather, these orders tend to be submitted by liquidity traders.

Consistent with the model, examination of the predictive ability of $M(p)$ shows a significant positive correlation between $M(p)$ and realized future returns. We predict the stock return from open to close by running a time series regression for each stock on our 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 total volume (predicted to have a positive coefficient) and $M(p)$ (predicted to have a positive coefficient). The coefficients on each one of these variables are highly significant, with the predicted sign. The average adjusted $R^2$ of the regressions is 0.162.

Our third empirical implication is consistent with existing empirical evidence. Figure 2 in Kandel, Sarig and Wohl (1999) depicts the average demand schedule of 27 Israeli IPOs. The documented demand curve is convex. Kalay, Sade and Wohl (2002) find a convex demand curve and concave supply curve in the respective “executable” areas. The executable area of the demand (supply) curve is at prices above (below) the equilibrium price.
In related theoretical works, Blume, Easley and O’Hara (1994), Campbell, Grossman and Wang (1993), and Llorente, Michaely, Saar and Wang (2002) show that volume can predict future returns. Evidence consistent with this prediction is documented in Campbell, Grossman and Wang (1993) and Llorente, Michaely, Saar and Wang (2002). 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: informed investors’ initial endowments and liquidity shocks of uninformed investors. By assumption, uninformed investors 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. Their trades seem to push 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. Cornelli and Goldreich (2001a), investigating the book-building process in Britain, find that investors submitting limit orders tend to get

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5 This paper contains an extensive review of the existing empirical evidence on the issue.
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 (2001b) find that 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.

We note that contrary to the model’s setting, the opening stage at the TASE is partially transparent: investors can see the three best bids and the best three offers. The information is incomplete as many bids and asks are unobservable, and the composition of the orders may change by the end of the session. We document the valuable information that the order book apparently contains. Our evidence demonstrates the potential significant effects on price efficiency and market liquidity that changes in the transparency of the limit order book have.

Our empirical findings highlight the importance of further investigating the effects of trading transparency6. The potential importance of trading transparency is 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 basic model. Section 2 develops empirical implications. Section 3 describes the market structure of the TASE and the data. Section 4 presents the empirical evidence. Section 5 concludes the paper.

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1. The Model

This section restates Hellwig (1980) and derives testable empirical implications. 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. 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 elapsed time between trading and the assets’ payoffs is negligible. There are two types of traders: $n$ informed traders (denoted $j = 1…n$) and an unspecified number of liquidity traders. Each informed trader observes a noisy signal of $\tilde{x}$:

$$\tilde{y}_j = \tilde{x} + \tilde{\epsilon}_j$$

The initial endowment of each informed trader is $W_0$ of the riskless asset. Every informed trader’s utility is based on $W_j$, the total wealth after the trading,

$$U(W_j) = -e^{\rho W_j}$$

where for simplicity we assume that $\rho$, the coefficient of risk aversion, is equal for all traders. The informed traders are “price takers”.

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7 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) extended Hellwig’s model to deal with multiple assets, Kyle (1989) extends Hellwig’s model by relaxing the assumption of price taking and by adding uninformed speculators, Grundy and McNichols (1989) and Brown and Jennings (1989) investigated the price revelation through time and Brennan and Cao (1996) analyzed the economic value of having more frequent trading.
As is typical, 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). For simplicity we assume that the expected net supply of the liquidity traders, $E\tilde{Z}$, equals zero.

The random vector $(\tilde{x}, \tilde{Z}, \tilde{\varepsilon}_1, ..., \tilde{\varepsilon}_n)$ has a normal distribution with mean $(\mu_x, 0, ..., 0)$ and a variance-covariance matrix $(\sigma^2, \Delta^2, s^2, ..., s^2) I_{n+2}$ 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 to the trading mechanism an excess demand function, $Q_j(p)$ 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 that total supply equal total demand. Hellwig’s model does not describe 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.

