THE UPSTAIRS MARKET FOR LARGE-BLOCK TRANSACTIONS: ANALYSIS AND MEASUREMENT OF PRICE EFFECTS

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Abstract

This paper examines the effects of large (block) transactions on the prices of common stocks. We develop an explicit model of the mechanism by which block trades are accomplished. The model yields several empirical hypotheses that are tested with a unique new data set. The data set covers nearly 4,240 transactions in the period 1985-1990, primarily in less liquid stocks. The blocks can be identified as either seller-initiated or buyer-initiated, and are all arranged in the 'upstairs' off-exchange market by either exchange members or non- exchange members. This knowledge is critical since the direction of hypothesized price effects depend on who initiates the trade and where it is executed. We find price impacts are positively related to trade size, and that this relation is non-linear, as predicted by the model. Trades executed on the OTC market have significantly larger price impacts than the impacts for comparable trades on the NYSE or AMEX. Further, there are significant differences in the price response to buyer-initiated and seller-initiated block trades.

1 Introduction

In 1975, about 17 percent of the shares traded on the New York Stock Exchange (NYSE) were traded in blocks of 10,000 or more shares, an average of 136 per day. Just 10 years earlier, the corresponding figure was 3 percent, with an average of 9 blocks per day. In 1990, block trading had increased to 49.6 percent of NYSE share volume, with an average of 3,333 blocks per day. The dramatic growth in block trading has led to increased academic interest in the price effects associated with large-block transactions. Yet, little is known about the mechanism by which large block transactions are achieved in the so-called upstairs market.[1]

Understanding the functioning of the market for large blocks is important for both theoretical and empirical reasons. From a theoretical perspective, the block trading mechanism operates in a manner quite distinct from dealer markets which have been the primary focus of research. First, unlike a dealer market, block trading is not anonymous in that the trade is negotiated between the block trader and the initiator of the block, possibly mitigating the adverse selection costs that are present when trading is anonymous.[2] Second, the block market resembles a search-brokerage mechanism, with multilateral transactions, rather than a dealer system, with bilateral transactions, because block traders often do not take active inventory positions but search for contra-parties to the trade. These important differences in the microstructure of the upstairs and downstairs markets may be associated with significant differences in price formation.[3]

From an empirical perspective, much more is known about the price effects associated with block trading. A number of papers have documented significant price impacts associated with large transactions, and also that these measured impacts increase with the size of the trade.[4]

[1] Since most block trades are arranged off the exchange, the block market has been referred to as the 'upstairs' market, to distinguish it from the 'downstairs' dealer market.

[2] Glosten and Milgrom (1985) demonstrate that the bid-ask spread may reflect adverse selection costs, and Easley and O'Hara (1987) and Glosten (1989) show that these costs are increasing with trade size.

[3] See, e.g., Burdett and O'Hara (1987), Seppi (1990), and Grossman (1991) for theoretical models of the upstairs market.

[4] See, e.g., Scholes (1972), Kraus and Stoll (1972), Mikkelson and Partch (1985), Holthausen, Leftwich, and Mayers (1987), Ball and Finn (1989), Choe, McInish, and Wood (1991), and Seppi (1992).

The objective of this paper is to increase our understanding, from both a theoretical and empirical perspective, of the effects of large transactions in the upstairs market on the prices of common stocks. We develop a theoretical model of the block trading mechanism that yields testable hypotheses that formalize and extend previously articulated predictions about the price effects associated with a block trade. For example, consistent with previous research, our model predicts that there are permanent (information related) and temporary (liquidity related) price impacts that are related to the size of the block. However, our model refines the predicted relation between temporary impacts and trade size to be bounded for sufficiently large trades due to the search nature of the market. Also, we show that permanent price effects need to be measured over a longer pre-trade period than previously analyzed in the literature to account for information that is potentially revealed to the market while the block is "shopped" before the actual transaction.

We investigate these hypotheses using a unique new data set of block trades negotiated in the upstairs market. These data differ from those used in previous empirical examinations of block trades in several important respects:

(1) The data employed here enable identification of the trade as either buyer- or seller-initiated. As a result, our analysis is not subject to the identification problem of previous studies that classify trades as either buyer- or seller-initiated based on whether the trade occurred on a 'plus tick' or a 'minus tick.' [5] Further, the accuracy of tick rules used in prior work on daily data can be directly investigated.[6] In our sample, the use of a tick test applied to daily data would result in the misclassification of 6.5% of the seller-initiated trades and 20.1% of the buyer-initiated trades.

[5]Chan and Lakonishok (1992) report the ability to distinguish between buyer- and seller-initiated trades in their sample of institutional trades. However, their sample is still subject to identification problems since, unlike our sample, they cannot distinguish between trades initiated internally by the institution and those initiated externally. Thus, the purchase of a large block by an institution, arranged in the upstairs market, but initiated by a liquidity-motivated seller would appear in their data as a low- (negative-) cost buy order rather than an high-cost sell order.

[6]Holthausen, Leftwich, and Mayers (1990) examine a subset of their sample of trades to verify the accuracy of their tick classification scheme and find that the tick test correctly classifies only 53% of their trades. Robinson and White (1991) report very similar results using data for Canadian stocks that identifies buyer- and seller-initiated transactions.

(2) Whereas previous studies of price effects of block transactions in the U.S. markets examine NYSE block trades, the blocks examined here are from the NYSE, AMEX and the OTC National Market System (NMS). In addition, our block trades are for stocks that reside in the bottom half of market capitalization on the NYSE; thus, the results document block price effects for less liquid stocks than previous studies.

(3) The trades in our sample represent the entire amount of the block. This is especially important because our model predicts a significant relation between the temporary price impact and the size of the block. In our data, block size is measured without error because the order is not broken-up across different periods or firms.

(4) The data provide information on a number of other variables of interest. We also know the identity of the broker who arranged the trade and, therefore, can examine hypotheses concerning the relation between impacts and broker characteristics such as exchange membership. The data set also records the brokerage commissions paid to execute the block trades, information that provides us with perspectives on both the direct and indirect costs of trading large-blocks.

Our empirical results are largely consistent with the predictions of the model:

(1) The *temporary* price impacts of block trades, especially for seller-initiated trades which make up the bulk of our sample, are substantially larger than found in previous studies, probably due to the relative illiquidity of the markets in which our sample of smaller stocks trade. Also, the temporary impacts are related to trade size in a nonlinear fashion.

(2) Consistent with most previous research, we find that although our *permanent* impacts measured on the block trade day are significant, they are not related to trade size. However, as suggested by the model, we find that the permanent impact on the trade date does not completely capture the information contained in the block trade. To the extent the block is "shopped" prior to the trade date (a distinct possibility for our illiquid stocks), there is information leakage that results in price movements prior to the trade date. We find that price movements prior to the trade date are significantly related to trade size, an instrument for the amount of information contained in the trade.

(3) We find significant asymmetries in the price impacts of buyer- versus seller-initiated trades. These asymmetries may reflect differences in the initiator's motivation for trade; buyer-initiated trades may be more likely to originate from traders with private information.

We view these results as characterizing more accurately the implicit and explicit costs of trading large blocks of stock in the upstairs market. The implications of our model for large trades, and the associated results, may also be useful for empirical studies of price impacts in the 'downstairs' market. Specifically, researchers need to be careful about assumptions of linearity of the relation between price impact and trade size when the range of trade size under study includes very large trades that were likely to have been negotiated in the upstairs market.[7]

The paper proceeds as follows. In section 2 we describe the process by which block trades are arranged, and develop a model of block trading that provides a set of testable hypotheses. In section 3, we describe our data and provide summary results for our sample of block trades. Section 4 reports on tests of our model's hypotheses and the corresponding implications for assessing the implicit costs of trading. Section 5 summarizes the paper.

