MEASURING STOCK ILLIQUIDITY

An Investigation of the Demand and Supply Schedules at the TASE****

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Abstract

We show that estimating the demand and supply elasticity at the opening stage at the Tel Aviv Stock Exchange is highly sensitive to which of the reasonable measures is used. We compare the estimated elasticity of excess demand at the opening to the elasticity measured during the continuous trading. Though the elasticity of excess demand increases throughout the day, we find the largest elasticity at the opening. We document a demand schedule that is more elastic than the supply schedule. Our measure of price impact in call auctions is larger for buys than for sells and its reversal is smaller.

JEL classification: 10, 14

1. Introduction

The elasticity of demand for stocks has long been an issue in financial economics. In perfect capital markets investors have access to infinitely elastic demand and supply curves. Yet, recent empirical evidence indicates that the elasticity of demand for stocks is far from infinite.[1] Bagwell (1992) examines a sample of 31 share repurchases and documents a fairly inelastic supply curve (with an elasticity of approximately 1).[2] A higher elasticity of demand (of 37) is reported in Kandel, Sarig and Wohl (1999), who investigate a sample of 27 Israeli IPOs sold in a uniform auction. Similarly, Liaw, Liu and Wei (2000) find a demand elasticity of 24 for a sample of 52 Taiwanese IPOs sold via a discriminatory auction.[3]

To date, demand elasticity has been estimated around significant corporate events such as IPOs and share repurchases, which conceivably are associated with unusual demand and supply schedules. The marketing of an IPO is an invitation for buyers to come and buy the unusually large supply. Perhaps the lengthy IPO marketing process and its predetermined timing explain the relatively larger elasticity documented. Even the less

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[1] Market frictions such as unrealized capital gains, asymmetric information and divergence of opinions with short sales constraints (among others) result in finite elasticity of demand for stocks.

[2] Hodrick (1999) reports that the curve is less elastic when the firms repurchase their shares via a fixed price tender offer.

[3] There have been several attempts to indirectly examine the elasticity of the demand for stocks. The first attempt is the Scholes (1972) study of secondary distributions. He finds a price discount that is related to the identity of the seller and not to the quantity sold. Loderer, Cooney and Van Drunen (1991) control for possible information effects, yet find a significantly negative price effect around the announcement of seasoned issues of preferred stocks. They conclude that a finite elasticity of demand explains this finding. Ofek and Richardson (2000) and Field and Hanka (2001) document a significant negative price effect around the announcements of the end of lockup periods. The market expects the increased supply of stocks to depress the price, indicating finite demand elasticity. Harris and Gurel (1986), Shleifer (1986), Beneish and Whaley (1996) and Lynch and Mendenhall (1997) report a positive price reaction to the inclusion of a stock in the S&P 500 index. Kaul, Mehrotra and Morck (2000) report a positive price reaction to an increase in the floats and the index weights of 31 stocks on the Toronto Stock Exchange 300 index. The anticipated purchase of the stocks by index funds is expected to increase the market price, indicating finite supply elasticity. The results are consistent with finite demand and/or supply elasticity but the evidence on the magnitude is limited. See Wurgler and Zhuravskaya (2001) for a survey of these results.

publicized share repurchases produce larger elasticity than typical daily trading. Corporate announcements prepare the public for the share-repurchase process, thereby inviting potential suppliers of stocks. Our paper examines the supply and the demand schedules for stocks on a typical trading day.

Our data include all the orders (transactions) that were placed (executed) at the opening of the Tel Aviv Stock Exchange (hereafter TASE) for 105 stocks during 167 trading days. With these data we can precisely construct the demand and the supply schedules for each stock at the opening stage of each day. The opening stage, in which all market participants can submit orders and all transactions take place at 10:00, provides a natural environment for such an experiment.[4]. We compare our sample to stocks traded at US exchanges. Based on market capitalization, the Israeli stocks analyzed in our paper are not that different from stocks traded in the US, though our sample stocks have lower volumes than stocks traded on the US exchanges.

Our data enable the estimation of the elasticity of the demand and the supply schedules at one point in time. The measurement of elasticity using stock prices at different points in time is problematic. The measured price change could be a reaction to the quantity demanded (shift along the demand curve) or a reflection of change in the stock value (a shift of the demand curve). For example, the documented negative price effect associated with the end of lock up periods (see Ofek and Richardson (2000) and Field and Hanka (2001)) is consistent with finite demand and supply elasticity. Yet, one cannot rule out change in the stock value (henceforth informational effects) as a possible

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[4] Similar opening procedures exist in other computerized exchanges around the world such as the Paris Bourse (for a detailed description see Biais, Hillion and Spatt (1999), who analyze the price discovery at the opening stage), the Toronto Stock Exchange, the Tokyo Stock Exchange, and the Madrid Stock

alternative explanation. The documented positive price effect associated with inclusion in a stock index (see Harris and Gurel (1986), Shleifer (1986), Beneish and Whaley (1996), Lynch and Mendenhall (1997) and Kaul, Mehrotra and Morck (2000)) is consistent with finite demand and supply elasticity. Index funds must buy the stock and their purchases can create price pressure due to finite supply elasticity. There is, however, a reasonable alternative explanation. Inclusion in an index changes the stock's expected liquidity, thereby increasing its market value. It is difficult to determine the fraction of the price change that is associated with finite elasticity separately from that related to change in the fundamental value of the asset. Our study is free from this difficulty.

We report the elasticity of the demand and the supply as measured at the end of the opening process on 167 different days. We present several different estimates of the elasticity of demand and supply, focusing initially on two measures that can be viewed as upper and lower bounds of the elasticity. The first estimate (the lower bound) is calculated assuming that all the stocks are potentially for sale. Stockholders who choose not to sell are assumed to do so because the offered prices are not high enough. Thus, we standardize the change in the quantity demanded by the total number of shares outstanding (hereafter quantity-adjusted elasticity). The evidence indicates that both the supply and the demand curves are highly inelastic. The mean (median) quantity-adjusted elasticity of demand for our 105 sample stocks is around 0.05 (0.03). The supply schedule is inelastic as well. The mean quantity-adjusted elasticity of supply in our sample is 0.055 with a median of 0.03. The resulting mean quantity-adjusted elasticity of excess demand (0.105) implies that in order to buy 0.1% of a company's outstanding

Exchange. On dealer markets such as NASDAQ there is no special procedure for the opening stage (see Cao, Ghysels and Hatheway (2001)).

stocks, one has to push up the price by more than 1%. The highly quantity-adjusted inelastic supply and demand schedules result in the development of special mechanisms that create temporary liquidity to facilitate trades of unusually large magnitude. Such mechanisms are upstairs market (for blocks), the IPO process and tender offers. Yet, absent a special mechanism, the typical trader in a typical day faces quantity-adjusted inelastic demand and supply for stocks.

The second estimate of elasticity (the upper bound) assumes that stockholders who do not participate in the opening process are out of the market at any price. Under this assumption the relevant universe of stocks is the quantity traded that morning. Hence, we standardize the change in the quantity demanded by the quantity traded during the opening (hereafter volume-adjusted elasticity). Measured with respect to the volume of trade, the resulting elasticity is much higher: 415.4 (267) for demand (supply). We find that both the demand and the supply schedules, measured with respect to the volume of trade at the opening, are quite elastic. The remainder of the paper compares elasticity at different points in time, in different trading environments, and under different market conditions. Hence we focus only on quantity-adjusted elasticity

We find the demand curve to be significantly more elastic than the supply curve. This result makes sense. If short sales are costly, as is the case in Israel, the pool of investors supplying the shares is limited to the original owners. This is a significantly smaller pool than the universe of potential buyers. Fewer potential sellers can result in a lower elasticity of supply.

We find the mean demand quantity-adjusted elasticity for price increases above the opening price to be dramatically higher than the measured quantity-adjusted elasticity for price decreases. The opposite is found for the supply curve. Note that limit orders to sell (buy) at below (above) the eventual equilibrium price will be executed. Hence, the evidence indicates that demand and supply schedules are more elastic in what we define as the executable region. In this region, measured quantity-adjusted elasticity of supply and demand is quite sensitive to the magnitude of the assumed percentage price change. We find significantly larger quantity-adjusted elasticity for smaller price changes. In the non-executable region, quantity-adjusted elasticity is lower and insensitive to the magnitude of the percentage price change.

Next, we compare the elasticity estimated at the opening to the elasticity measured during the continuous trading stage. We obtain data containing the bid-ask spread and depth during the trading day.[5] We use this information to estimate the quantity-adjusted elasticity of excess demand during the trading day. Given the available data, the elasticity of the excess demand is computed for a price difference equal to one half of the bid-ask spread. We estimate the quantity-adjusted elasticity at predetermined intervals of 30 minutes starting at 10:30 and ending at 15:30. We find variation in the estimated mean quantity-adjusted elasticity of excess demand during the trading day, from a low of 0.023 to a high of 0.034. The evidence indicates that the mean quantity-adjusted elasticity of excess demand is increasing during the continuous trading stage. This evidence is consistent with the predictions of models of sequential trade with information asymmetry (see Glosten and Milgrom (1985)). The information revealed during the trading day mitigates the severity of the adverse selection problem. Sequential trading models with asymmetric information predict a lower elasticity of excess demand during the opening. The opening follows a long period without trade and investors have less information about the equilibrium price. In contrast, we find significantly higher quantity-adjusted elasticity of excess demand at the opening than at any other point in time during the trading day.[6] The opening call auction seems to aggregate liquidity to one point in time. This concentration of trades can be purely mechanical: the market is closed prior to opening and deferred transactions are executed at the first opportunity[7]. Alternatively, in the spirit of Admati and Pfleiderer (1988), many traders choose to trade at one point in time (the opening) to reduce their trading costs.