**The Equilibrium:**

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

$$Q_j(p) = \frac{E(\tilde{x} \mid y_j, p) - p}{p\text{VAR}(\tilde{x} \mid y_j, p)}$$

(1.1)
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 $1 \leq j \leq n$:

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

(1.2)

where $A$ and $K$ are parameters dependent on the values of $n$, $\rho$, $\sigma$, $\Delta$, $s$. The equilibrium requires $\sum_{j=1}^{n} Q_j(p^*) = Z$ and therefore the equilibrium price is

$$p^* = (1-A) \mu_x + A \bar{y}_j - \frac{1}{nk} Z$$

(1.3)

To understand the equilibrium equation, denote $u_j=(1-A) \mu_x + Ay_j$. This is a weighted average of the signal investor $j$ received and the unconditional expected value of $\bar{x}$, $\mu_x$. We refer to this variable as the "valuation of investor $j". Therefore the net demand function may be represented as:

$$Q_j(p) = K(u_j - p)$$

(1.4)

It can be shown that $K$, the slope of the function, is decreasing in the risk aversion coefficient, $\rho$ 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 $\mu_x$ and the average of the private signals, minus the “noise” term associated with $Z$ (the net supply of the liquidity traders). The derivation of the empirical implications requires a separation of the net demand functions into their components - demand and supply. This restatement of the model enables the derivation of several empirical implications.

For every $1 \leq j \leq n$:

$$Q_j(p) = D_j(p) - S_j(p)$$

(1.5)

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8 A and K are obtained by solving the non-linear equation set 7 in Hellwig’s model.
where \( D_j(p) = \text{Max}[0, K(u_j - p)] \), \( S_j(p) = \text{Max}[0, K(p - u_j)] \) \hspace{1cm} (1.6)

Similarly we separate the net supply of the liquidity traders:

\[ Z = Z_s - Z_d \] \hspace{1cm} (1.7)

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

\[ \text{2. Empirical Implications} \]

We demonstrate that the shape of the demand and the supply schedules contains information about the true value of the asset, \( \tilde{x} \). We focus on the holding period profits, \( \tilde{x} - p^* \). From (1.3) and (1.7) it can be seen that knowing \( Z_s \) and \( Z_d \) reveals \( \tilde{y}_j \) which is a sufficient statistic for \( x \). From (1.3) and the definition of \( y_j \) it can be shown that

\[ E(\tilde{x} - p^* | Z) = \frac{1}{nK} Z = \frac{1}{nK} (Z_s - Z_d) \] \hspace{1cm} (2.1)

As \( nK > 0 \), there is a positive (negative) correlation between \( Z_s \) (\( Z_d \)) and a subsequent change in the stock price. The temporary price pressure associated with \( Z_s \) (\( Z_d \)) pushes the price down (up) and therefore the future price change tends to be positive (negative). Next we construct a variable that measures the presence of the informed traders on the “buy” side relative to the sell side. This variable does not require data on \( Z_d \) and \( Z_s \).

Let us assume for simplicity and without loss of generality that \( y_n \geq \ldots \geq y_1 \), and define \( D(p) \) and \( S(p) \) as the aggregate demand and supply functions, respectively:

\[ D(p) = Z_d + D_1(p) + \ldots + D_n(p) \] \hspace{1cm} (2.2)

\[ S(p) = Z_s + S_1(p) + \ldots + S_n(p) \] \hspace{1cm} (2.3)
Proposition 1

The slope of $S(p)$ is increasing in $p$. The absolute value of the slope of $D(p)$ is decreasing in $p$.

Proof: see Appendix

Example 1

To demonstrate Lemma 2 and its corollary, let us consider the case of $u_1=10$, $u_2=14$ and $K=1$. The individual demand and supply schedules are depicted in Figure 1-A. The aggregate demand and supply schedules are depicted in Figure 1-B. It can be seen that the supply curve is flatter for prices greater than 14 than for those below 14. The reason is that a price change from 14 to 15 increases the supplied quantities of both investors, while price changes below 14 do not affect the supply of investor 2, which is zero in this range. For the same reason the demand curve is flatter at prices lower than 10.