2 A Model of the Upstairs Market for Block Trades

2.1 An Overview of the Upstairs Market

The operation of the upstairs market is quite different from the familiar dealership market, so before describing the model formally, we briefly review the mechanics of block trading. The process begins when the initiator of a large-block transaction contacts a competitive block trader. Unlike a specialist, the block trader is not under an affirmative obligation to take the other side of the transaction. Rather, a typical block trader will use his client list to locate contra-parties for the block. In this respect, the mechanism resembles a search or brokerage market. Locating potential contra-parties for the block is costly and the block

[7]For example, Hausman, Lo, and MacKinlay (1990) use an ordered probit model to analyze intraday price movements. They report that to achieve a reasonable fit for their model they had to truncate large trades in addition to taking a logarithmic transformation of order size. Other researchers, e.g., Glosten and Harris (1988), have noted that the estimated effect of quantity on price is lower than expected.

trader charges commissions to offset his search costs. The more contra-parties the block trader finds to take the opposite side of the trade, the smaller the price impact of the block, but the higher the commission costs.[8] The block trader also acts as a repository for his clients' latent demands to trade, in the event that an active buyer or seller should appear.[9] These latent demands, much like limit orders, provide liquidity and limit the price impact of the trade.

After identifying contra-parties to accommodate the trade, the block trader determines the price at which the block will clear, essentially playing the role of a broker who brings buyers and sellers together. Often, the block trader will 'position' part of the block into inventory to limit the price impact of the trade, acting as a dealer as well as a broker. As the block trader is risk averse, he or she will not position the block without price concessions from the initiator. In a competitive market, the block trader must obtain the best possible price for the initiator. In equilibrium, the block trader simultaneously determines the total commission fees, the portion of the block he or she will position, and the block price, given the strategic choices of the other agents.

Once the trade has been arranged, it is brought to the exchange floor for formal execution if the block broker is an exchange member. Crossing may require additional trades with pre-existing limit orders on the specialist's book. To avoid such restrictions, many blocks are crossed after exchange hours on international markets. Blocks arranged by third market (non-exchange) brokers do not require crossing with the specialist. We turn now to the formal model of this block market.

2.2 The Basic Framework

Consider a market for a single risky security and a riskless asset, the numeraire.[10] The unknown value of the security at time T in the future is a random variable, denoted by

[8] Burdett and O'Hara (1987) develop a model of sequential search where the optimal number of searches is determined by the information costs of locating additional bidders.

[9] Grossman (1991) argues that the upstairs market provides a mechanism by which these latent demands can be expressed.

[10] Without loss of generality, we normalize the riskless rate of interest to zero.

$\tilde{v}$. We are concerned with the price path of the security around a block transaction that occurs at calendar time t_b. Let t_0 be the calendar time of the trade preceding the block, t_1 be the time of the trade immediately after the block, and t_d be the time at which the decision to trade the block is made, where $t_d < t_0 < t_b < t_1 < T$. Associated with trading at times t_d, t_0, t_b, and t_1 are the prices p_d, p_0, p_b, and p_1 respectively. Note that only the block transaction price p_b represents a trade in the upstairs market; all other prices represent 'downstairs' dealer-auction market prices.

Our objective in the following subsections is to develop a simple model of block trading to analyze the price movements around the time of the trade. It is useful to distinguish between the *permanent* and *temporary* components of the price changes around a block trade.[11] The permanent component represents the change in the market's perception of the security's value due to the block transaction. Following previous empirical research, we define the permanent component, π, as the deviation of the price following the block from the price before the block:

$$\pi \equiv p_1 - p_0.$$

We also find it useful to define a new measure of a permanent impact with reference to an earlier price. Let $\pi^d \equiv p_1 - p_d$ represent the permanent impact relative to the decision price. We argue below that on both theoretical and empirical grounds the permanent impact is best measured using π^d, not π as do most empirical researchers.

The temporary component represents the transitory price movement necessary to provide the liquidity to absorb the block. We define the temporary component, τ, as the deviation between the block price and the price following the block where:

$$\tau \equiv p_b - p_1.$$

The total price impact associated with the block trade, $p_b - p_0$, is the sum of the two components. We focus primarily on the temporary component which captures the price response to the actual mechanics of block trading.

[11]These distinctions are often used in the empirical literature on block trading. See, for example, Kraus and Stoll (1972).

With these definitions, we turn to the formal model of the block trading mechanism. There are three types of agents in the model: a trader who initiates the block trade, a block trader (market maker) who helps arrange the trade, and a group of traders who take the opposite side of the block transaction. Agents maximize their utility given their conjectures regarding the strategic behavior of other agents and their beliefs about the value of the security. In the Bayes-Nash equilibrium, agents' conjectures regarding strategies are correct and their predictions of the asset's value are based on rational expectations.

We examine the trading sequence in reverse order, analyzing first the traders who eventually take the opposite side of the block, and then considering the block trader's choice of the number of contra-parties to locate and the amount to position, and finally the strategy of the initiator of the trade.

2.3 The Decision of a Potential Trader

Let Q represent the number of shares the initiator wishes to trade, where $Q > 0$ is interpreted as a buy order and $Q < 0$ is a sell order. The trade size chosen by the initiator is determined endogenously, and we describe the optimization problem below. The initiator contacts a block trader who maintains a list of clients or potential traders. Each of these traders (denoted by $i = 1, \ldots, N$) has a mean-variance utility function over final period wealth of the form:

$$E_i[\widetilde{W}_i] - \left(\frac{\rho_i}{2}\right) \sigma_i^2[\widetilde{W}_i] \tag{1}$$

where $\widetilde{W}_i$ is the (random) wealth at time T, ρ_i is trader i's coefficient of absolute risk aversion, and $E_i[\cdot]$ and $\sigma_i^2[\cdot]$ represent the mean and variance operators, given trader i's information. We assume that the block trader and the trade initiator also have mean-variance utility functions of this form. Wealth $\widetilde{W}_i$ is a random variable given by:

$$\widetilde{W}_i = (\tilde{v} - p_b)q_i + c_{0i} \,. \tag{2}$$

where $\tilde{v}$ is the final-period value of the risky asset, q_i is the number of shares of the risky security traded by i, with the sign convention that purchases are positive and sales are negative, c_{0i} is trader i's initial cash holdings, and p_b is the price at which the shares are traded. Substituting equation (2) into equation (1), and maximizing utility with respect to q_i, we derive the demand function for trader i:

$$q_i = \frac{E_i[\tilde{v}] - p_b}{\rho_i \sigma_v^2} \tag{3}$$

The mean and variance are conditional upon information concerning the block size (i.e., we assume Q is observed by all these traders) as well as any information available regarding the identity of the trade initiator and his motives for trading. This assumption requires some comment. If a counter-party observed only the portion of the trade offered by the block trader, but had rational expectations regarding how a large-block trade was broken-up, they form unbiased expectations about the size of the total order, and hence make unbiased inferences about the value of the asset. Thus, the assumption is a convenient way of saying that the counter-party traders have rational expectations. For simplicity, we also assume that contra-parties have homogeneous beliefs and have the same attitude toward risk. This implies that q_i is the same for all traders. Differences in beliefs or risk would lead to differences in the amount bought or sold across traders, but would not substantially affect our analysis of the price movements around block trades.

Consider the case of a seller-initiated block (i.e., $Q < 0$) and suppose the block trader has located $N \geq 1$ potential 'buyers' for the block. (For the moment, we take N as given.) Let z represent the amount of the block positioned by the block trader, with the usual sign convention that $z > 0$ represents a purchase. The market clearing condition is $-Q = \sum_i q_i(p_b) + z$, so that the block price is a function of Q, given z and N, which we denote by:

$$p_b(Q; z, N) = E[\tilde{v}] + \frac{Q + z}{N\alpha} \tag{4}$$

where $\alpha = \frac{1}{\rho \sigma_v^2}$. Note that the block trader cannot take the same side of the trade as the initiator, implying that z and Q are of opposite sign.

Equation (4) demonstrates that the block price is affected by the size and direction of the trade. It also shows that the block trader's ability to find willing traders to participate in the block transaction on the opposite side or to position the trade will mitigate the price impact of the block. Whether the block trader positions the trade or not depends on the costs of absorbing shares into inventory and his estimate of the value of the security. The following subsection models this decision explicitly.

2.4 The Decision of the Block Trader

The equilibrium price of the block depends on the block trader's actions in determining the number of contra-parties found and the amount of the block positioned. We assume that block traders are competitive, a reasonable assumption given that there is no binding commitment by the initiator.