The next natural question to ask is what is the price impact of orders that are submitted to the opening. To date, the extensive literature estimating price impact has focused mainly on continuous trading.[8] Ours is a call auction environment requiring different measures. We suggest the following: the price impact of an order is the difference between the opening price and the opening price that would have resulted without that order. Since we have all the orders, we can compute both prices. We estimate the price impact of a stock by the average price impact of all its executed orders during the sample period. The mean price impact of our 105 sample stocks is 0.57% with a minimum of 0.0085% and a maximum of 2.16%.[9] As expected, we find the price impact of a stock to be inversely related to its volume of trade.

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[5] We thank Isabel Tkatch for providing us the data. For more detailed information see Tkatch (1999).

[6] Note that the smallest price difference at the opening is typically one tick while during the continuous trading stage it has a mean (median) of 11 (7) ticks. When we estimate the quantity-adjusted elasticity of excess demand at the opening for a price difference of 11 ticks we obtain a lower elasticity than that estimated during the continuous stage (0.022).

[7] Some trades are too small for the continuous trading session and must be executed only at the opening. Yet, while we find that 41 % of the orders submitted to the opening stage are "small", their aggregate value is a small fraction (7%) of the submitted orders.

[8] For an extensive review of this literature see Keim and Madhavan (1997, 1998), Madhavan (2000) and Stoll (2000).

[9] Kehr, Krahnen and Theissen (2001) suggest a similar measure of price impact in a call auction. They differ from us in that they compute the price impact of a hypothetical market order to buy and an order to sell the same amount. They estimate orders of two different sizes: a round lot and the historical mean transaction size of the stock. The estimated price impact is the average of these two price impacts (to

The evidence indicates that the price impact of larger quantities (demanded or supplied) is bigger. We compute the potential price impact of a limit order given at the end of the opening session for various quantities and limit prices. Not surprisingly, for orders of equal size we find a larger price impact and a higher probability of execution the bigger the limit price. Similarly, we find that the larger orders submitted with the same price limit lead to a larger price impact.

The next step is the investigation of potential differences between the price effects of buyers and sellers. Financial economists have argued that the price impacts of these two groups can be very different. As mentioned above, short sales constraints create asymmetries in the pool of potential buyers and sellers. In such an environment, sellers are constrained to the stocks they own, while buyers can choose any stock they want. Consequently, buy orders are more likely to be motivated by information about the underlying value of the stock. The existing empirical evidence is consistent with this prediction. However, to the best of our knowledge, it is limited to transactions involving institutional investors and block trading.

Our environment is very different from that of block trading and our data are not limited to institutional traders. Yet, we do find a similar price effect. For 84 firms, or 80% of our sample, the average price impact of the buyers is higher than that of the sellers. The mean price impact of the buyers and the sellers is 0.74% and 0.61%, respectively, and the median price impact of the buyers is 0.62% and of the sellers it is 0.44%. We find a significantly larger price impact during periods of market decreases than during periods

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differentiate the two measures, we will refer to theirs as the hypothetical price impact). When we use their method of adding an average market order, we find a bigger price impact. The mean hypothetical price impact of a buy (sell) order is 1.28% (1.37%) compared to estimates obtained with our measure of 0.74% (0.61%). This is to be expected as ours is a measure that mixes the price impact of limit orders and market of increases. Similarly, orders placed in periods in which the stock price itself decreased have a significantly larger price impact. However, in all periods buys have a larger price impact than sells. A fraction of the price impact we document seems transitory. A positive (negative) price impact is followed by a negative (positive) return. This phenomenon is more pronounced for sellers.

This paper is organized as follows. Section 2 provides institutional details on the market structure and describes the data. In section 3 we present the elasticity of the demand and supply schedules, the quantity-adjusted elasticity of excess demand during the opening, and the excess demand quantity-adjusted elasticity at predetermined points in time during the continuous trading stage. The price impact of buyers and sellers in a call auction is presented in section 4. Finally, section 5 contains our conclusions.

2. Data and Trading Environment at the TASE

2.1 The Trading Environment

There are 33 members at the TASE and no market makers. Unlike the Paris Bourse, there are no hidden limit orders at the TASE. The identity of the member posting an order is unknown. During the sample period, trading at the TASE is conducted in three stages:[10] the opening stage (8:30-10:00), the continuous bilateral trading system (10:00-15:30), and the closing session in which transactions are executed at the closing price (15:30-15:45). This paper focuses on the opening stage. During the opening, investors submit limit and market orders. Starting at 9:00, the TASE continuously calculates and displays the projected price and trading volume for each security. These projections are

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orders and theirs is the price impact of a market order. Indeed, we find a smaller difference between the two measures of price impact for more liquid stocks.

the price and trading volume that would have resulted from instantaneous execution of the displayed orders. At that time potential investors can see the volume of orders at each of the three best bid and offer prices. Submitted orders can be changed or canceled until 9:45. During the last 15 minutes of the opening stage (from 9:45 to 10:00) submitted orders that can affect the equilibrium price cannot be canceled. Unlike the continuous trading stage, there is no restriction on the minimum number of shares per order in the opening stage.

The opening price, determined by the intersection of the supply and demand schedules, is set at 10:00. If demand and supply intersect at more than one price, the exchange chooses the price closest to the previous day's closing price. Consistent with other exchanges, execution is carried out first by price priority and then by time priority. During the opening stage, price changes from the base price (the previous day's closing price) are limited to 10%. Hence, a purchase or a sell market order is identical to a limit order at 10% above or below the base price.

During the period we investigate, January 25th to September 28th 1998, trading at the opening represented 10.1% of the total daily trading volume.[11] The number of orders placed at the opening stage constitutes 42% of the total orders placed at the TASE during the trading day. The Shekel value of the orders submitted at the opening is 25% of the Shekel value of the daily order volume.[12] Orders not filled at the opening stage are automatically transferred to the continuous trading phase with the original time priority and price limit.

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[10] See Kalay, Wei and Wohl (2002) for a detailed description of the TASE market structure.
[11] Madhavan and Panchapagesan (2000) document that at the NYSE 9.7% of the value of trading takes place during the opening.

During the continuous trading stage, traders can observe the three best bid and offers of each side of the market. The relative tick size (tick/price) varies from 0.05 percent to 0.5 percent of the price. A minimum amount of approximately $4,000 applies to orders placed in the continuous stage. The opening and closing sessions have no quantity restrictions.

2.2 The Data

Our study focuses on 105 stocks traded at the TASE. The period investigated is January 25th to September 28th 1998 (167 trading days).[13] Our data include all the orders that were placed at the TASE opening stage for the period investigated for all the sample stocks.[14] For each order we have the date, stock ID, the time of the order, the limit price, the quantity ordered, the quantity executed, whether the order was placed by a buyer or a seller, and the time of order cancellation. With these data we can precisely construct the demand and the supply curves for each stock at the opening on each day.

Further, the database we use includes all the transactions that took place at the TASE opening during the period investigated. For each transaction we have the date, the stock ID, the time of transaction, the stock price and the quantity traded. We also have the daily closing price, the daily opening price and the daily trading volume for each security in our sample. We have daily data on the TA-100 stock index (which consists of the 100 most liquid stocks). Tkatch (1999) has generously provided us with the data used in her

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[12] The Shekel is the local currency in Israel. During the sample period $1 equals approximately 3.75 Shekels.

[13] During the period 1997 to 1998 TASE moved from call auctions to continuous trading. By January 1998, 105 stocks had moved to a continuous trading environment. By and large these are the most liquid stocks traded at the TASE. We have data on each one of these stocks for the entire period investigated.

[14] Extremely rare cases in which the exchange delayed the opening procedure were excluded.

study: the bid-ask spread and the respective depth during the trading day. Data are obtained for 96 out of our 105 stocks for 157 trading days in our sample period.

Table 1 compares our sample to stocks listed for trade on the major US exchanges – AMEX, NASDAQ, and the NYSE. 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 (quartile 1 has the highest capitalization and quartile 4 the lowest). 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, have a lower trading volume 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. Table 2 provides descriptive statistics on the orders and transactions at the opening session. The mean number of orders per stock during the opening session is 31. The mean Shekel value of these orders is 1,142,267. A large fraction of these orders are not executed during the opening stage. The mean number of transactions per stock during the opening is 11 and the mean Shekel value of these transactions is only 148,490. Figure 1 describes the TA-100 index during the sample period, indicating relatively stable market conditions.

3. The Elasticity

The textbook definition of elasticity of demand (or supply) is the percentage change in quantity demanded (supplied) corresponding to a percentage change in price (formally, $[\Delta q/q]/[\Delta p/p]$). Figure 2 describes the demand and the supply functions at the opening stage of a randomly selected stock (out of the 105 in our sample) on a randomly selected day. As it shows, demand (supply) curves are negatively (positively) sloped, having negative (positive) elasticity. We will present elasticity in absolute values. Figure 2-A, describes the excess demand: the demand minus the supply.

The change in the quantity demanded (supplied) in response to a percentage change in price is easy to compute. The question is how we should standardize the change in the quantity demanded (supplied) to come up with the percentage change. In other words, what is the relevant universe of shares for sale at the opening process on a given day? One possible assumption is that all shares are for sale. This would be true if all the existing stockholders follow the pre-opening process and some avoid trading only because the price is right. For a large enough change in the market price more of them are likely to trade. Hence, they are an integral part of the market and should be included in the demand (supply) curve. Thus, the change in the quantity demanded corresponding to a percentage change in the stock price should be standardized by the number of shares outstanding. This measure will give us the lower bound on the elasticity. The opposite assumption is that market frictions such as monitoring costs keep all the other stockholders away from the market at any price. Under this assumption, the relevant universe of shares is the number of shares traded (or the number of orders in the book).