We can now define the variable used in the empirical investigation:

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

Proposition 2

a. If $p<u_1$ then $M(p)=1$

b. If $u_j = p < u_{j+1}$ where $j=1,\ldots,n-1$ then $M(p) = \frac{n-j}{n}$

c. If $p=u_n$ then $M(p) = 0$
Proof

From Lemma 2.

\[ M(p) \] is a measure of the relative number of informed investors who value the risky asset at more than its price. The measure can be computed for any price level. For example, \( M(p^*) = 1 \) implies an equilibrium price smaller than the valuation of all the informed traders \( (u_1, \ldots, u_n) \). This can happen as a result of the price pressure of a large net supply \( (Z) \) by liquidity traders. To scale the measure such that it ranges in value between \(-1\) and \(1\) we define

\[ DIRECTION = 2*M(p^*)-1. \]

At the extreme, when \( DIRECTION = 1 \) (\(-1\)) the valuations of all the informed investors are higher (lower) than the equilibrium price. Consequently, a positive (negative) return is expected.

Proposition 3

For every realization \( x \) and \( y_1, \ldots, y_n \), \( DIRECTION \) and \( (x - p^*) \) are positively correlated.

Proof of Proposition 3

For any realization \( x \) and \( y_1, \ldots, y_n \), \( p^* \) is determined by \( Z \). Since \( DIRECTION \), which equals \( 2*M(p^*)-1 \), is decreasing in \( p^* \) and \( (x - p^*) \) is decreasing in \( p^* \) they are positively correlated.

Q.E.D

The following two examples help understand the economic intuition underlying our model.
Example 2

Consider the following simple example. Suppose that there is only one informed trader, $i$. As is the case in such an equilibrium, his excess demand function is linear; assume it to be $q = 10 - p$. The informed investor’s valuation of the asset is 10. We can separate this excess demand function into a demand function $D_i(p) = Max[0, 10 - p]$ and a supply function $S_i(p) = Max[0, p - 10]$. Figure 2-A describes the demand and the supply schedules. The equilibrium price is 10 and obviously there is no trade.

Insert Figure 2-A here

Now assume further that the demanded and supplied quantities of liquidity traders are $Z_d = Z_s = 2$. In this case the demand function is

$$D = 2 + D_i(p) = 2 + Max[0, 10 - p]$$

and the supply function is

$$S = 2 + S_i(p) = 2 + Max[0, p - 10]$$.

Figure 2-B details these schedules. The equilibrium price remains 10, while two units are traded among the liquidity traders. The informed investor does not trade nevertheless she provides the price discovery in this equilibrium.

Insert Figure 2-B here

Now suppose, as depicted in Figure 2-C, that the demanded quantity of the liquidity traders, $Z_d$, is 3. The excess demand of the liquidity traders pushes the equilibrium price up to 11. At a price of 11 the informed trader is willing to bridge the gap and supply the missing unit to the liquidity traders. The excess demand of the liquidity traders ($Z_d > Z_s$) is manifested by a demand curve that is steeper than the supply curve around the equilibrium price. A steep supply curve and a flatter demand curve around the equilibrium price are an indication of excess supply by the liquidity
traders \((Z_s > Z_d)\). In this case the equilibrium price is “pushed” down from its true value.

Insert Figure 2-C here

**Example 3**

Using Hellwig’s (1980) model we compute the values of the parameters \(A\) and \(K\) corresponding to assumed values for \(n, \rho, \sigma, \Delta, s\). This example is based on a numerical solution of the equations Hellwig (1980) developed to determine \(A\) and \(K\).\(^9\)

Suppose the economy is described by the following values: \(n=6\), \(\rho=10\), \(\mu_s = 10\), \(\sigma=1\), \(\Delta=1\), \(s=2\). The implied values for \(A\) and \(K\) are 0.231 and 0.117, respectively.

The signals of the six informed investors \(\left(y_i\right)’s\) are assumed to be 8, 9, 10.5, 11.5, 12.5 and 14. Therefore the \(u_i’\)s (which are \((1-A) \mu_s + Ay_i\) ) are 9.54, 9.77, 10.12, 10.35, 10.76 and 10.92, respectively. The demand function of investor 1 is \(D_1(p) = \text{Max}[0, 0.117(9.54 – p)]\) and her supply curve is \(S_1(p) = \text{Max}[0, 0.117(p - 9.54)]\).