Consequently, the block trader chooses the number of potential traders and the amount to be positioned to ensure the best price (net of commission costs) for the initiator, subject to the block trader being no worse off than before the trade. In other words, the decision must leave his utility at the reservation level, i.e., the utility from pre-trade wealth.

The block trader, like other traders, is assumed to have a mean-variance utility function over final period wealth. We assume that any commission income the block trader obtains is exactly offset by his (observable) costs, in keeping with our assumption of a competitive market. Accordingly, if the block trader positions z, his utility is given by equation (1):

$$E[U(\widetilde{W})] = (E[\tilde{v}] - p_b)z + c_0 - \left(\frac{\rho}{2}\right)\sigma_v^2 z^2 \tag{5}$$

where c_0 is the block trader's holding of riskless assets. Then, the position taken by a competitive block trader z satisfies $E[U(\widetilde{W})] = c_0$. Observe that one solution to this equation is $z = 0$, implying that with fixed inventory costs, the block trader is unwilling to position the block at the block price. Indeed, many block traders act only as brokers, and will not to take any part of the order into inventory.[12] However, there is an alternative solution that dominates the trivial solution. Setting expected utility in equation (5) to the reservation

[12] Such policies may reflect inventory carrying costs or the difficulty for the principal (i.e., the shareholders of the block trading firm) in monitoring the actions of the agents (i.e., those responsible for making trading decisions) in real time.

level of c_0, we see that the amount the block trader wishes to position is given by:

$$z = 2\alpha(E[\tilde{v}] - p_b). \tag{6}$$

Equation (6) shows the block trader's demand is price sensitive, and depends on N, which we still take as given, only through the price p_b. As block positioning reduces the price impact of the trade, the initiator is strictly better off when z is positive than when $z = 0$, and a block trader who is willing to position part of the transaction will do so in a competitive market.[13] Later, we consider the special case where $z = 0$, i.e., the block trader is a pure broker, not a broker-dealer.

Using equations (6) and (4), the block price is:

$$p_b(Q; N) = E[\tilde{v}] + \frac{Q}{\alpha(N+2)}. \tag{7}$$

In an efficient market, the post-trade price in the downstairs market p_1 reflects the expected value of the security, given public information and the size of the trade, i.e., $p_1 = E[\tilde{v}]$. Equation (7) implies, therefore, that the temporary effect is:

$$\tau = p_b - p_1 = \frac{Q}{\alpha(N+2)}. \tag{8}$$

We have assumed so far that the number of contra-parties, N, is a constant; we now consider the more realistic case where the block trader can search for potential contra-parties to the transaction. Since locating potential buyers and sellers is costly, block traders charge commissions to find additional contra-parties to absorb the block. Increasing the number of traders participating in the block transaction increases search costs and hence the initiator's commission fees, but decreases the price impact faced by the initiator since the block is absorbed by more contra-parties.

[13]This presumes that the block traders do not spread the order amongst themselves, which is a reasonable assumption given the way the market functions. For example, Robinson and White (1991) report that transactions between block traders are quite rare. If the block trader can get K other block traders to share in the amount positioned, then equation (6) is modified by replacing α with α/K, and the rest of the analysis is unchanged. Later, we extend the model to permit costly search for potential contra-parties, some of whom may be other block traders.

We assume the commission fees offset the block trader's search costs so as to keep expected utility constant, in keeping with our assumption of a competitive upstairs market. A competitive block trader chooses the number of searches to minimize the total expected execution costs, which consist of the total price impact and the direct commission costs, of the initiator. At the optimal number of searches, the marginal cost of locating an additional trader must equal the expected marginal benefit in terms of a better price on the entire amount of the trade. In a competitive market with no agency costs, all upstairs market makers must quote prices that minimize total execution costs. Otherwise, competitors could quote better prices and still earn positive economic profit.

Formally, we suppose the block trader already has a client list of n_0 potential traders, where $n_0 \geq 0$. If n_0 is small, even a small trade may have a large price impact, so the block trader may find it optimal to find additional parties to accommodate the trade. Suppose that the block trader can locate additional traders through a search process. We assume that the marginal cost of finding a trader is $\phi \geq 0$. Here, ϕ represents not only the direct cost of contacting a potential trader, which is generally quite small, but also the costs associated with the eventual physical distribution of the securities and the potential reputational costs if the trade turns out to be informationally motivated.[14] Let n_s be the number of traders found through the search process, so that $N = n_0 + n_s$.

Burdett and O'Hara (1987) suggest that the greater the search intensity, the greater the pre-trade price impact. They construct a model where a block trader searches sequentially for contra-party traders, and the marginal search costs are interpreted as the marginal permanent price impact from revealing the impending trade to an increasingly large group of traders. Here, because traders have rational expectations, the transaction price of the block reflects the trade size irrespective of when this information is revealed. Indeed, if it were possible for a block trader to somehow fool counter- parties into underestimating the size of the total trade by limiting the number of searches, he or she would soon develop a reputation for such actions and traders would avoid dealing with him. The effect of search on the

[14]In our model, all contacts lead to eventual trades, an assumption that can be relaxed by allowing potential traders to have dispersion in their reservation prices without altering our basic conclusions.

permanent price impact is not a real cost and is not included in ϕ.

However, as suggested by Burdett and O'Hara (1987), it is likely that increasing the number of counter-parties increases the speed at which the market incorporates the news of the block. Accordingly, we assume that the greater the search intensity (as measured by N), the greater the information leaked to the market, and hence the closer the prior price p_0 to the eventual post-trade price, p_1. We discuss this further when we model the permanent price impact.

Note that the costs for locating contra-parties may differ for buyer- versus seller-initiated trades. Ignoring integer constraints (i.e., treating n_s as a continuous variable), the marginal cost to contacting a potential trader is ϕ. The marginal revenue is the expected decrease in the price impact as a result of a change in the number of traders beyond n_0, multiplied by the size of the trade. Formally, marginal revenue is the derivative of total revenue $-Qp_b(Q; n_0 + n_s)$ with respect to n_s, where $p_b(Q; N)$ is the price functional in equation (7). Equating expected marginal revenues and costs implies that the optimal number of traders identified through the search process, assuming an interior solution, is:

$$n_s = \frac{|Q|}{\sqrt{\alpha\phi}} - n_0 - 2 \tag{9}$$

If the number of traders implied by equation (9) is not positive, we have a corner solution and $n_s = 0$. In equilibrium, therefore, the block is divided equally among N ($N = n_0 + n_s$) traders where:

$$N = \max[\frac{|Q|}{\sqrt{\alpha\phi}} - 2, n_0]. \tag{10}$$

Substituting equation (10) into equation (7), we see that in the case of a block sell:

$$p_b(Q) = p_1 - \min[\frac{|Q|}{\alpha(n_0 + 2)}, \sqrt{\frac{\phi}{\alpha}}]. \tag{11}$$

Equation (11) shows that the temporary price impact of a block sale, $p_1 - p_b$, is bounded below by $\sqrt{\frac{\phi}{\alpha}}$, the level at which the block trader actively searches for counter-parties to the trade. Setting $n_s = 0$, the critical size limit can be easily computed from equation (10) as $\bar{Q} = \text{sign}(Q)\sqrt{\alpha\phi}(n_0+2)$. For a small sized sell order (i.e., for $0 > Q \geq \bar{Q}$), it may not pay to engage in costly search, and in this case, the block price is a decreasing function of trade size. A similar result obtains for block buys, although the upper bound may be different because it may be costlier to find traders who are willing to sell or sell short. We have established proposition 1.

Proposition 1 *For blocks below a critical size, the temporary price component is a linear function of trade size. For blocks above the critical size limit, the temporary price component is a constant which is positively related to the costs of locating contra-parties, the degree of risk aversion, and the variance of the risky asset's return.*

The proposition implies that when the block trader can search for contra-parties to the block, the temporary component is a non-linear function of trade size. For trades below $\bar{Q}$, the block trader acts as a market maker, setting prices in the same manner as a 'downstairs' dealer. Thus, our model can accommodate a downstairs system co-existing with the upstairs market for small trades. If there are fixed costs to going upstairs, the dealer market will be preferred for small trades. However, for trades beyond $\bar{Q}$, the upstairs market produces lower price impacts than the dealer market because search is possible. It is the search-brokerage aspect of the upstairs market that bounds the temporary impact. Evidence consistent with this is reported by Robinson and White (1991), who find that for relatively small blocks (under 20,000 shares), both block traders and dealers actively trade on a principal basis, but that as block size increases, market makers interest declines substantially.