Standardizing the change in the quantity demanded by this lower number results in higher elasticity. We will relate to this volume-adjusted elasticity measure, equal to the quantity-adjusted elasticity divided by the turnover (the opening volume divided by the market capitalization), as the upper bound on elasticity. In the next section we present the estimated elasticity under both set of assumptions.

3.1 Estimation of the Demand and Supply Elasticity

We use data from the opening stage to compute the demand (supply) elasticity for each one of our 105 stocks. For each stock, *i*, we compute the demand (supply) quantity-adjusted elasticity using the 167 days in our sample period as follows:

$$\eta_{i,k} = 1/167 \ \Sigma_{t=1,167} [(\Delta q_{i,t,k}/Q_{i,t})/(\Delta p_{i,t,k}/p_{i,t})]$$

where

t (1,.., 167) is day t

k (-10, -5, -3,-1,1,3, 5, 10) is the number of ticks; k = -3 (for example) is a price reduction of 3 ticks relative to the opening price [15]

i (1,2,..,105) is stock i

p_{it} is the opening price on day t

$\Delta p_{it,k}$ is the difference between the limit price and the opening price on day t

[15] The tick size on the TASE is a function of the security market price. For securities with market prices in excess of 200 Shekels the tick size is 1 Shekel. For securities with market prices of 20-200 Shekels the tick size is 0.1 Shekel. Finally for securities in the 2-20 Shekel price range the tick size is 0.01 Shekel.

$\Delta q_{itk,}$ is the difference between the quantity demanded (in number of shares) at the limit price and at the opening price on day t

Q_{it} is the number of outstanding shares.[16]

The quantity-adjusted elasticity of the demand (supply) is then computed by averaging out the 105 estimates of quantity-adjusted elasticity as follows:

$$\eta_k = 1/105 \, \Sigma_{i = 1,105} [\eta_{i,k}].$$

In describing the results we use the following notation: E_D+ and E_D- denote the elasticity of the demand curve calculated for an increase and a decrease in price. E_S+ and E_S- denote the elasticity of the supply curve calculated for an increase and a decrease in price.

The first line in Table 3 reports these measures of quantity-adjusted elasticity for a one-tick price change. The mean quantity-adjusted elasticity of demand (supply) of our sample stocks for a one-tick price change is 0.083 (0.009) with a median of 0.052 (0.006). The excess demand (demand minus supply) is inelastic too. The mean quantity-adjusted elasticity for a one-tick price increase (decrease) is 0.092 (0.118). [17]

Next we follow an identical procedure and calculate the volume-adjusted elasticity of demand and supply. The only difference in the estimation process is the standardization of the change in the quantity demanded by the volume at the opening session. We

[16] The number of outstanding shares is adjusted monthly for each stock in our sample.

[17] The same tick can imply a different percentage change in the stock price. Hence, the computation of elasticity of demand or supply for a one-tick price change may be mixing different percentage price changes. To examine the effects of this method of estimation on the results we estimate the elasticity assuming a constant percentage price change for all the stocks all the time. The mean quantity-adjusted elasticity found for a 0.25% assumed percentage price change is 0.105 for E_D+, 0.019 for E_D- , 0.016

standardize the change in the quantity demanded (or supplied) by the equilibrium quantity demanded (or supplied)) at the opening, assuming a one-tick price change.

Not surprisingly, as Table 3 shows, the estimates of volume-adjusted elasticity obtained are much higher (a mean volume-adjusted elasticity of demand of 415.4 and a mean volume-adjusted elasticity of supply of 267).[18] Thus, the estimate of elasticity is highly sensitive to the method of standardization. We calculate additional versions of elasticity of demand and supply where we standardize the change in the quantity demanded (supplied) by the total daily share volume and number of shares in the book at the opening. As expected the magnitudes of the elasticity estimated are between the values of our two measures of elasticity reported above. Both demand and supply schedules are elastic when measured with respect to the traded (or ordered) quantity of shares and highly inelastic when measured with respect to the total quantity of shares outstanding.

In Table 4, we document a significantly negative (cross-sectional) correlation between our measures of elasticity for a one-tick price change ("quantity adjusted" and "volume adjusted") and the relative tick size (tick size/price). A smaller relative tick size leads to more elastic demand. The quantity-adjusted elasticity is not related to the mean daily volume, nor is it related to estimates of the respective market value. As reported in Table 4, however, the quantity-adjusted elasticity is positively correlated with the respective turnover. Thus, the evidence indicates that a larger volume of trade for a given level of capitalization results in higher quantity-adjusted elasticity, while the volume-

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for E_S+ and 0.130 for E_S-. These results are very close to those obtained when the assumed price change equals one tick.

[18] One cannot infer the mean turnover from the ratio of the mean volume-adjusted elasticity to the mean quantity-adjusted elasticity. Formally, the relationship between the two is as follows: E(quantity-adjusted

adjusted elasticity is negatively correlated with turnover and with daily volume. It is possible that the standardization by volume creates a mechanical negative correlation between the estimated volume-adjusted elasticity and these variables. Surprisingly variance of stock returns is not correlated with either quantity-adjusted or volume-adjusted elasticity.

3.2 The Properties of the Quantity-Adjusted Elasticity of the Demand and the Supply

Figure 3 details the median quantity-adjusted elasticity of demand and supply for one, three, five, and ten ticks price changes. The figure is divided into two regions. On the right we present evidence for the executed orders (E_D+ and E_S-) and to the left we describe evidence for the orders that were not executed (E_S+ and E_D-). The median quantity-adjusted elasticity of supply and demand for executed orders are much higher. Interestingly, for executed orders, the demand and supply quantity-adjusted elasticity are lower for bigger price changes. For orders that were not executed we find that demand and supply quantity-adjusted elasticity are not sensitive to the size of the price change.[19] Figure 3 also documents an interesting empirical regularity. Around the equilibrium market price, the demand quantity-adjusted elasticity for a price increase is much higher than the quantity-adjusted elasticity for a price reduction. In fact, for a one-tick price change, the mean and median demand quantity-adjusted elasticity for a price increase is

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elasticity)= E(volume-adjusted elasticity*turnover) = E(volume-adjusted elasticity) * E(turnover) + cov (volume-adjusted elasticity, turnover).

[19] The difference in measured quantity-adjusted elasticity for executed orders and for orders that were not executed for the various tick sizes is statistically significant. This evidence is obtained by subtracting the demand (supply) quantity-adjusted elasticity for 3-tick price changes from the quantity-adjusted elasticity

approximately six times the mean and median demand quantity-adjusted elasticity for a price reduction. The exact opposite is true for the supply curve. The mean (median) supply quantity-adjusted elasticity for a one-tick price decrease is 11 (7.5) times the mean (median) supply quantity-adjusted elasticity for a one-tick price increase. One may wonder why we find such a difference between the quantity-adjusted elasticity measured for orders in the two regions. Transaction costs can help explain this puzzling empirical regularity. Small investors pay a minimum commission whether or not their orders are executed[20] . We therefore expect small investors to avoid submitting limit orders prior to the opening, where the limit is way out of the money, as they almost surely will not be executed. Consequently one would expect to find fewer limit orders with limits that are unlikely to be executed than orders with limits that are expected to be executed. Thus, we expect to find fewer orders in the non-executable region and a lower elasticity. They can also reduce the sensitivity of the measured quantity-adjusted elasticity to the size of the price change.

We find the demand curve to be more elastic than the supply curve. An estimate of the demand quantity-adjusted elasticity is the average of the quantity-adjusted elasticity for a one-tick price increase and the quantity-adjusted elasticity for a one-tick price decrease. We compute the demand and supply quantity-adjusted elasticity for each one of our sample firms. For a one-tick price change, the demand curve is more elastic than the supply curve for 82 of our 105 sample firms. We reject the hypothesis that the probability of drawing a firm with larger supply quantity-adjusted elasticity is equal to

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computed for a one-tick price change for each one of our sample firms. We reject the hypothesis that the difference is equal to zero at the one percent level (t values of 9.35 for the demand and 4.81 for the supply).

[20] If an order is executed the commission paid is proportional to the resulting volume which is usually higher than the minimum commission.

the probability of drawing a firm with a more elastic demand at the 0.0001 significance level ($p < 0.0001$ for a two-sided binomial test). The demand curve of 83 of our 105 sample-firms is more elastic than the supply curve for a three-tick price change ($p < 0.0001$). If short sales are extremely costly (as is the case in Israel), the pool of investors supplying the shares is limited to the original owners. This is a significantly smaller pool than the universe of potential buyers. Fewer potential sellers can result in a lower elasticity of supply

As can be seen from Figure 1, the sample period is characterized by two periods: "mostly increases" and "mostly decreases". To examine the possible effects of market conditions on the measured elasticity, we divide the sample into two periods: the first containing days in which the market increased and the second consisting of days where the market decreased. Calculating the quantity-adjusted elasticity of demand and supply separately for each sub-sample, we find insignificant differences between the two estimates of quantity-adjusted elasticity.