Figure 3 details the aggregate demand and supply curves of the six informed traders (denoted D and S). Note that the demand (supply) curve is convex (concave). The demand and the supply schedules intersect at a price of 10.21 that is the average \(u\).

Now consider the effect of adding some liquidity “noise”. Let us assume \(Z_s=0\) and \(Z_d=0.3\), that is, we include some new liquidity demand. The relevant demand curve (including the liquidity demand) is denoted by \(D_1\). The new intersection with the supply curve is at a price of 10.64. This is equal to the previous price of 10.21 plus the effect of the new noise: \(\frac{0.3}{6*0.117}\). Similarly, the demand curve with \(Z_d=0.6\) is \(D_2\) and the equilibrium price in this case is 11.06. It can be seen that a larger \(Z_d\)

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\(^9\) Equation (7c) in Hellwig (1980) contains a typo: the first term should be multiplied by \(\gamma\). We thank Martin Hellwig for clarifying this.
increases the stock price to higher values, a higher stock price being associated with a flatter supply curve and/or a steeper demand curve. $M(p)$, which measures the ratio of slopes of the demand and the supply schedule, decreases as $Z_d$ increases. $M(p)$ also represents the proportion of informed traders that value the stock at above its market price. Consequently, $M(p)$ is smaller for larger stock prices. In our example, three investors have a higher valuation than 10.21. Therefore at this point $|D'(p)| = S'(p) = 3\times0.117$ and $M(10.21) = 0.5$. Similarly, $M(10.64) = 2/6$ and $M(11.06) = 0$. Figure 4 depicts the relation between $Z$ and $M$ in this example.

Insert Figures 3 and 4 here

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 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 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.,

$$1/\left[ \rho_j \text{VAR}_j(\tilde{x} \mid y_j, p) \right].$$

Kyle (1989) extends Hellwig’s model by relaxing the assumption of price taking and by 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.

3. Data and the Opening Stage at the TASE

3.1 The Opening Stage

Trading at the TASE is conducted in three stages: an opening stage (8:30 a.m.-
10:00 a.m.), a continuous bilateral trading system (10:00 a.m. –3:30 p.m.), and a
closing session in which transactions are executed at the closing price (3:30 p.m.-
3:45 p.m.). The trading system is a computerized limit order book as in Paris Bourse
and in many exchanges around the world.10 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 until 9:45. 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

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

3.2 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 3.1. Other stocks, which are less liquid, moved to the system during the sample period (see Kalay, Wei and Wohl (2001)). 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 for market order), the quantity ordered, buy / sell indication and an indication for 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 2 observation 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. Table 1 (which is drawn from Kalay, Sade and Wohl (2002)) compares our sample to stocks traded on the major US
exchanges – NYSE, NASDAQ, and AMEX. The market capitalization of our sample stocks is not significantly different from that of a typical US firm. We divide our sample into quartiles based on market capitalization. For example, as Table 1 reveals, the mean market capitalization of stocks belonging to the second quartile is 214.8 $million. We find that 84% of the stocks listed for trade on the AMEX, 76% of the stocks traded on NASDAQ, and 27% of the stocks listed on the NYSE have lower capitalization. Our sample stocks, however, are less liquid than the corresponding US stocks. The mean monthly $volume of the second quartile (ranked based on $volume) is higher than that of 54% of the stocks traded on AMEX, 30% of the stocks traded on NASDAQ, and 6% of the stocks traded on the NYSE.

4. Methodology and Results

4.1 The Information Content of the Demand and Supply Curves

Hellwig’s model is a one-period model in which there is a trading session followed by payoffs. Therefore the opening sessions in stock exchanges like the Paris Bourse fit the model more closely than does the continuous trading stage. Nevertheless, the opening stage in the TASE differs from Hellwig’s model in some respects:

- There is a partial pre-trade transparency: investors can see the projected opening price and volume. They can also see the total ordered quantity at each one of the three best (“aggressive”) bids and offer prices. Of course these data typically change during the opening session.
- There is no exogenous payment $x$. Instead we estimate it with $R$ – the return from the opening to the closing of
the day.\textsuperscript{11}

- Investors cannot submit demand functions. They have to approximate them with limit orders. The limit orders are restricted by the tick size (ranging from 0.05\% to 0.5\%).
- The 10\% limit on price change (from the previous close) eliminates pure market orders.
- The number of investors in each day-stock session is relatively small (the average number of executed orders is around 14), therefore they probably do not behave as price takers. This is not a serious problem as Kyle (1989) relaxes the price taking assumption of Hellwig’s model.