Note that our assumption that ϕ is a constant important for this result. Allowing for diseconomies beyond a certain point implies that the temporary component begins to rise again after a certain point. For example, if the number of potential traders is fixed, then equation (8) implies that the temporary price effect is linear in block size once the pool of counter-parties is fully tapped. Proposition 1 implies that a block trader with an efficient networking operation will have lower search costs (i.e., lower ϕ) and hence a smaller temporary effect. Our data allows us to distinguish trades executed in the upstairs market through exchange-member brokers from those executed by third-market (non-exchange member) brokers who specialize in block transactions. Since the third-market brokers have larger and more efficient networks, the proposition implies that the temporary effects associated with transactions executed through third-market brokers should be less than that of exchange members, particularly for larger trades where locating contra-parties is essential to minimizing the price impact of the trade. Since the costs of finding buyers may differ from the costs of finding sellers, the price effects of buyer and seller-initiated transactions may be asymmetric. Finally, if more is known about higher priced securities (or alternatively, larger market capitalization firms) so that σ_v^2 is decreasing with the mean of $\tilde{v}$, then a higher initial price (p_0) implies a higher degree of demand responsiveness (i.e., α), and hence that the size of the temporary effect is decreasing in price.

In our model, commission costs are determined endogenously, so that we can describe them explicitly. Using equation (10), the total commission fees paid by the initiator are $C = \max[|Q|\sqrt{\frac{\phi}{\alpha}} - \phi(n_0+2), 0]$. Observe that for $|Q| > \sqrt{\alpha\phi}(n_0+2)$, the commissions paid are a linear function of trade size. The following proposition is immediate:

Proposition 2 *For block trades above a critical size, commission costs are an increasing linear function of trade size, where the slope coefficient is positively related to search costs, risk aversion, and the variability of the asset's return.*

Intuitively, while higher search costs imply higher commissions, greater price responsiveness implies fewer searches and lower commission costs. We note that if the block trader incurs fixed costs in arranging the trade, the amount positioned is zero, and the commission schedule is a linear function of trade size.

The model also has implications for the amount of the block positioned by the block trader:

Proposition 3

- *If the block trader is a broker-dealer, the amount positioned, as a percentage of trade size, is a decreasing function of block size beyond a critical level; below this level, the amount positioned is a constant fraction of block size.*

- *If the block trader is a pure broker (i.e., $z = 0$), the temporary price impact of a block is larger and commission costs are higher than for a block positioner. The temporary* *price impact is still a bounded function of trade size.*

The first part of the proposition follows immediately from our earlier discussion of the search-brokerage activity of the block trader. The second part of the proposition relates to a special case where the block trader is a pure broker and does not act as a market maker. Setting $z = 0$ in equation (4), we obtain $p(Q; N) = E[\tilde{v}] + \frac{Q}{N\alpha}$, where the number of traders found is given by $N = \max[\frac{|Q|}{\sqrt{\alpha\phi}}, n_0]$. Using these relations, the block price can be expressed as:

$$p_b(Q) = p_1 - \min[\frac{|Q|}{\alpha n_0}, \sqrt{\frac{\phi}{\alpha}}]. \tag{12}$$

Then, the result follows immediately from comparing equations (11) and (12). Thus, irrespective of whether the block trader is simply a broker or acts as a broker-dealer by positioning part of the block, the key insight of proposition 1, i.e., that the temporary impact is bounded, remains true.

Direct evidence for the first part of proposition 3 is provided by Robinson and White (1991). Using detailed data on block trades in 29 Canadian companies listed on the Toronto Stock Exchange and a U.S. stock exchange, they find that registered traders (market makers) and block traders are less likely to take a position in a block trade as the block size increases. Further, they find that block trades between client investors who by-pass block positioners and market makers have greater price effects and are more likely to occur outside the quoted bid-ask spread than block trades completed with the assistance an intermediary.

We turn now to the optimization decision of the initiator.

2.5 The Decision of the Initiator

To close the model we must describe the initiator's choice of order size. We assume that the full-information price of the risky asset, v, can take on one of two possible values, v_1 and v_2, where $v_1 < v_2$, and suppose that, prior to the trade decision, the probability that $v = v_1$ is μ. As a result, the downstairs price when the block trader is first contacted is $p_d = \mu v_1 + (1 - \mu) v_2$.[15]

[15]This implicitly assumes that the outstanding supply of the security is zero, a convenient normalization.

Given the strategies adopted by the traders and the block broker, the initiator (indexed as agent 0) faces a price schedule that is a function of trade size, denoted by $p_b(Q)$. From equation (11), this price reflects not only the temporary effects of the trade but also the fact that the expected beliefs of the counter-parties to the trade, $E[\tilde{v}]$, may also be a function of trade size because the initiator may have private information. We assume the initiator, like all other agents in the model, is risk averse. There are two types of initiators. The first type, an informed trader, is assumed to observe the value of the risky asset at time T. The second type, the uninformed trader, has no private information and trades to hedge an undiversified position. Let x denote the uninformed initiator's (unobservable) holdings of the risky asset, where x can be positive or negative.

The initiator, who has rational expectations, recognizes the effect of trade size on price and chooses Q accordingly. Thus, Q is the solution to:

$$\max_{Q} E_0[\tilde{v}](Q+x) - p_b(Q)Q - \left(\frac{\rho}{2}\right)\sigma_0^2(Q+x)^2 \tag{13}$$

where $E_0[\tilde{v}]$ and σ_0^2 denote the expected value and variance of the security from the initiator's viewpoint. This maximization problem is well-defined if $p_b(Q)$ is block price

For an informed trader, $E_0[\tilde{v}] = v$ and $\sigma_0^2 = 0$. By contrast, an uninformed trader's expectation of the asset's value is just the prevailing price in the market (before news of the impending block leaked out), i.e, $E_0[\tilde{v}] = p_d$ and $\sigma_0^2 > 0$. Intuitively, p_d is the expected value of the security in the downstairs market, while p_0 is the market price just before the trade. In our model, because of leakage in the search-brokerage process, p_0 reflects the downstairs market's perception about the value of the asset given public information about the size of the trade. This expectation gives some weight to the possibility that the trade was motivated by an informed trader. Thus, for a block seller, $p_0 < p_d$. However, if the initiator does not possess any private information, his beliefs are reflected by p_d.

Thus, in the case of a seller-initiated transaction, the expected value of the security from the viewpoint of the block trader and other contra-parties is a weighted average of the equilibrium price if the initiator were uninformed (i.e., p_d), and the equilibrium price if the initiator were informed, (i.e., v_1), where the weights are the posterior probabilities that the trader is uninformed and informed, respectively, given the trade size. Since the post-trade price is this expectation, we obtain:

$$p_1 = p_d + \zeta(Q)(v_1 - p_d) \tag{14}$$

where $\zeta(Q)$ denotes the market's posterior probability that the trader is the informed type, given the trade size.

In our model, it can be shown that the probability $\zeta(Q)$ is an increasing function of absolute trade size, for trade sizes beyond a critical level. To see this, consider two possible sell orders, Q' and Q'' such that $Q'' < Q' < \bar{Q} < 0$, and suppose that $\zeta(Q'') < \zeta(Q')$. From equations (14) and (11), we see that the temporary effect is constant implying that if $\zeta(Q'') < \zeta(Q')$, then $p_b(Q'') > p_b(Q')$. Since the profits of an informed initiator, given by $(v_1 - p_b)Q$, are strictly larger with Q'' than with Q', it follows that $\zeta(Q'') = 0$, which contradicts our initial assumption. It is straightforward to extend this argument.[16]

Now consider the pre-trade price p_0. As noted above, p_0 may already impound information about the size of the block, since the negotiation process involves leakage of information. To formalize this notion, we assume that the greater the number of counter-parties contacted, the more precise the public's estimation of the size of the block. Formally, let $\hat{Q}$ be the public's estimate of the size of the block at time 0 given the leakage in the upstairs market. We assume that, through leakage, the predicted size of the block is an increasing function of the number of contacts or equivalently the time spent shopping the block.[17] Using the argument used to derive equation (14), we have:

$$p_0 = p_d + \zeta(\hat{Q})(v_1 - p_d) \tag{15}$$

Recall that the permanent component $\pi = p_1 - p_0$. Then, from the discussion above we have $\pi = (\zeta(Q) - \zeta(\hat{Q}))(v_1 - p_d)$. This expression shows that if the block has been extensively

[16] In equilibrium, the price schedule $p_b(Q)$ is the best-response to the initiator's trading strategy summarized by equation (13). See, for example, Kyle (1985), Admati and Pfleiderer (1988), Foster and Vishwanathan (1990), who provide conditions under which the revision in beliefs is linear, and Glosten and Harris (1988) and Madhavan and Smidt (1991), who estimate models based on this assumption.