3.3 The Elasticity of Excess Demand at the Opening and during the Continuous Trading Stage

We find that the quantity-adjusted elasticity of excess demand is significantly larger during the opening than at any point in time during the continuous trading stage. The data available to us are the bid-ask spread during the trading day and the amount supplied at the ask and demanded at the bid. Consider a simple example. Suppose the bid is 20.25 Shekels and at this price 100 shares are demanded. The best ask is 20.75 Shekels and at that price 200 shares are supplied. At a price of 20.25 there is excess demand of 100. An increase of price by 0.5 of a Shekel to 20.75 creates an excess supply (or negative excess demand) of 200. Hence, corresponding to a change of 0.5 in the price there is a reduction of 300 in the excess demand. We standardize the price change by the mid point of the bid-ask spread and the change in the quantity demanded by the total number of shares outstanding. We estimate the quantity-adjusted elasticity at pre-determined intervals of 30 minutes starting at 10:30 and ending at 15:30. Formally, we calculate the elasticity of excess demand during the continuous stage as follows:

$\eta_i = 1/157 \ \Sigma_{t=1,157} [(\Delta q_{i,t,}/Q_{i,t})/(\Delta p_{i,t,}/p_{i,t})]$

where

t (1,.., 157) is day t

i (1,2,..,96) is stock i

p_{it} is the mid point of the bid-ask spread

Δp_{it} is the difference between the best bid and the best ask

$\Delta q_{it,}$ is the quantity demanded at the best bid plus the quantity supplied at the best ask

Q_{it} is the number of shares outstanding.

The quantity-adjusted elasticity of the demand (supply) is then computed by averaging out the 96 estimates of quantity-adjusted elasticity as follows:

$$\eta = 1/96 \ \Sigma_{i=1,96} [\ \eta_i].$$

As Table 5 describes, we find that the estimated quantity-adjusted elasticity of excess demand at the opening is significantly higher (at the 0.1% level) than at any point in time during the continuous trading stage.[21] The quantity-adjusted elasticity measured during the continuous trading stage varies from a low of 0.023 to a high of 0.034. The quantity-adjusted elasticity estimated at the opening, 0.0978, is much higher. Our results are consistent with the hypothesis that the mean quantity-adjusted elasticity of excess demand increases during the continuous trading stage. The mean quantity-adjusted elasticity at 14:30, 15:00, and 15:30 are significantly higher than the mean quantity-adjusted elasticity at 10:30, 11:00 and 11:30. We performed both a t-test and a binomial sign test and find significant differences at the 0.1% level.

The increase of the elasticity of excess demand during the continuous trading stage is consistent with the prediction of models of sequential trading with asymmetric information (see Glosten and Milgrom (1985)). During the day the information asymmetry decreases as traders learn about the valuation of the asset by observing the behavior of other players in the market and the resulting prices.[22] Following the same logic one would expect the opening to have the lowest elasticity. The opening stage follows a long period without trades and information asymmetry should be at its highest point. Yet, we find the highest elasticity of excess demand at the opening. This evidence is consistent with Admati and Pfliederer (1988), whose model predicts endogenous concentration of trade to some points in time in an attempt to reduce trading costs. A simple alternative explanation for the increased elasticity at the opening, however, is the execution of many deferred transactions at the first opportunity following the relatively long market closure.

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[21] For this comparison we computed the mean quantity-adjusted elasticity at the opening for the same sample of 96 stocks.
[22] This prediction is consistent with empirical findings (see Madavan, Richardson and Roomans (1997)) and the experimental evidence in Bloomfield, O' Hara and Saar (2002).

Note that the price difference we used for the calculation of elasticity at the opening is one tick while during the continuous trading stage we used half the spread, which has a mean (median) of 11 (7) ticks. When we estimate the quantity-adjusted elasticity of excess demand at the opening for a price difference of 11 (7) ticks we obtain a lower elasticity than that estimated during the continuous stage: 0.022 (0.028).[23] In other words, the opening is more liquid than the continuous trading stage for small price changes and small quantities.

4. Price Impact

It seems natural to extend the analysis and investigate the impact of specific orders on the equilibrium price. The price impact of an order is measured by its effect on the equilibrium price. Estimating the price impact is an issue that has interested financial economists for a long time. Previous attempts, however, were limited to investigations of price impact in continuous trading environments. Keim and Madhavan (1997, 1998), Madhavan (2000), and Stoll (2000) detail and analyze the extensive literature on this matter. The main difficulty in these attempts is the determination of the equilibrium price in the absence of the order or the transaction in question.

Our case is much easier as we compute the price impact of an order in a call auction. We know precisely how the TASE sets the opening price. Given a set of orders to sell (price and quantity) and similar information on the buy side of any stock, we can follow TASE procedure and compute the opening price. We can then omit a buy (or sell) order and follow the same procedure to set the opening price after the omission. The percentage

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[23] We would like to thank the referee for suggesting this measure.

change in the auction price is the price impact of the omitted order. Panels A and B of Appendix A contain a detailed example of the calculation of the price impact.

The absolute value of the percentage change in the opening price resulting from the omission of an order is its measured price impact. The price impact of each stock in our sample is estimated for every day in the period we investigate. The estimated price impact of a stock on a given day is the (equally-weighted) average price impact of all its executed orders (to buy and to sell) during the opening stage of that day. The price impact of the stock is then the (equally-weighted) average of the daily price impacts. To get an estimate of the price impact, we average the price impact of the 105 stocks in our sample giving each stock an equal weight. The estimated price impact is 0.57%, its median is 0.48%, and the standard deviation is 0.47. We divide the sample into quartiles based on traded volume (quartile 1 has the highest trading volume). The mean price impact of sellers (buyers) in quartiles 1-4 are 0.09%, 0.36%, 0.68%, 1.31% (0.14%, 0.52%, 0.93%, 1.38%). We also computed the weighted average price impact, the weights being equal to the relative quantity of the order in question. The results are very similar. The mean of the weighted average price impact is 0.7%, the median is 0.6%, and the standard deviation is 0.48.

At this point a word of caution is warranted. When we exclude an order we keep all the other orders intact, which is not necessarily what happens in the real world. It is reasonable to expect investors observing a change in the set of orders to buy a stock to react by adjusting their orders to sell. There is simply no way to measure such a hypothetical response by the other players.

4.1 The Hypothetical Price Impact

Kehr, Krahnen and Theissen (2001) (hereafter KKT) suggest another measure of price impact in a call auction. They estimate the price impact at the opening session of the Frankfurt Stock Exchange.[24] KKT compute the price impact of a stock (at a given point in time) by adding a hypothetical market buy order and a hypothetical market sell order and averaging their effects on the opening price.[25],[26] Panel C in Appendix A describes an example of such a calculation.

We use our TASE data to estimate the hypothetical price impact that results from adding an average sized market order to the buy and sell orders. We follow the same procedure and compute a market impact for every stock using our 167 days. The hypothetical price impact is the equally weighted average of the price impact of our 105 stocks. As expected, we find significant differences between the two approaches. The hypothetical price impact is substantially larger. The average price impact of adding a buy (sell) order is 1.28% (1.37%). The "hypothetical" price impact is significantly larger than the "actual" price impact (p-value 0.0001 in both t-test and binomial tests). This seems reasonable as the hypothetical price impact measures the effect of a market order. Our measure is a combination of the effects of market orders and limit orders (some of them quite tight). One would expect a lower price impact resulting from a mixture of market and limit orders. Our examination of the hypothetical price impact for different quantities and price limits, reported in section 4.4, indeed corroborates this conjecture.

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[24] Their work involves a comparison of execution costs during the opening call session to these costs in the continuous trading session.

[25] KKT's sample consists of 15 stocks. They document that the mean of the sum of the price impact of buyers and sellers of adding average orders at the opening is 2.396%. The equivalent number using our data is 2.65%.

The two measures of price impact are significantly (p-value <0.001) negatively correlated (in cross-section) with the log market value of the stock, the log daily volume and the turnover (volume / value). Both are significantly positively correlated with the stock's daily variance. The p-values for the price impact and hypothetical price impact are 0.001 and 0.098 respectively. Both measures are uncorrelated with the relative tick size.

4.2 The Price Impact of Different Limit Orders

Our measure of price impact estimates the change in the opening price that would have resulted from the elimination of existing orders (one by one). It is also interesting to explore the price impact of other trading strategies. We investigate the relationships between the price impact of an order and its size and limit price. Further we document the effects of changes in the limit price and size of the order on the probability of its execution. We conduct the following experiment. We compute the hypothetical price impact of orders of different sizes having different limit price. We repeat this exercise for three different order sizes – 0.001%, 0.0005%, 0.0001% of capitalization, and for three different price limits – market orders, 5% price change (increase [decrease] for buyers [sellers]), and 1% price change. The results are described in Figure 4. As expected, the price impact increases with the size of the order. A higher price limit results in a larger price impact but also has a bigger probability of execution. An order with a

[26] Unlike TASE (and the Paris Bourse), at the Frankfurt Stock Exchange the specialist may interfere after observing the demand and supply curves. The estimated hypothetical price impact ignores this possibility.

relatively tight price limit of 1.0% has a 74% execution rate while orders with a higher price limit of 5% have a 97% execution rate.[27]

4.3 The Information Content of the Price Impact and the Price Impact of Buyers Compared to the Effects of Sellers

The price impact of sellers can be systematically different from the price impact of buyers. In fact the existing literature indicates that such a difference is to be expected. Kraus and Stoll (1972) and Holthausen, Leftwich and Mayers (1990) examine block trading and document a stronger price recovery following a block trade at a minus tick than following a positive tick blocks. Chan and Lakonishok (1993, 1995) examine 37 large institutional money management firms over two and a half years and find asymmetric responses of prices to purchases and sales. Purchases of stocks are accompanied by an increase in their price. They observe no tendency for the price to reverse the trend after the trade. In contrast, sales of stocks seem to decrease the market price. Yet, they document an almost complete price recovery subsequently. Chan and Lakonishok also find substantial cross-sectional variation in the price impact. Keim and Madhavan (1995) examine 21 institutions and find that it takes longer to execute bid orders than equivalently sized ask orders. This evidence is consistent with the hypothesis that these institutions minimize the larger price impact of buy orders by spreading their execution over a longer time period. Keim and Madhavan (1997) examine the magnitude and determinants of transaction costs for the sample described above and document that buys, especially in small stocks, are generally more costly than the equivalent sells. These

[27] These estimates are upward biased since we assume full execution if the limit is equal to the price.

findings are not unique to the US markets. Gemmil (1996) conducts research on block trading at the London Stock Exchange and also finds that the price impact of buys are larger than the price impact of sells, both temporarily and permanently. Investigating a sample of NYSE stocks, Mingelgrin (2000) finds that large buyer-initiated net order flow tends to be followed by a further price increase, while seller-initiated net order flow does not lead to a price decrease. Saar (2001) addresses the asymmetry between buyers and sellers theoretically and finds that the history of price performance influences the asymmetry: the longer the run-up in a stock's price, the less the asymmetry. Typically investors do not hold the market portfolio. They hold portfolios containing a limited number of securities. Liquidity needs can force (or motivate) them to sell some of these securities. In contrast, the decision to buy is not constrained to a limited number of securities. It seems, therefore, that the decision to sell is more likely to be driven by liquidity shocks than is the decision to buy a particular security. Consequently, with short sale constraints, a buy order is more likely to convey information about the underlying value of the stock than is an order to sell.