Central to the model is the assumption that orders come from two sources: informed 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 (see equation 2.1).

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

\textsuperscript{11} We obtained qualitatively similar results using a sample of open-to-open stock returns.
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%.

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. This evidence indicates that our sample is characterized by more liquidity-motivated sells than liquidity-motivated buys. Our proxy of the future stock return (denoted \( \text{RETURN} \)) is the realized return between the opening and the closing during the same trading day.

Proposition 2 predicts a positive correlation between \( \text{DIRECTION} \) and future return. \( \text{DIRECTION} \) is a linear transformation of \( M(p^*) \), \( \text{DIRECTION} = 2 * M(p^*) - 1 \). This measure ranges in value between \(-1\) and 1. It represents the proportion of informed investors who value the stock more than its equilibrium price. The estimate of \( \text{DIRECTION} \) involves derivatives of quantity demanded and quantity supplied with respect to small changes in the price. Since in reality the demand and supply schedules are not continuous, we construct an approximate measure \( \text{DIRECTION}^* \) by defining:

\[ \text{Dif}_D = \text{the difference between the demanded quantity } \frac{1}{2}\% \text{ below the equilibrium and the demanded quantity } \frac{1}{2}\% \text{ above the equilibrium}; \]

\[ 12 \text{ In the few cases in which these variables are greater than 1 (in these cases there is partial execution in the opening price), we limit the values to be 1.} \]

\[ 13 \text{We replicate the experiment using non-standardized quantities of market orders. The results obtained are qualitatively similar.} \]

\[ 14 \text{This evidence is consistent with the findings of Kalay, Sade and Wohl (2002). It is different from our simplifying assumption that } E(Z) = 0, \text{ i.e., there is symmetry between the buyers and the sellers.} \]

\[ 15 \text{The spirit of the results does not change with open-to-open returns.} \]
$Dif_{S} =$ the difference between the supplied quantity $\frac{1}{2}\%$ above the equilibrium and the supplied quantity $\frac{1}{2}\%$ below the equilibrium.

Thus,

$$DIRECTION^* = \frac{2*Dif_{D}}{(Dif_{D} + Dif_{S})} - 1$$

Our a priori conjecture is that $DIRECTION = 0$, implying symmetry between buyers and sellers. We find a mean $DIRECTION^*$ of 0.11, showing an apparent tendency in our sample for the demand curve to be flatter than the supply. In 12.0% (16.7%) of the cases it has an extreme value: -1(1).

We use an additional explanatory variable that has been shown to affect future returns – lag return, $LR$. Lag return is 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:

$$R_{it} = \alpha + \beta_{1i}Z_{d}^*_{it} + \beta_{2i}Z_{s}^*_{it} + \beta_{3i}DIRECTION^*_{it} + \beta_{4i}LR_{it} + \epsilon_{it} \quad (4.1)$$

where

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

The results are reported in Table 2. The first regression 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 uninformed traders than aggressive informed 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 $-I_i^{*}\beta_{1i}$. 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 uninformed traders than buy market 
orders. A potential explanation for this asymmetry stems from limitations on short 
sells. These limitations 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.\(^{16}\)

The second regression tests the predictive power of $DIRECTION^*$. Consistent 
with the model, the coefficient is indeed positive and significant. The third regression 
looks at the three variables $Z_d^*$, $Z_s^*$ and $DIRECTION^*$ together. All the coefficients 
are significant and with the right sign. In the fourth regression we test the explanatory 
power of lag return ($LR$). The lag return is indeed significantly negative. The fifth 
regression examines the effect of adding $LR$ to the model’s explanatory variables 
($Z_d^*$, $Z_s^*$ and $DIRECTION^*$).