[17] Since N is a (weakly) increasing function of Q, this assumption follows from rational expectations.

'shopped' (so that $Q = \hat{Q}$), the permanent component may be zero, and there may be no permanent effect associated with even a very large trade. Indeed, permanent effects may be negative, if the realized trade is smaller than was anticipated at time t_0. With the alternative definition of the permanent effect, i.e., π^d, no such problems arise. The following proposition follows immediately:

Proposition 4 *The permanent impact relative to the decision price (i.e., π^d) is an increasing function of trade size and the prior probability that the trade is information motivated. The permanent impact relative to the pre-trade price (i.e., π) is a decreasing function the number of searches (or the time since the trading decision), and can be negative.*

From an empirical perspective, the proposition clearly illustrates the need to appropriately define the permanent impact. Using the pre-trade impact can produce highly misleading results, as we show below.

The proposition implies that if higher priced stocks (associated with higher market values) suffer less from problems of information asymmetry, they will have lower permanent effects. Note further that the block market differs from the standard dealership market in that trading is not anonymous, so that ζ may depend on the identity and reputation of the trade initiator. So, blocks of the same size may have very different price impacts. For example, a large order placed by a pension fund that frequently rebalances its portfolio may be associated with a low value of ζ and hence a small price effect.[18] It is also possible that ζ depends on whether the trade is buyer or seller-initiated. For example, many block traders keep detailed records of the stock holdings of large investors. Thus, the block trader may be more likely to ascribe liquidity motives to a sell order from an initiator whose total stockholdings are large relative to the order. With buy orders, it may be more difficult to discern liquidity motives for trade, especially if the initiator has no current stockholdings.

Propositions 1–4 yield a number of hypotheses that are testable given our data. In the following section, we discuss these data in more detail and provide some summary results.

[18] Forster and George (1991) show that anonymity plays a critical role in determining market quality.

3 Data and Summary Results

3.1 The Data

The data file used is constructed from the transaction records of a trader of small, illiquid stocks in the upstairs market. The block trades that we examine are those in which the firm selectively takes the opposite side of large trades, initiated by others, in which the firm is willing to take a position — in particular, stocks that reside in the smallest half of market capitalization.[19] Thus, the block trades in our sample represent externally initiated trades where the firm was the passive counter-party. A condition for the firm to take the other side of the trade is that they "clean out" (get all of) the initiator's order. As a result, our block quantities represent the entire amount of the trade, which is the relevant quantity for testing the hypotheses suggested by the model.

Our data consists of trade prices, number of shares traded, trade date, commissions paid and broker identity for block transactions during the period July 1985 to December 1990. The trades are not time-stamped (within the day), although given the extremely large size of these blocks relative to the normal volume of trading in these shares, the block transactions would be easily identifiable on intra-day transactions tapes. The sample used consists of 3,394 seller-initiated blocks and 846 buyer-initiated blocks.

To examine the price effects associated with these block transactions, we compute total, permanent, and temporary price impacts on the day of the block. We compute the total price impact, temporary impact, and permanent impact (all in return form) as, respectively:

$$\Delta = \frac{p_b - p_0}{p_0} \tag{16}$$

$$\tau' = \frac{p_b - p_1}{p_b} \tag{17}$$

$$\pi' = \frac{p_1 - p_0}{p_0} \tag{18}$$

where p_0 is the closing price of the stock on the trading day prior to the block trade, p_1 is

[19] The cutoff is determined by the median market capitalization for stocks trading on the NYSE, but their list also includes AMEX and OTC National Market System (NMS) stocks that fall into this category.

the closing price of the stock on the trading day after the block trade, and p_b is the price of the block.

Since infrequent trading is prevalent in our sample of small stocks (our trades are sometimes the only trade of the day), the use of closing prices instead of intraday pre- and post-block prices will not likely influence our computed price impacts adversely. Additionally, nearly 15 percent of our block trades are reported as the closing price on the CRSP file for that day. For this reason, we measure the temporary and permanent impacts out to the close of the trading day after the block.[20] To detect any longer-run effects of the block transaction on the price of the stock, we also recorded returns for the 21 trading days (1 month) on both sides of the block day.

Recall that the block price effects described in propositions 1 and 4 are stated in dollar price changes. Our predictions regarding the effects of trade size on the price effects are unaffected by using a definition in returns form. However, the predictions relating to prices require more care. The total, permanent, and temporary components are hypothesized to be decreasing functions of price when they are defined in absolute terms. Therefore, defining them in return form (dividing by price) does not alter our hypotheses about the effects of price levels on these effects.

Before describing our results, we must address a potential difficulty, namely that the empirical hypotheses suggested by the model relate to a particular stock whereas our empirical analysis is cross-sectional. In our case, however, this does not represent a serious problem. First, the stocks in our sample are relatively homogeneous since they are all smaller NYSE stocks or comparably sized AMEX or OTC-NMS stocks. Second, the model's predictions are tested in such a way as to minimize the distortions created by differences among stocks in market capitalization and trading activity, for example, by scaling trade size by the number of outstanding shares. Third, we performed tests for sub-samples of the data sorted by size and price, and verified that our results held in general.

[20]There is also the possibility of bid-ask bias as suggested by Blume and Stambaugh (1983), which would tend to reduce the measured price impact. However, when impacts are defined in level form, there is no systematic bid-ask bias. Since our results also hold for price changes, the potential biases appear to be small.

3.2 Summary Results: Seller-Initiated Trades

Tables 1 and 2 contain summary statistics for our sample of blocks. Table 1 reports results for the seller-initiated blocks, table 2 for the buyer-initiated blocks. The tables contain estimated means (standard deviations) of total, temporary, and permanent price impacts for the sample. Also included are the sample medians for the trade price, market capitalization, number of shares in the block, and the number of shares in the block expressed as a percent of the total number of shares outstanding, as well as the number of blocks.

Panel A of Table 1 reports summary statistics measured within each sample year and Panel B reports statistics across all three exchanges for the entire period. Averaged over all years and all exchanges, the total impact of the seller-initiated blocks is -4.06 percent. Consistent with previous research, there appears to be a large 'temporary' price effect (-2.94 percent), and a smaller (1.34 percent) 'permanent' price effect associated with the block trade. These block-day price changes are more dramatic than those documented previously because of the illiquid markets in which the stocks in this study trade. [21] The median price of the blocks here is $7.79 for firms with a median market capitalization of $54 million. Some blocks are smaller than 10,000 shares, the definition applied by the NYSE in classifying block transactions. We include all trades of at least 5,000 shares, since a trade of this magnitude in a very thinly traded stock may represent an economically large trade.

The findings are largely the same in each year of the sample, although there does appear to be a tendency for the blocks in the period 1987 to 1990 to display substantially larger temporary price effects – about 3 percent compared to 1.5 percent and less in the first two years. The results for the separate exchanges, reported in panel B, tell basically the same story. Interestingly, the OTC NMS blocks displayed larger temporary effects (-3.28 percent) than the NYSE and AMEX blocks (-1.54 and -2.73 percent), although the market

[21] These results are consistent with the impacts reported by Loeb (1983) for block trades with a similar degree of difficulty involving stocks with similar market capitalizations. To the contrary, Chan and Lakonishok (1992) report an average total impact of 0.25 percent for a sample of large institutional trades of small stocks. However, these latter results seem unreasonably low, not only relative to other impacts reported in the literature, but also relative to the typical bid-ask spreads of 2 to 4 percent for such stocks. In such large trades, the initiator would presumably pay at least half the bid-ask spread, even if he didn't move the price of the stock.

capitalizations of the NMS block firms were generally smaller and the size of the NMS blocks were larger. We estimate regressions below that test for differences across exchanges while holding constant price and trade size.