So far the investigation as to the possible differential effects of buy and sell orders has been limited to institutional investors and block trading. Our environment is not similar to the market for block trading. Many block traders use the “upstairs market maker”, who forms a syndicate of players to take the other side of the trade. Moreover, usually the identity of the seller/buyer is known. Our evidence is not limited to trades of institutional investors. Yet, in spite of these differences, we do find the same effects. The price impact of buy orders is significantly higher than the price impact of sell orders. The mean price impact of the buyers (sellers) is 0.74% (0.61%) and the median is 0.62%

(0.44%).[28] For 84 firms in our sample (80%), the average price impact of the buyers is higher than that of the sellers (significant at the 0.1% level).[29]

To estimate the effects of market conditions on the price impact we calculate the price impact of orders submitted during days of market increases as well as the price impacts of orders during days with reduction in the market. We also estimate the price impact of orders submitted during days in which the stock price in question has gone up separately from days of a price decline. The results are described in Table 6. We find a significantly higher price impact for both buyers and sellers during periods of market decline (t=0.0198). We also find significantly higher price impact for both sellers and buyers during days of stock price declines (t = 0.0001). However, the estimated median price impact of the sellers is lower than that of the buyers in all market (or stock price) conditions.

The order size is another factor that can affect the estimated price impact. [30] To control for this, we run a time-series OLS regression of the order price impact on its size (in Shekels) and a dummy variable capturing the side of the order (which takes the value of 1 (0) if placed by a buyer (seller)). We run this regression for each firm in the sample. [31] Indeed, consistent with the existing evidence, we find a positive coefficient on size for 90% of the regressions. Larger orders, other things equal, have a larger price impact. For 83 firms (79%) we document a positive coefficient on the dummy variable (p-value =

[28] The weighted average price impact for buy (sell) orders is 0.84% (0.71%), with a median of 0.77% (0.56%).
[29] For 80 firms in our sample (76.2%) the weighted average price impact of the buyers is higher than that of the sellers.
[30] We find that the average buy order is statistically larger than the average sell order (24,442 Shekels versus 17,913 Shekels, respectively, with a t value of 8.85).
[31] Since the absolute value of the price changes during the opening are limited to 10%, the data are subject to both upper and lower censoring. Hence, we also estimated the above model using the two-limit Tobit model that allows for both upper and lower censoring. Our results are robust to the method employed.

0.0001 in a binomial test). The evidence indicates that the bigger price impact of buy orders cannot be explained solely by differences in the size of the order.

Table 6 describes the price impact of buyers and sellers for four sub-samples of stocks differing in their trading volume. The estimated price impact of sellers and buyers increases as the volume of trade decreases. The cross-sectional correlation between the price impact of sellers and buyers (0.81) is significantly positive. Yet, in each quartile we find a larger price impact for buyers than for sellers.

4.4 Buyers, Sellers, and the Permanent Price Impact

If an order to sell is more likely to be liquidity driven, its price effect should be temporary in nature. Consequently, we should expect a price reversal following the immediate sale. If buy orders are more likely to contain information about the value of the underlying stock, the price increase associated with the buy is more likely to be permanent. It is less likely to be followed by a price reversal. The existing evidence indicates that the price reversals for sellers are indeed higher than for buyers.

To address this issue, we estimate for each stock the relationship between the average price impact for each day for buyers and sellers and the subsequent return measured from the opening to the closing. In other words, we estimated the equation:

$$R_{i,t} = \alpha_i + \beta_{1i} * PIB_{it} + \beta_{2i} * PIS_{it} + \varepsilon_i$$

where

i is stock i, i = 1..105

t is an index for the trading day t=1…167

$R_{i,t}$ is the subsequent return measured from opening at time t to closing

$PIB_{i,t}$ is the mean buyers' price impact on stock i on day t (in absolute value)

$PIS_{i,t}$ is the mean sellers' price impact on day t (in absolute value).

The estimated coefficient of PIB (PIS) measures the price reversal associated with the price impact of buyers (sellers). For example, β_1= -0.6 implies that 60% of buyers' positive price impact tends to reverse in the subsequent trading in it. In the 105 OLS regressions that we run, we find that the price impact of both the sellers and the buyers is followed by a price reversal. However, the price impact of the buyers is followed by a smaller reversal than is that of the sellers: the mean of β_1 is -0.506 and the mean of β_2 is 0.768. We compute the difference between the estimated β_1 and the estimated β_2 for each one of our 105 stocks.[32] In 80 of the 105 pairs of betas, β_2 is larger than β_1 in absolute values (p value = 0.0001 for a two-sided binomial test).

5. Conclusions

This paper investigates the supply and demand schedules at the TASE. The mean quantity-adjusted elasticity of both is around 0.05. We document less elastic supply curve relative to the demand curve. The low quantity-adjusted elasticity highlights the need for temporary-liquidity-creating mechanisms (e.g., upstairs trading for block trading, IPOs, tender offers) to help absorb unusually large trades. We calculate the quantity-adjusted

[32] The estimated coefficients are unbiased even when the residuals are correlated and consequently the standard errors are biased. One can still use the cross-sectional standard deviation of the estimated coefficients to calculate the p value.

elasticity of excess demand during the trading day, finding that it increases significantly during the continuous trading stage. This evidence is consistent with sequential trading models with asymmetric information (Glosten and Milgrom (1985)), which predict that the asymmetric information is the highest in the opening as uncertainty about other traders' valuations is high. . During the day, as investors observe the trading activity of other market participants, the information asymmetry is reduced. Consequently a lower elasticity is expected in the opening. Yet the quantity-adjusted elasticity estimated at any point in time during the continuous trading stage is significantly lower than the quantity-adjusted elasticity estimated at the opening. This evidence is consistent with Admati and Pfliederer (1988), whose model predicts concentration of trades to preferred points in time during the day. Consistent with the same model, the opening stage seems to attract more traders. Note that some of them, small traders, have no choice as their typical trades are below the required minimum quantity necessary for trades during the continuous stage. The presence of small traders at the opening can attract others who may prefer to trade with them. In addition, the concentration of traders at the opening can be explained by their inability to trade for a relatively long period (since the previous day's closing).

We suggest a new measure of price impact suited for call auctions: the difference between the price with and without an order. Consistent with the hypothesis that an order to buy conveys more information than an order to sell, we find that buyers have a bigger price impact than sellers. This result corroborates the existing evidence on the information content of the trades of institutional investors and block traders in a continuous trading environment. It seems to us that this asymmetry is driven by short sales constraints. With these constraints, the seller is restricted to the stocks he owns while the buyer can choose from a significantly larger pool. We believe that for the very same reason the demand curves are more elastic than the supply curves. Finally, we find a bigger price impact for both buyers and sellers during periods of market decline and during periods of reduction in the stock price in question. However, the buyers have a larger price impact irrespective of the market conditions or the direction of trade in the stock price in question. We find that limit orders for larger size result in a bigger price impact. A submission of a higher (lower) limit price by buyers (sellers) result in a bigger price impact and a larger probability that the order submitted will be executed.

REFERENCES

Admati A. and Pfleiderer, P., 1988, A Theory of Intraday Patterns: Volume and Price Variability, Review of Financial Studies 1, 3-40.

Bagwell, L. S., 1992, Dutch Auction Repurchases: An Analysis of Shareholder Heterogeneity, Journal of Finance 47(1), 71-105.

Beneish, M. and Whaley, R., 1996, An Anatomy of the “S&P Game”: The Effects of Changing the Rules, Journal of Finance 51(5), 1909-1930.

Biais, B., Hillion P. and Spatt C., 1999, Price Discovery and Learning During the Preopening Period in the Paris Bourse, Journal of Political Economy 107, 1218-1248.

Bloomfield, R., O’Hara M. and Saar G., 2002, The “Make or Take” Decision in an Electronic Market: Evidence on the Evolution of Liquidity, Working Paper, Cornell University and NYU.

Cao, C., Ghysels, E. and Hatheway, F. M., 2000, Price Discovery without Trading: Evidence from the Nasdaq Preopening, Journal of Finance 55(3), 1339-1365.

Chan, L. K.C. and Lakonishok, J., 1993, Institutional Trades and Intraday Stock Price Behavior, Journal of Financial Economics 33, 173-199.

Chan, L. K.C. and Lakonishok, J., 1995, The Behavior of Stock Prices around Institutional Trades, Journal of Finance 50(4), 1147-1174.

Field L. C., and Hanka, G., 2001, The Expiration of IPO Share Lock-ups, Journal of Finance 56(2), 471-500.

Gemmil, G., 1996, Transparency and Liquidity: A Study of Block Trades on the London Stock Exchange under Different Publication Rules, Journal of Finance 51(5), 1765-1790.