$LR$ and $DIRECTION^*$ are highly significant. However, $Z_d^*$ and $Z_s^*$ are not 
significant by binomial tests. Therefore in regression 6 we drop $Z_d^*$ and $Z_s^*$. 
Indeed, the mean adjusted $R^2$ is almost not affected, and it remains quite high (0.239 
instead of 0.242). Dividing the stock sample into four sub-samples according to 
their average trading volume (in NIS), we obtain the results are qualitatively similar 
results to those reported in Table 2 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 2, in the second regression, 26 of the 26

\(^{16}\) For related evidence and a discussion of this explanation see Kalay, Sade and Wohl (2002).
coefficients of \( DIRECTION^* \) 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. Indeed, the first regression is consistent with this conclusion. According to the model these variables are sufficient statistics for future return. However, empirically, these variables when added to \( DIRECTION^* \) and \( LR \) do not contribute to the explanatory power of the regression. The differences between the assumptions of Hellwig’s model and our experiment (discussed in Section 4.1) are a potential explanation for this finding. An alternative explanation is that indeed uninformed investors tend to submit aggressive orders, but not necessarily “market” orders.

To test this 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 \( AGGRESSIVE_d^* \) \( (\text{the quantities in “aggressive” buy orders}) / (\text{total volume}) \), and the size-adjusted supply of the liquidity traders as \( AGGRESSIVE_s^* \) \( (\text{the quantities in “aggressive” buy orders}) / (\text{total volume}) \), 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:

\[
R_{it} = \alpha_i + \beta_{i1} Z_{it} + \beta_{i2} AGGRESSIVE_{d}^* + \beta_{i3} Z_{it} + \beta_{i4} AGGRESSIVE_{s}^* + \epsilon_{it} \quad (4.2)
\]

where

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

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 uninformed investors 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 \(t\) 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).

4.2 Empirical Evidence: A Convex Demand and a Concave Supply Schedules

Corollary 1 states that the demand curve is convex and the supply curve is concave (see Figure 3, related to Example 3). These predictions are consistent with Figure 2 in Kandel, Sarig and Wohl (1999). The figure depicts the average demand schedule for 27 Israeli IPOs. The evidence in Nyborg, Rydqvist and Sundaresan (2002) on Swedish bond auctions, however, is quite different. Figure 4 of their study shows reverse-S shaped demand curves: convex at prices above the equilibrium price and concave below it.

The convexity-concavity predictions are also consistent with the findings of Kalay, Sade and Wohl (2002), who find convex demand and concave supply curves in the “executable region”. For the demand (supply) curve, the executable region is at prices above (below) the equilibrium price. Kalay, Sade and Wohl (2002) find evidence inconsistent with the model for the “non-executable region”. The elasticity of demand and supply in the non-executable region seems smaller than in the executed areas. The explanation for this empirical regularity that Kalay, Sade and Wohl provide is based on the costs of order submission. Our model assumes costless

\[17\text{ In the few cases in which these variables are greater than 1 (in these cases there is partial execution}\]
submission of investor’s demand and supply curves. In the real world, investors have
to approximate their true demand and supply curves by limit orders. A submission of
each order is associated with direct costs (fees) and indirect costs (monitoring).
Therefore it is not worthwhile to submit a detailed demand and/or supply schedule of
orders if the likelihood of execution is low.

5. Conclusions

This paper examines the information content of buy (sell) orders at prices
significantly above (below) the eventual equilibrium price in a call auction. A large
fraction of such orders lead to inelastic demand (or supply) schedule around the
equilibrium price. Hence, we also investigate the information content of the elasticity
of the demand and the supply schedules. We use Hellwig’s (1980) Noisy Rational
Expectations Equilibrium (NREE) model to study the informational content of the
supply and demand schedules. Our empirical examination, however, is applicable
to other versions of modeling this concept (e.g., Kyle (1989)). Hellwig’s (1980)
model results in linear excess demand functions of the informed investor. Based on
their private information, different informed investors have different linear excess
demand function. By separating the excess demand function into demand and supply,
we develop the following testable empirical implications: (1) buy (sell) market orders,
representing the “noise traders”, lead to temporary price increases (decreases) and are
thus negatively (positively) correlated with future return; (2) At larger (smaller)
prices, the more informed are willing to sell (buy), resulting in a flatter supply

\[^{18}\text{See related work by Cho and Krishnan (2000), who use Hellwig’s (1980) model to estimate parameters such as the precision of the information of the informed traders.}\]
(demand) curve at higher (lower) prices. In other words, we show that the supply
(demand) curve is concave (convex).