The magnitude of the block-day price effect is perhaps placed in better perspective in figure 1 which contains the average price behavior for the seller-initiated blocks for the two months surrounding the block trade date. To compute the series, we first computed daily returns for each block-firm's stock for the two months surrounding the block day. Value-weighted returns were then computed across all stocks for each day in the two-month period, and a wealth series was created by initially 'investing' $1 and recording the day-by-day movements in this wealth index. The spike on the block day (the temporary price effect) is an obvious departure from the downward trend that these stocks experience in the month prior to the block trade (which itself is more than 5 percent).[22] After the block trade, there is no obvious trend in the returns of the seller-initiated blocks. The downward movement in price before the block suggests that the permanent price effects computed in previous studies, using only prices on the day of the block trade, may reflect a *lower bound* on the actual permanent effects associated with the transaction. In many cases, blocks are unsuccessfully 'shopped' for several weeks prior to the actual trade date, permitting the market to incorporate the information associated with the block prior to the actual transaction.[23]

Finally, we note that for this sample, the use of the tick test to identify trades as seller-initiated transactions (i.e., by comparing the block price to the previous day's closing price) would result in 220 seller-initiated trades (about 6.5% of the sample) not being correctly classified.

[22] We reproduced figure 1 by computing *market-adjusted* returns for each stock for the 21 days on either side of the block day, where market-adjusted returns are defined simply as the firm's stock return less the CRSP equal-weighted market. The market-adjusted plot portrays the same downward trend prior to the block, with the same magnitude.

[23] See Nelling (1992) who has collected data relating to the length of time the blocks in our sample were shopped prior to the actual trade.

3.3 Summary Results: Buyer-Initiated Trades

Table 2 reports summary statistics for the sample of buyer-initiated blocks for the entire sample and separately for each year and by exchange. The table provides an interesting contrast with table 1 for the sample of seller-initiated trades. First, there are far fewer buyer-initiated trades than seller-initiated trades. Buyer-initiated trades constitute approximately 20% of the total sample; these proportions are very similar to the proportions reported in other studies of large trades. Second, the buyer-initiated blocks in table 2 tend to be for stocks with larger prices and market capitalization than those in table 1 since the firm's sell list will tend to contain larger stocks that are exiting the small capitalization universe in which it normally takes positions. Third, the price effects are in the hypothesized direction, but are of a somewhat smaller magnitude than for the seller-initiated results in table 1. Another difference between tables 1 and 2 is readily apparent; only after 1988 is the temporary impact of the right sign for this sample of buyer-initiated blocks.[24] Even after 1988, the magnitude of the temporary impact is very small. The proportion of the firm's dollar sell volume accounted for by buyer-initiated block trades declined sharply over this period.

The asymmetry in the temporary components of buyer- versus seller-initiated trades is puzzling. However, this result appears to be pervasive in the literature on block price impacts. Similar results are found in Kraus and Stoll (1972), Scholes (1972), Holthausen, Leftwich, and Mayers (1987), Ball and Finn (1989), and Chan and Lakonishok (1992). The asymmetry may arise because of differences in the information content of a buyer- versus a seller-initiated trade, as suggested when we modeled the initiator's decision.

For our data, the asymmetry may be partially explained by the fact that the passive investment strategy of the firm is common knowledge and presents an option to informationally motivated buyers. An initiator with private information knows that the firm is willing to sell stocks for liquidity reasons once the capitalization of these stocks exceeds the bottom half of NYSE capitalization. The fact that the temporary impacts had the wrong sign in the

[24]Table 2 does not report the temporary impact for those quintiles in which the temporary impact is greater than zero.

early years of our sample is consistent with the idea that the firm incorrectly assessed the probabilities of dealing with agents with private information in selling stock. Thus, while the firm may sell at a price above the last trading price, the price continues to rise following the trade; equivalently, the price set for the trade is too low relative to the market's expectation of the trade price because the firm is eager to sell for liquidity reasons. Thus, the temporary impact is subsumed into the permanent impact for buyer-initiated transactions. The decline in the dollar volume of the firm's block sales over this period (as a percentage of the firm's total selling volume) is also consistent with this hypothesis.

The direction of the temporary impacts for buyer-initiated blocks suggests the use of the tick test to identify trades as buyer- initiated transactions may produce serious biases; indeed, we find that 170 buyer-initiated trades (about 20.1% of the sample) would be not be correctly classified with this methodology. The permanent price effects in table 2 are largely the same for all the exchanges. Interestingly, the persistent upward post-block price movement for nearly three weeks for the buyer-initiated blocks documented in figure 2 reinforces the notion that the buyers may have been informationally motivated.

4 The Determinants of Block Price Effects

4.1 Summary Statistics

To measure the determinants of block price effects, we first simply divide the sample of blocks according to block size measured by number of shares traded as a percent of the total number of shares outstanding. Separately for the buys and sells, trades are sorted on trade size and divided into quintiles. Average price impacts are computed for each quintile. Table 3A reports results for seller-initiated blocks and Table 3B reports the buyer-initiated blocks. The findings for the seller-initiated blocks in Table 3A indicate that the total and temporary price impacts are positively related to the size of the block. Proposition 1 predicts that the absolute value of the temporary effect is positively related to trade size, so this finding confirms the model and is also consistent with previous research. Proposition 4 predicts that no particular relation between the permanent effect, as measured relative to the previous trade date, and the size of the trade. We find no obvious relation between the trade0day permanent impact and block size for the seller-initiated blocks. This finding is consistent with most results in the literature.[25]

Proposition 4 implies that measurement of the permanent component on the block date may understate the information effect if the block was extensively 'shopped' prior to actual execution. If that were true, then information is revealed in the pre-block price behavior, and the permanent effect measured relative to the decision price is an increasing function of trade size. To this end, we report the total price change for the 21 days prior to the block in the fourth column of Table 3A. The average pre-block price movements are strongly related to trade size, suggesting that the larger is the block, the greater is the tendency for the information component to be incorporated into price prior to actual execution of the block. In a cross-sectional regression of the pre-trade price change on the stock price and block size (as defined in tables 1 and 2), the coefficient on block size is -0.0112 with a t-value of -3.77. Intuitively, the very fact that a large-block trade is impending conveys information to the market (the so-called 'over-hang'), and the larger the block, the greater the information contained in that signal.[26]

Perhaps more convincing evidence in favor of this hypothesis is provided in a recent paper by Nelling (1992). Analyzing these same block data, but augmented with information on the number of days that the block was "shopped," Nelling (1992) finds a significant relation between the pre- trade price movement and the length of time the block trade took to arrange. This phenomenon is implicit in our model since the search process takes time and involves a leakage of trade information. Earlier studies that ignore the effect of pre-trade information leakage may understate the permanent impact. However, such information leakage may be less of a problem for the larger, more liquid stocks examined in most previous studies.

The results for the buyer-initiated blocks, given in Table 3B, are less clear. The average block- day price changes for the quintiles based on trade size do not display the same strong

[25]The exception is Kraus and Stoll (1972).

[26]An alternative, but less compelling, explanation for this finding is that the sale was triggered by the initial decline in price.

relation with trade size that was observed for the seller-initiated sample. There is some evidence of a relation between the total price impact and the size of the block, but it is less dramatic than for the seller- initiated trades. The permanent impacts, however, do appear to be strongly related to trade size.

Apparently for the buyer-initiated trades, there is less information leakage about the impending trade *prior* to the trade so that a significant relation between the permanent impact and trade size remains at the time of the trade. One explanation may be that block purchases, since they involve negotiations primarily with large current stockholders, occur under conditions of greater secrecy than block sales. Although there is evidence of significant pre-trade price movement in table 3B, it is not significantly related to trade size. The temporary impacts for buyer-initiated trades indicate that, in general, the post-trade price was at or above the block price.[27] As we noted above, this finding can be explained by our model if the firm under-estimated the signal content of buyer-initiated trades or was willing to sell stock at a lower premium than expected by the market because of its passive trading strategy. In the case of seller-initiated blocks, however, the firm selects among a large number of stocks that fall into its trading universe.