Glosten L. and Milgrom P., 1985, Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders, Journal of Financial Economics13, 71-100.

Harris, L. and Gurel, E., 1986, Price and Volume Effect Associated with Changes in the S&P 500 List: New Evidence for the Existence of Price Pressures, Journal of Finance 41(4), 815-829.

Hodrick, L. S., 1999, Does Stock Price Elasticity Affect Corporate Financial Decisions?, Journal of Financial Economics 52, 225-256.

Holthausen, R. W., Leftwich, R. W. and Mayers, D., 1990, Large Block Transactions, the Speed of Response, and Temporary and Permanent Stock Price Effects, Journal of Financial Economics 26, 71-95.

Kalay, A., Wei, L. and Wohl, A., 2002, Continuous Trading or Call Auctions: Revealed Preferences of Investors at Tel Aviv Stock Exchange, Journal of Finance 57(1), 523-542.

Kandel, S., Sarig, O. and Wohl, A., 1999, The Demand for Stocks: An Analysis of IPO Auctions, Review of Financial Studies 12(2), 227-247.

Kaul, A., Mehrotra, V. and Morck, R., 2000, Demand Curves for Stocks Do Slope Down: New Evidence from Index Weights Adjustment, Journal of Finance 55(2), 893-912.

Kehr, C.H., Krahnen, J. P. and Theissen, E., 2001, The Anatomy of a Call Market, Journal of Financial Intermediation 10(3-4), 249-270.

Keim, D. B. and Madhavan, A., 1995, Anatomy of the Trading Process: Empirical Evidence on the Behavior of Institutional Traders, Journal of Financial Economics 37, 371-398.

Keim, D. B. and Madhavan, A., 1997, Transactions Costs and Investment Style: An Inter-exchange Analysis of Institutional Equity Trades, Journal of Financial Economics 46, 265-292.

Keim, D. B.and Madhavan, A., 1998, The Cost of Institutional Equity Trades, Financial Analyst Journal Jul/Aug, 50-59.

Kraus, A. and Stoll, H. R., 1972, Price Impact on the New-York Stock Exchange, Journal of Finance 27, 569-588.

Liaw G., Liu Y. and Wei K.C. J., 2000, On the Demand Elasticity of Initial Public Offerings: An Analysis of Discriminatory Auctions, working paper. HKUST Business School

Loderer, C., Cooney, J. and Van Drunen, L., 1991, The Price Elasticity of Demand for Common Stock, The Journal of Finance 46(2), 621-651.

Lynch, A. W and Mendenhall, R. R., 1997, New Evidence on Stock Price Effect Associated with Changes in the S&P 500 Index, The Journal of Business 70(3), 351-383.

Madhavan A., 2000, Market Microstructure: A survey, Journal of Financial Markets 3(3), 205-258.

Madhavan A. and Panchapagesan, V., 2000, Price Discovery in Auction Markets: A Look Inside the Black Box, Review of Financial Studies 13, 627-658.

Madhavan, A., Richardson, M., and Roomans, M., 1997, Why Do Security Prices Change? A Transaction-Level Analysis of NYSE Stocks, Review of Financial Studies 10(4), 1035-1064.

Mingelgrin, D. H., 2000, The Informational Content of High-Frequency Trading Activity, Working paper, Wharton.

Ofek, E. and Richardson, M., 2000, The IPO Lock-Up Period: Implications for Market Efficiency and Downwards Sloping Demand Curves, working paper, Stern School of Business, NYU.

Saar, G., 2001, Price Impact Asymmetry of Block Trades: An Institutional Trading Explanation, Review of Financial Studies 14(4), 1153-1181.

Scholes, M., 1972, The Market for Securities: Substitution versus Price Pressure and the Effects of Information on Share Prices, The Journal of Business 45(2), 179-211.

Shleifer, A., 1986, Do Demand Curves for Stocks Slope Down?, Journal of Finance 41(3), 579-90.

Stoll R. H., 2000, Friction, Journal of Finance 55(4), 1479-1514.

Tkatch, I., 1999, Description of Trading During the Continuous Stage at the Tel Aviv Stock Exchange (in Hebrew), Master's Thesis (under the supervision of Eugene Kandel), Hebrew University, Jerusalem, Israel.

Wurgler, J. and K. Zhuravskaya, 2002, Does Arbitrage Flatten Demand Curves For Stocks, Journal of Business, 75(4), 583-608.

Table 1
Comparison with US Exchanges

Table 1 compares our sample to stocks traded at US 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 into 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).

Panel A – Market Values ($Millions)

Quartile	Our Sample	AMEX - % below	NASDAQ - %below	NYSE - %below
1	1000.8	97	95	63
2	214.8	84	76	27
3	81.3	64	54	11
4	30.0	35	29	3

Panel B – Mean Monthly Volume ($Millions)

Quartile	Our Sample	AMEX - % below	NASDAQ - %below	NYSE - %below
1	2.29	62	36	9
2	1.66	54	30	6
3	1.02	42	22	3
4	0.4	21	10	1

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

Quartile	Our Sample	AMEX - % below	NASDAQ - %below	NYSE - %below
1	5.57%	75	35	45
2	2.59%	45	15	18
3	1.51%	24	7	6
4	0.62%	9	2	1

Table 2
Descriptive Statistics – Daily Opening Stage Averages

Descriptive statistics of the total mean and medians of the number and value of orders and transactions during the opening stage at the TASE for the period January 25th to September 28th 1998 on a per session basis. For each stock in our sample we compute the historical mean, median, maximum, and minimum of the number and value of orders and transactions per session for our sample period. Panel A describes the averages of these statistics (mean, median, maximum, and minimum) of the number of orders and the Shekel value of the orders (one $ equals roughly 3.75 Shekels). Panel B reports averages of these statistics for the number and value of the transactions executed during the opening stage. We divide our sample into quartiles according to the average daily trading volume and calculate the variables described above for each quartile (1=highest trading volume quartile, 4=lowest trading volume quartile).

Panel A: ORDERS – Averaged Per Daily Opening Stage

		Quartile 4 (26 stocks)	Quartile 3(26 stocks)	Quartile 2 (27 stocks)	Quartile 1(26 stocks)	The 105 stocks
Number of Orders	Mean Per Session	11	18	23	73	31
	Median Per Session	11	17	22	65	29
	Max Per Session	31	47	68	368	128
	Min Per Session	2	5	7	27	10
Volume of Orders In Shekels	Mean Per Session	186,032	364,423	685,330	3,352,590	1,142,267
	Median Per Session	157,417	316,301	536,219	2,263,285	815,619
	Max Per Session	764,463	1,498,900	5,292,153	46,639,395	13,470,094
	Min Per Session	16,125	54,213	83,824	574,915	181,332

Panel B: TRANSACTIONS –Per Daily Opening Stage

		Quartile 4 (26 stocks)	Quartile 3(26 stocks)	Quartile 2 (27 stocks)	Quartile 1(26 stocks)	The 105 stocks
Number of Transactions	Mean Per Session	2	4	7	32	11
	Median Per Session	2	3	6	27	10
	Max Per Session	12	19	35	235	75
	Min Per Session	0	1	15	8	2
Volume of Transactions In Shekels	Mean Per Session	12,277	28,396	69,147	487,192	148,490
	Median Per Session	10,903	20,641	42,471	293,366	91,375
	Max Per Session	128,853	240,507	874,036	7,504,390	2,174,443
	Min Per Session	0	87	299	39,279	9,707

Table 3
The Sensitivity of the Elasticity Calculations to the Specific Adjustment Being Used

We use data from the opening stage of the TASE to compute 4 different estimations of the demand (supply) elasticity for each one of the 105 sample stocks. The first (quantity-adjusted elasticity) is adjusted according to the outstanding shares, the second (volume-adjusted elasticity) is adjusted according to the opening volume, the third is adjusted according to the daily volume and the fourth is adjusted according to the total level of shares that are at the book at the time of the opening. For each stock and adjustment we compute the demand (supply) elasticity using the 167 days in our sample period. For each adjustment, the estimated elasticity is the mean of these 105 numbers. E_D+ (E_D-) is the elasticity of the demand curve calculated for increase (decrease) in price. E_S+ (E_S-) is the elasticity of the supply curve calculated for increase (decrease) in price.

Adjustment	E_D+	E_D-	E_S+	E_S-
Outstanding Shares	0.083	0.013	0.009	0.105
Opening Volume	415.4	117.8	63.6	267.0
Daily Volume	102.98	13.35	10.08	141.16
Opening Book	77.96	10.45	6.15	59.33

Table 4
Cross-Sectional Determinants of Elasticity

The table reports correlation coefficients (and p-values) for measures of elasticity of excess demand (quantity-adjusted and volume-adjusted) and the respective stock characteristics for the 105 stocks in our sample. The sample period is January 25th to September 28th 1998. For each stock we estimate the "relative tick" by the mean ratio tick size/stock price during the sample period. We estimate the variance of close-to-close returns ("variance") for each stock in the sample. "Average daily volume" is the average trading volume in Shekels during the sample period computed for each stock. "Average market value" is the average market value in Shekels during the sample period estimated for each stock. The turnover of each stock ("turnover") is estimated by the ratio of its mean daily volume divided by its mean market value.