The paper introduces a new measure calculated around the equilibrium price:
\[ M(p) = \frac{|D'_s(p)|}{S'_s(p) + |D'_d(p)|} \]
(where \(D(p)\) and \(S(p)\) are the demand and the supply
curves, respectively). This measure ranges between 0 and 1 and it represents the
relative number of informed investors whose valuation is higher than the price \(p\). Therefore, at the equilibrium price, this measure is positively correlated with future
return.

The empirical implication regarding concavity-convexity is consistent with empirical findings in previous papers. Therefore we focus on the information contents of the curves. We use a unique database of all orders submitted during the opening sessions at the TASE. Overall we find strong evidence consistent with 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 \(M(p)\) and future returns. Contrary to “market” buys and sells, \(M(p)\) 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.

The evidence indicates that buy orders convey more information than sell orders, an asymmetry that can be explained by the differential costs of trading. Since short sells are more costly, informed investors will better utilize positive information. Sell orders are therefore more likely to be motivated by liquidity considerations.
The assumption of lack of transparency in the model does not fit our trading environment precisely. Investors, including those at the TASE, are able to some extent to observe these curves, though any observation is incomplete and has limited information content. 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.
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.


Appendix

Proof of Proposition 1

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 \( S_j'(p) = K \)

Proof

Directly from (2.1).

Q.E.D.

From Lemma 1 and (2.2) and (2.3) it can be seen that

a. If \( p > u_a \) 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

\[ D'(p) = -(n-j)K \text{ and } S'(p) = jK. \]

\[ D'(p)_- = -(n-j+1)K, D'(p)_+ = -(n-j)K, S'(p)_- = (j-1)K \text{ and } S'(p)_+ = jK. \]

Q.E.D.
Figure 1-A (related to Example 1)
Figure 1-B (related to Example 1)

![Graph showing the relationship between price and quantity with curves labeled D and S.](image-url)
Figure 2-A (related to Example 2)
Figure 2-B (related to Example2)
Figure 2-C (related to Example 2)
Figure 3: This is an example of demand and supply schedules under our model. The parameters are $n=6$, $\rho=10$, $\mu_c=10$, $\sigma=1$, $\Delta=1$, $s=2$. In this case $A\approx 0.231$ and $K\approx 0.117$. The signals of the six informed investors ($y_i$’s) are $8$, $9$, $10.5$, $11.5$, $12.5$ and $14$.

The supply curve is with $Z_s = 0$. The demand curves are with $Z_d = 0$ (D), $Z_d = 0.3$ (D1) and $Z_d = 0.6$ (D2).
Figure 4 - related to Example 3
Table 1 - Comparison with U.S. Exchanges

Table 1 compares our sample to stocks traded at U.S. exchanges (AMEX, NASDAQ, and NYSE). Stocks are compared by their market values, by their mean monthly dollar volume, and by their mean monthly turnover. The sample period is February-September 1998. We divide our sample of 105 stocks to quartiles based on market value (Panel A), mean monthly trading volume (Panel B), and mean monthly turnover (Panel C). Our statistics are based on data provided in CRSP for 722 stocks traded on AMEX, 4710 stocks traded on NASDAQ, and 2750 stocks traded on NYSE. The table reports the percentage of firms with market value, volume, and turnover below the sample statistics for the appropriate quartile. For example, 84% of the firms traded on AMEX have market values lower than the mean market value of the third quartile of our sample firms (which is 214.8 million Dollars).