4.2 Regression Results

In this subsection we estimate regressions for the temporary and permanent impacts to confirm the summary measures reported in table 3. We begin by estimating the following regression for the temporary impacts:

$$\begin{aligned} \tau_i &= \beta_0 + \beta_1 D_i^{OTC} + \beta_2 PINV_i + \beta_3 Q_i + \beta_4 (Q_i - Q^{50\text{th}}).D_i^{50\text{th}} + \\ &\quad \beta_5 (Q_i - Q^{75\text{th}}).D_i^{75\text{th}} + \beta_6 D_i^{3rd} + \beta_7 Q_i D_i^{3rd} + \epsilon_i \qquad (19) \end{aligned}$$

where D_i^{OTC} is a dummy variable that equals one if block trade i is an OTC stock and zero otherwise, $PINV_i$ is the price inverse, Q_i is the (absolute) number of shares traded divided by the number of shares outstanding, Q^j is the j^{th} percentile of the distribution of shares

[27]We again do not report in the table the temporary impact for those quintiles in which the temporary impact is greater than zero.

traded, D^j equals one if Q_i exceeds Q^j and zero otherwise, D_i^{3rd} equals one if block trade i was done by a 3[rd] market broker and zero otherwise.

The regression equation (19) is motivated by our model. The coefficient β_1 allows us to test for systematic differences in the price impacts of exchange versus non-exchange transactions. The coefficient β_2 captures the effect of price on the temporary component. With price acting as a proxy for market value or liquidity, the effect should be negative. Proposition 1 predicts a non-linear relation between price impact and trade size.[28] In particular, the price impact is hypothesized to be increasing, but at a decreasing rate beyond a certain size. By including the slope dummies for trades exceeding the 50[th] and 75[th] percentiles, we can examine this hypothesis in a general way. In the case of a seller-initiated trade, for example, we would expect $\beta_3 < 0$ and β_4 or β_5 to be positive.

Table 4A reports estimates of equation (19). The first regression in panel A is for seller-initiated transactions, which comprise almost 80% of our sample. The coefficient of the OTC dummy variable, β_1, is significantly negative, suggesting that temporary costs are higher (for seller-initiated transactions, the temporary impact is negative) for non-exchange stock trades. The results show that there is a highly significant inverse relation between the temporary impact and the price level. This finding is consistent with our model since higher priced stocks tend to be associated with higher levels of market capitalization, making it easier and cheaper to find a counter-party for the trade. Further, more information may be available for higher priced stocks, implying counter-parties take larger opposing positions, reducing the temporary impact.

Turning to the effect of trade size, we find that the magnitude of the temporary impact is significantly related to trade size, as shown by β_3. Proposition 1 implies that, other things equal, the temporary effect is constant beyond a certain trade size. Evidence for this hypothesis is provided by the fact that the sign of β_4 is positive and almost equal in magnitude to the coefficient β_3. Thus, the temporary effect is largely constant for trade sizes above the median. Similarly, β_5 is also positive, although much smaller in magnitude.

[28]This is also predicted by Proposition 3 for the case of a block trader who acts solely as a broker.

Finally, the coefficients on the third-market broker dummy and interaction variables are both insignificant, indicating that neither the magnitude of the impact nor its relation with block size is affected by the choice of the broker.

The second regression in panel A contains results for the temporary impacts for buyer-initiated trades. As with the case of seller-initiated blocks, temporary impacts are smaller for exchange trades and for higher priced securities. However, there is one important difference from the previous case. The coefficients on the block size variables are exactly the reverse in sign of our predictions. Larger trade sizes appear to reduce the temporary price impact, but the trade size coefficients are not statistically significant. There are two possible explanations for this finding. First, the sample size for block buys is much smaller than that for block sells. Second, participants in the upstairs market know the identity and trading strategy of the management firm from whom we obtained these data. Consequently, when a stock moves out of the firm's trading universe, other traders know the firm has liquidity motivations for selling and submit buy orders. In this case, although a trade may be classified as buyer-initiated, the trade was really triggered by the firm's own trading strategy. The negative temporary impacts for buyer-initiated trades may be explained by this argument, which also provides an explanation for the seemingly anomalous findings of table 4A. As noted earlier, this finding is also consistent with the firm incorrectly assessing the probability that a buyer-initiated trade was informationally motivated. Finally, there is evidence that the temporary price impacts are lower for buyer-initiated trades executed through a third-market broker, as shown by β_6. However, since $\beta_7 > 0$, the variable costs are greater in the third-market.

Figure 1 suggests that using the pre-trade price to proxy for p_0 in computing the permanent impact may seriously understate the magnitude of this component, because the market impounds information conveyed by the impending block well before the trade. Accordingly, we measure the permanent impact using the price that prevailed 21 days before the block was traded. Table 4B contains results from estimating equation (19), where the dependent variable is this measure of the permanent impact. For seller-initiated trades the OTC dummy has no effect. However, the magnitude of the permanent impact is strongly inversely related to the price of the security. In contrast with the summary results in table 3A, we find evidence that larger trade sizes imply higher permanent impact for the seller-initiated trades, but this effect is also bounded for sufficiently large trade sizes as shown by the coefficients β_4 and β_5. For the third- market broker variables, only β_6 is statistically significant and negative, implying larger permanent effects for third-market brokers.

The estimates for the permanent impact regression for the buyer-initiated trades indicates that permanent effects are larger for OTC trades. However, the results for price are the opposite of that predicted; higher prices appear to induce larger permanent effects for buyer-initiated trades. Unlike the temporary price impacts for the buyer-initiated trades, the permanent impacts are positively related to trade size, as predicted, but the relation is weak. Again, the coefficients β_4 and β_5 indicate that the permanent impact is bounded for large trade sizes. The weak statistical significance of trade size is consistent with the 'buyer-initiated' trades being perceived as largely liquidity motivated. The third-market variables are insignificant.

When the permanent impact was measured using the previous day's price as the base, the regression provided little explanatory power; further, the magnitude of the impact was not related to trade size. This suggests that studies of price impacts that ignore the effect of the 'overhang' may seriously understate the permanent impacts of the trade.

To summarize, the results for seller-initiated trades provide strong support for the model. The results for buyer-initiated trades, however, are not so strong, possibly because there are far fewer buys than sells or because of systematic differences in the pricing of buyer-initiated versus seller- initiated trades.

4.3 Analysis of Commissions

The analysis so far has focused on the price impacts associated with large-block trades. These impacts provide a measure of implicit trading costs. In this section, we turn to the analysis of explicit trading costs. The data file contains information on the commissions paid for executing large-block trades. We use only commission data for NYSE and AMEX transactions where commission per share was greater than zero. (For some exchange transactions where commission data was not known, commissions were erroneously recorded as zero.) We also excluded obvious data errors where the per share commission was unreasonably large. After applying these filters, there were 428 seller-initiated transactions and 222 buyer-initiated transactions.