	Quantity-adjusted Elasticity	Volume-adjusted Elasticity
Relative tick	-0.368 (0.001)	-0.606 (0.001)
Variance	0.087 (0.377)	-0.005 (0.958)
Average daily volume	-0.121(0.217)	-0.254 (0.009)
Average market value	-0.034 (0.727)	-0.008 (0.935)
Turnover	0.362 (0.000)	-0.218 (0.025)

Table 5

<u>The Comparison of the Excess Demand Elasticity at the Opening to the Elasticity during the Continuous Trading Stage</u>

The table describes the behavior of the elasticity of excess demand during the trading day. The elasticity of excess demand is measured at the opening and during the trading day at intervals of 30 minutes. The elasticity of the excess demand at the opening estimated for each of the 96 stocks in our sample is the average of the elasticity calculated for a one-tick price increase and that calculated for a one-tick price decrease. The estimation of the elasticity of excess demand of each stock uses the 167 trading days available to us. The estimated elasticity provided in the table is the <u>mean</u> of these 96 numbers. The elasticity of the excess demand at the continuous trading stage is estimated using the bid and ask spread and depth during the trading day. The percentage price change estimated for each stock is the difference between the ask and the bid price divided by the mid point of the bid-ask spread. The corresponding percentage change of quantity estimated for each stock is the sum of the quantity demanded at the best bid and the quantity supplied at the best ask divided by the number of outstanding shares. This elasticity is estimated for each of the 96 stocks in our sample at intervals of 30 minutes during the trading day. The mean of the 96 estimated elasticity at time t (t = 10:30,…, 15:30) is reported in the table.

Time during the Trading Day	Elasticity of Excess Demand
10:00 – Opening	0.0978
10:30	0.023
11:00	0.025
11:30	0.028
12:00	0.031
12:30	0.032
13:00	0.032
13:30	0.033
14:00	0.032
14:30	0.034
15:00	0.033
15:30	0.033

Table 6

Price Impact under Different Market Conditions

Table 4 compares the price impact of buyers and sellers in days of market (stock) increase to the price impact in days of market (stock) decline. The price impact of buyers (sellers) in a given stock is the effect of excluding an existing buy (sell) order on its opening price, averaged over all buy (sell) orders in relevant trading days. The sample size is 105 stocks traded at the opening stage of the TASE, and the period covered is January 25th to September 28th 1998 (a total of 167 trading days). In the table we report the mean, median, and p-value of the difference.

	PRICE IMPACT BUYERS			PRICE IMPACT SELLERS		
	mean	median	p-value dif	mean	median	p-value dif
Market Up	0.71%	0.54%		0.55%	0.37%	
Market Down	0.78%	0.71%	0.0198	0.67%	0.44%	0.0002
Stock Up	0.68%	0.53%		0.48%	0.38%	
Stock Down	0.80%	0.70%	0.0040	0.80%	0.46%	<.0001

Figure 1: <u>Daily Values of the TA-100 Index during the Sample Period (1/25/98 – 9/28/1998).</u>

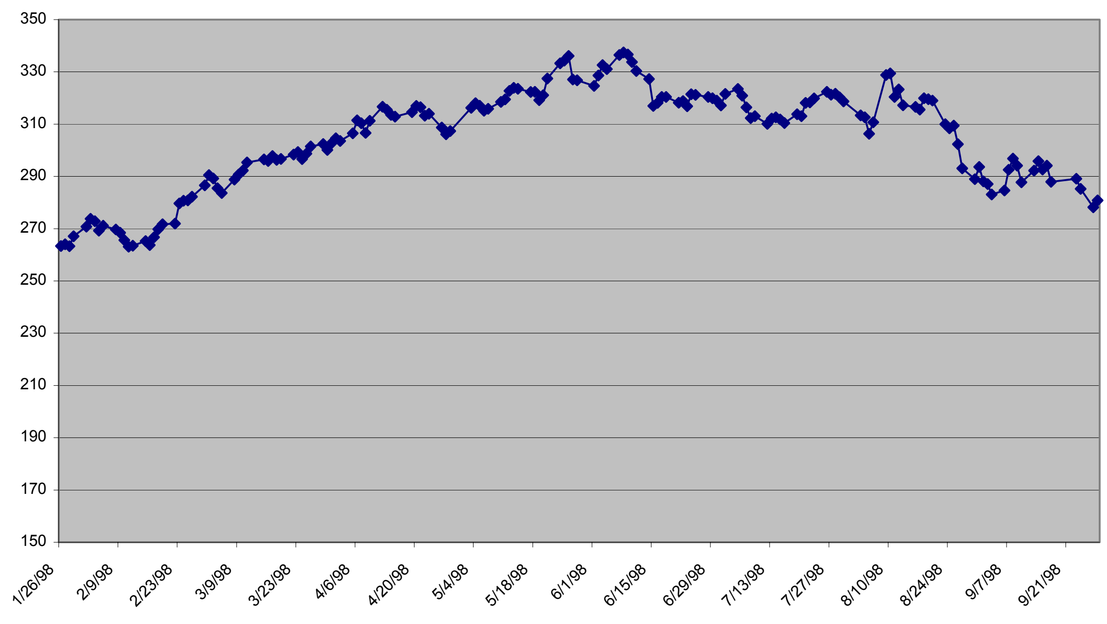


Figure 2: The Demand and the Supply Functions of Stock 169011 on January 26th 1998.

The figure describes the quantity of shares demanded (and supplied) at various prices in Shekels. The day chosen is a Monday (not the first trading day of the week). In choosing the day we made sure that it is not a day in which the stock index options expires. The firm is chosen randomly out of the 105 firms in our sample.

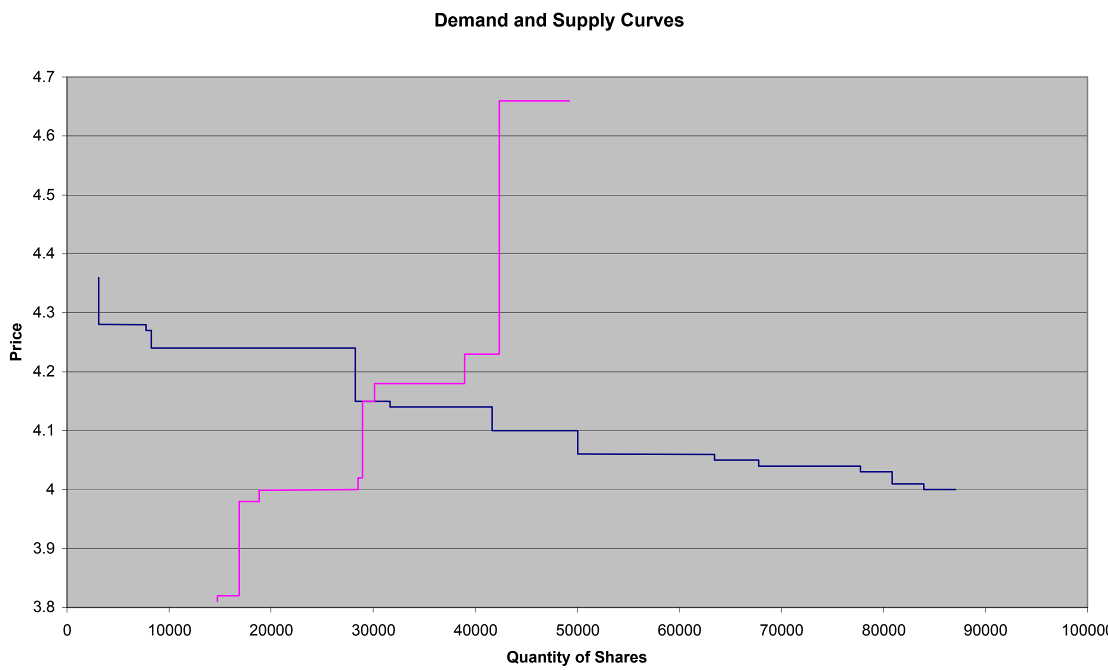


Figure 2-A: The Excess Demand of Stock 169011 on January 26th 1998.

The figure describes the excess demand of stock 169011 on January 26th 1998 (Figure 2 above details the same stock at the same point in time period). The excess demand is constructed by subtracting the supply schedule from the demand schedule.

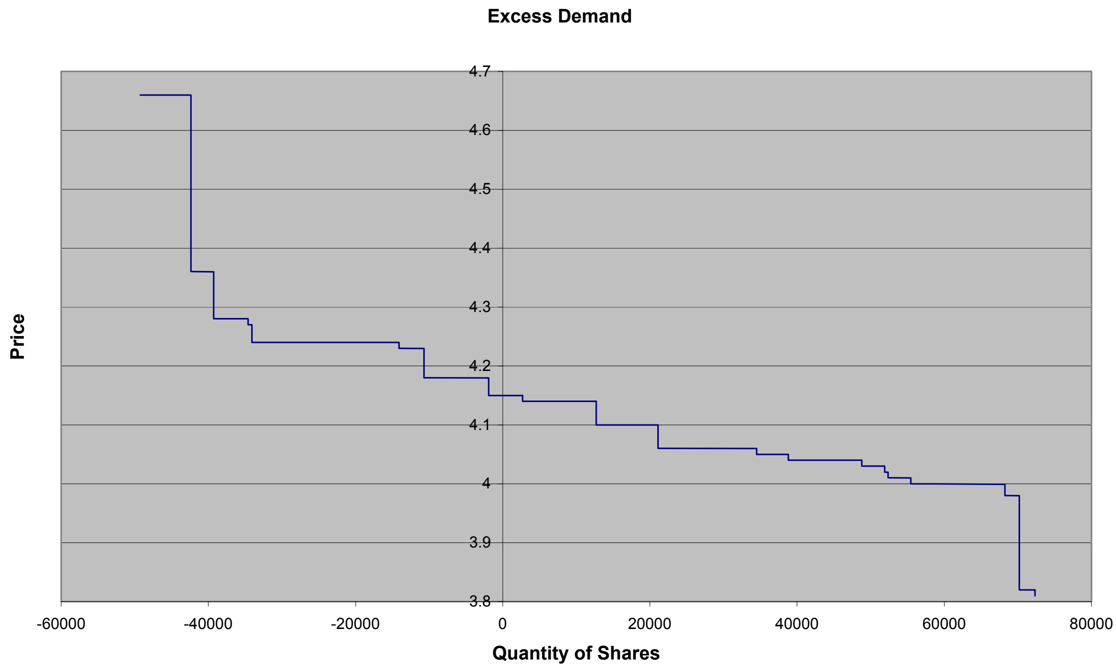


Figure 3: <u>The Elasticity of the Demand and Supply</u>

We use data from the opening stage at the TASE to compute the demand (supply) elasticity for each one of the 105 sample-stocks. For each stock we compute the demand (supply) elasticity using the 167 days in our sample period. The estimated elasticity is the **<u>median</u>** of these 105 numbers. E_D+ (E_D-) denotes the elasticity of the demand curve calculated for increase (decrease) in price. E_S+ (E_S-) denotes the elasticity of the supply curve calculated for increase (decrease) in price. E- (E+) denotes the elasticity of the excess demand computed for price decrease (increase). The elasticity is computed for a one, three, five and ten-tick price increase and price decrease.