Panel A – Market Values ($Millions)

<table>
<thead>
<tr>
<th>Quartile</th>
<th>Our Sample</th>
<th>AMEX - % below</th>
<th>NASDAQ - %below</th>
<th>NYSE - %below</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1000.8</td>
<td>97</td>
<td>95</td>
<td>63</td>
</tr>
<tr>
<td>2</td>
<td>214.8</td>
<td>84</td>
<td>76</td>
<td>27</td>
</tr>
<tr>
<td>3</td>
<td>81.3</td>
<td>64</td>
<td>54</td>
<td>11</td>
</tr>
<tr>
<td>4</td>
<td>30.0</td>
<td>35</td>
<td>29</td>
<td>3</td>
</tr>
</tbody>
</table>

Panel B – Mean Monthly Volume ($Millions)

<table>
<thead>
<tr>
<th>Quartile</th>
<th>Our Sample</th>
<th>AMEX - % below</th>
<th>NASDAQ - %below</th>
<th>NYSE - %below</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.29</td>
<td>62</td>
<td>36</td>
<td>9</td>
</tr>
<tr>
<td>2</td>
<td>1.66</td>
<td>54</td>
<td>30</td>
<td>6</td>
</tr>
<tr>
<td>3</td>
<td>1.02</td>
<td>42</td>
<td>22</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>0.4</td>
<td>21</td>
<td>10</td>
<td>1</td>
</tr>
</tbody>
</table>

Panel C – Mean Monthly Turnover ($Volume/Market Value)

<table>
<thead>
<tr>
<th>Quartile</th>
<th>Our Sample</th>
<th>AMEX - % below</th>
<th>NASDAQ - %below</th>
<th>NYSE - %below</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.57%</td>
<td>75</td>
<td>35</td>
<td>45</td>
</tr>
<tr>
<td>2</td>
<td>2.59%</td>
<td>45</td>
<td>15</td>
<td>18</td>
</tr>
<tr>
<td>3</td>
<td>1.51%</td>
<td>24</td>
<td>7</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>0.62%</td>
<td>9</td>
<td>2</td>
<td>1</td>
</tr>
</tbody>
</table>
Table 2 – Predicting Future Return

We estimate time series regressions for each of the 105 stocks in our sample. The dependent variable is \( \text{RETURN}_{it} \) = the return (in percentage) of stock \( i \) measured from the opening session of trading day \( t \) to its closing. The explanatory variables are \( Z_{d*it} \), \( Z_{s*it} \), \( \text{DIRECTION}^{*it} \), and \( LR_{it} \) (the lag of return). The numbers presented are the average betas 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.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTANT</td>
<td>0.480 (11.46)</td>
<td>0.647 (12.12)</td>
<td>0.469 (10.79)</td>
<td>0.455 (14.04)</td>
<td>0.378 (10.23)</td>
<td>0.436 (12.17)</td>
</tr>
<tr>
<td>( Z_{d*} )</td>
<td>-0.966 (-8.24)</td>
<td>-----</td>
<td>-0.229 (-2.11)</td>
<td>-----</td>
<td>0.096 (1.01)</td>
<td>-----</td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>-----</td>
<td>37</td>
<td>-----</td>
<td>57</td>
<td>-----</td>
</tr>
<tr>
<td>( Z_{s*} )</td>
<td>1.569 (14.52)</td>
<td>-----</td>
<td>0.830 (7.77)</td>
<td>-----</td>
<td>0.195 (2.61)</td>
<td>-----</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>-----</td>
<td>85</td>
<td>-----</td>
<td>60</td>
<td>-----</td>
</tr>
<tr>
<td>( \text{DIRECTION}^{*} )</td>
<td>-----</td>
<td>1.174 (29.83)</td>
<td>0.988 (27.20)</td>
<td>-----</td>
<td>0.722 (19.00)</td>
<td>0.749 (20.20)</td>
</tr>
<tr>
<td></td>
<td>105</td>
<td>103</td>
<td>-----</td>
<td>-----</td>
<td>101</td>
<td>102</td>
</tr>
<tr>
<td>( LR )</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-0.367 (-16.45)</td>
<td>-0.275 (-12.90)</td>
<td>-0.280 (-12.67)</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>7</td>
<td>8</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>0.089</td>
<td>0.145</td>
<td>0.181</td>
<td>0.185</td>
<td>0.264</td>
<td>0.250</td>
</tr>
<tr>
<td>( R^2 \text{-adj} )</td>
<td>0.075</td>
<td>0.139</td>
<td>0.162</td>
<td>0.179</td>
<td>0.242</td>
<td>0.239</td>
</tr>
</tbody>
</table>