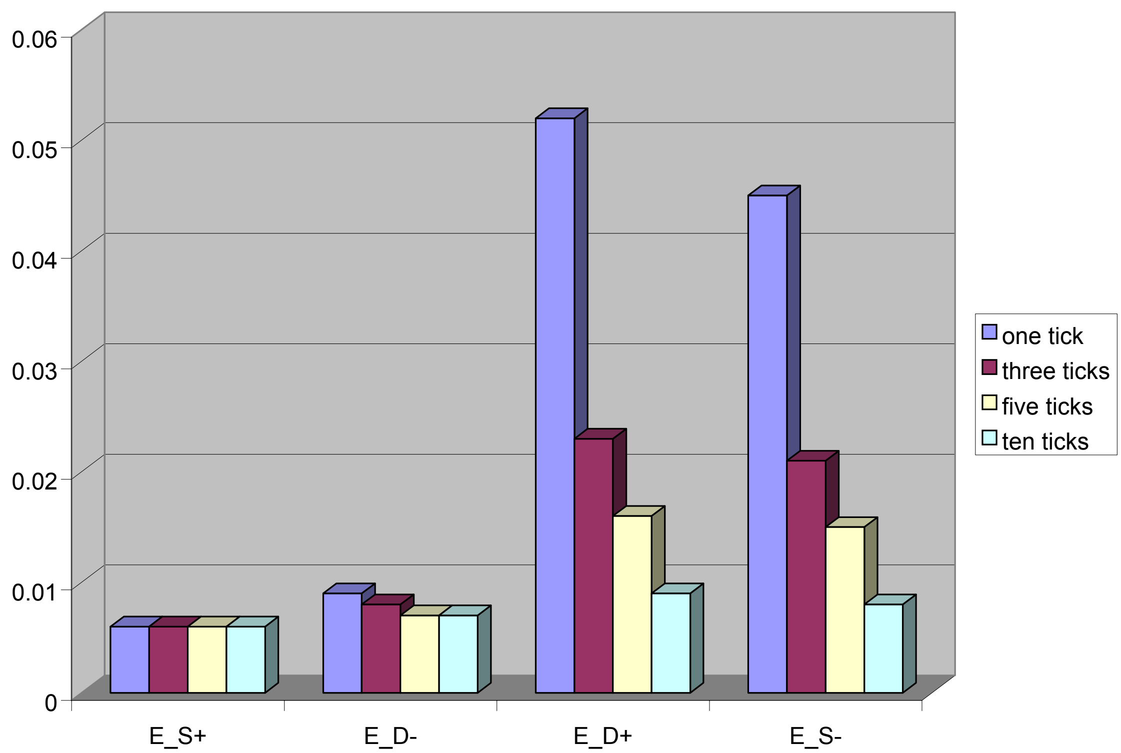
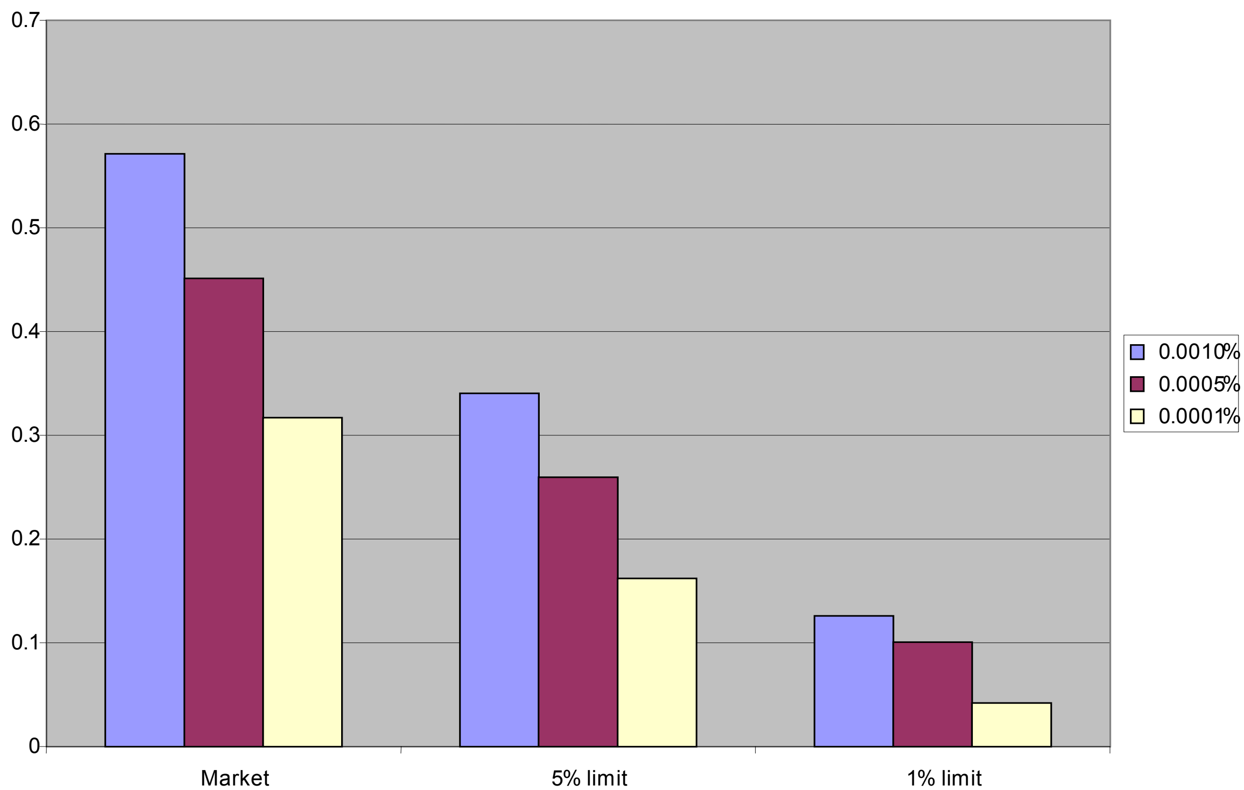


Figure 4: The Hypothetical Price Impact

We estimate the hypothetical price impact of buyers and sellers of our 105 sample stocks. The hypothetical price impact of buyers (sellers) is the effect of adding a buy (sell) order on the opening price. We estimate the price impact for each stock by taking the average price impact for each one of our 167 sample days. We compute the mean of the price impacts of our 105 sample stocks. We repeat this exercise for three different order sizes – 0.001%, 0.0005%, 0.0001% of the capitalization, and for three different price limits – market orders, a 5% price change (increase [decrease] for buyers [sellers]), and a 1% price change (increase [decrease] for buyers [sellers]).



Appendix A

Panel A – An Example Illustrating the Calculation of the Price Impact

The example assumes one order at the specified quantity at each price limit. The second (fourth) column lists the quantity demanded (supplied) and the third (fifth) details the cumulative demand (supply) at current or higher (lower) prices**.**

Price Limits	Buy Quantity	Buy Cumulative	Sell Quantity	Sell Cumulative	Trading Volume
298	500	1502	700	700	700
299	400	1002	300	1000	1000
300	2	602	500	1500	602
301	400	600	500	2000	600
302	200	200	500	2500	200

Given these demand and supply curves the opening procedure at the TASE will result in an opening price of 299 and the volume trading at the opening is 1000.

Panel B – The Demand and Supply Curves Excluding the Order to Buy 400 at Price 301.

Price Limits	Buy Quantity	Buy Cumulative	Sell Quantity	Sell Cumulative	Trading Volume
298	500	1102	700	700	700
299	400	602	300	1000	602
300	2	202	500	1500	202
301	0	200	500	2000	200
302	200	200	500	2500	200

Given the new demand and supply curves the opening price calculated by the same procedure is 298, and the volume of trade is 700. Hence, the price impact of the omitted buy order is [(299/298)-1]*100 = 0.34%

Appendix A – Continued

Panel C – An Example Illustrating the Calculation of the Hypothetical Price Impact

We add a buy order of 400 at a price limit of 330 to the example detailed in Panel A. Given the maximum price change of 10% this is identical to adding a market order.

Price Limits	Buy Quantity	Buy Cumulative	Sell Quantity	Sell Cumulative	Trading Volume
298	500	1902	700	700	700
299	400	1402	300	1000	1000
300	2	1002	500	1500	1002
301	400	1000	500	2000	1000
302	200	600	500	2500	600
330	400	400	0	2500	400

Given the new demand and supply curves, the opening price calculated by the procedure used at the TASE is 300, and the volume of trade is 1002. Hence, the price impact of the added buy order is [(300/299)-1]*100 = 0.33%.