Proposition 2 implies that commissions are a linear function of the number of shares traded, where the slope coefficient depends on the costs of placing the security with counterparties. These costs may increase for higher priced securities, suggesting that commissions may also depend on the price level of the security. Cost factors may also lead to differences between the commissions charged by third-market brokers and those charged by member brokers. To test these hypotheses, we ran the following regression for buyer- and seller-initiated transactions:

$$C_i = \beta_0 + \beta_1 Q_i + \beta_2 (Q_i - Q^{50\text{th}}).D_i^{50\text{th}} + \beta_3 p_i + \beta_4 D_i^{3rd} + \beta_5 D_i^{3rd} Q_i + \epsilon_i \tag{20}$$

where, for trade i, C_i is the commission paid (in dollars), Q_i is the (absolute) number of shares traded (in thousands of shares), $Q^{50\text{th}}$ is the median number of shares traded, $D^{50\text{th}}$ is a dummy variable that equals one if Q_i exceeds the median and zero otherwise, p_i is the stock price, and D_i^{3rd} equals one if block trade i was done by a 3[rd] market broker and zero otherwise. The coefficient β_2 measures non-linearities in the commission schedule. The estimated coefficients are shown in the table below (where the numbers in parentheses are the t-statistics):

β_0	β_1	β_2	β_3	β_4	β_5	R^2
Seller-Initiated Trades						
−555.00	101.62	−35.72	32.14	−147	7.89	0.92
(−4.24)	(14.95)	(−4.85)	(6.90)	(−1.62)	(3.88)	
Buyer-Initiated Trades						
−492.64	110.23	−27.27	19.04	−54.56	−1.11	0.97
(−2.33)	(11.41)	(−2.59)	(3.74)	(−0.34)	(−0.35)	

The regressions show that explicit transactions costs are far from negligible; the per share commission cost is approximately \$0.11 for buyer-initiated trades and \$0.10 for seller-initiated trades below the median. The similarity in the commission costs for buyer- versus seller-initiated transactions is interesting because it suggests that differences in the costs of locating counter-parties cannot explain the asymmetries in the price impacts described earlier; rather, the differences between block buys and sells probably reflects differences in the motivations of the trade originators. The mean commission fee paid was \$2,400 for the 423 seller-initiated transactions in the sample. For the 188 buyer-initiated transactions, the corresponding figure was \$2,893. The coefficient β_2 is negative in both cases, perhaps reflecting economies of scale in creating trading networks. However, the size of β_2 relative to β_1 implies that the implied departure from linearity is not very strong. For both buyer- and seller-initiated transactions, there are strong price effects; commissions are higher for higher priced securities. The third-market dummy variables are insignificant for the buyer-initiated transactions (perhaps because of the smaller sample size), but the results for the seller-initiated transactions indicate that per share commission fees charged by third-market brokers are almost 8% higher than those charged by member brokers. Finally, the large negative intercept (which is statistically significant in both cases) is predicted by proposition 2; intuitively, commissions for small trades are negligible since these trades are positioned.

5 Conclusion

We examine the effects of large (block) transactions on the prices of common stocks. Block trading is accomplished through a search-brokerage market that is very different from the dealer market where most transactions are executed. Consequently, a study of the price effects associated with large transactions should explicitly incorporate the process of price formation in the block market. We develop a simple model of block trading and test its predictions using a unique new data set obtained from a trader of small, illiquid stocks in the upstairs market. These data are more refined than those available to previous researchers. The trades we examine are all arranged in the 'upstairs' off-exchange market and can be identified as either seller-initiated or buyer-initiated. This knowledge is critical since the direction of hypothesized price effects depend on who initiates the trade and where it is executed.

We examined the total, permanent, and temporary components of price movements around a block trade. The temporary price impacts for our sample of block trades for small stocks, especially for seller-initiated trades, are substantially larger than found in previous studies. The temporary price impact is strongly positively related to trade size but is negatively related to price. The impacts for trades executed on the OTC market are significantly larger than the impacts for comparable trades on the NYSE or AMEX. There is also evidence that the temporary price impact of block trades is bounded for large trades, as hypothesized. This finding suggests that care should be exercised in empirically modeling the relation between price impact and trade size when the trades under analysis include both trades executed in the downstairs market and large-block trades that were likely to have been negotiated in the upstairs market.

We find that the permanent impacts measured relative to the previous trading day are significant, but are not related to trade size. Consistent with the model, however, we find that the permanent impact on the trade date does not completely capture the information contained in the block trade. To the extent the block is "shopped" prior to the trade date there is information leakage that results in price movements prior to the trade date. We find that price movements prior to the trade date are significantly related to trade size. This result suggests that permanent price effects need to be defined relative to a longer pre-trade period than previously analyzed in the literature to be measured accurately.

We find significant differences in the price response to buyer-initiated and seller-initiated block trades. These differences are particularly important in the response of price impact to order size and in the size and behavior of the components of the total price impact. These asymmetries could reflect differences in the initiator's motivation for trade, where buyer-initiated trades may be more likely to originate from traders with private information than seller-initiated trades.

We find little difference in the price impacts between exchange and non-exchange (third market) brokers. Explicit commission costs are non-trivial and are related to order size in a manner consistent with the model.

In summary, the results presented here suggest that the process of large-block trading in the upstairs market is complex and has a significant impact on short-run price dynamics.

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Table 1

Summary Statistics for Seller-Initiated Block Trades for NYSE, AMEX and OTC NMS Stocks for the Period July 1985 to December 1990

	Price Change[a]			Number of Blocks	Median Price	Median Market Cap ($ mill)	Median No. of Shares Traded ('000s)	Trade Size[b]	
	Total	Temporary	Permanent					Median	Inter-Quartile Range
A. All Exchanges									
1985	−3.05	−1.27	−1.83	128	$7.82	$47	17	0.33	0.33
	(0.20)	(0.36)	(0.38)						
1986	−3.09	−1.46	−1.70	438	10.07	65	15	0.23	0.39
	(0.14)	(0.18)	(0.20)						
1987	−4.19	−3.14	−1.23	725	8.44	58	23	0.37	0.63
	(0.14)	(0.20)	(0.21)						
1988	−4.01	−3.28	−1.03	1082	6.75	49	25	0.38	0.64
	(0.18)	(0.17)	(0.17)						
1989	−4.66	−3.47	−1.49	698	7.41	47	27	0.47	0.70
	(0.15)	(0.22)	(0.17)						
1990	−4.34	−2.85	−1.71	323	8.88	74	28	0.29	0.72
	(0.20)	(0.31)	(0.27)						
B. All Years									
All Exchanges	−4.06	−2.94	−1.34	3394	$7.75	$54	24	0.35	0.61
	(0.08)	(0.09)	(0.08)						
NYSE	−3.11	−1.54	−1.66	572	9.82	96	20	0.19	0.30
	(0.13)	(0.17)	(0.17)						
AMEX	−3.90	−2.73	−1.32	269	7.88	47	23	0.46	0.74
	(0.13)	(0.19)	(0.19)						
OTC	−4.29	−3.28	−1.28	2553	7.38	47	25	0.39	0.64
	(0.10)	(0.11)	(0.10)						

[a] The numbers in parentheses are standard errors.

[b] Trade size is the number of shares traded as a percentage of total shares outstanding.

Table 2

Summary Statistics for Buyer-Initiated Block Trades for NYSE, AMEX and OTC NMS Stocks for the Period July 1985 to December 1990

	Price Change[a]			Number of Blocks	Median Price	Median Market Cap ($ mill)	Median No. of Shares Traded ('000s)	Trade Size[b]	
	Total	Temporary	Permanent					Median	Inter-Quartile Range
A. All Exchanges									
1985	1.20 (0.23)	—	1.79 (0.55)	37	$25.13	$190	21	0.17	0.27
1986	1.83 (0.18)	—	2.19 (0.32)	96	25.07	236	20	0.17	0.21
1987	1.39 (0.17)	—	1.99 (0.35)	153	22.50	232	32	0.29	0.58
1988	1.86 (0.80)	—	1.69 (0.74)	44	20.94	165	35	0.28	0.58
1989	1.29 (0.10)	−0.26 (0.19)	1.03 (0.23)	222	19.10	181	24	0.15	0.29
1990	1.44 (0.15)	−0.27 (0.18)	1.16 (0.22)	294	17.50	168	14	0.15	0.21
B. All Years									
All Exchanges	1.45 (0.08)	—	1.45 (0.13)	846	$20.25	$194	20	0.18	0.29
NYSE	1.38 (0.12)	—	1.59 (0.16)	426	21.63	202	25	0.20	0.37
AMEX	0.95 (0.28)	—	1.15 (0.46)	102	18.32	170	20	0.24	0.38
OTC NMS	1.69 (0.12)	—	1.36 (0.21)	318	18.75	186	15	0.14	0.19

[a] The numbers in parentheses are standard errors.

[b] Trade size is the number of shares traded as a percentage of total shares outstanding.

Table 3

The Relation between Percentage Price Changes and Block Size

Average Total (Prior Close to Block), Temporary (Block to Next Day Close), Permanent (Prior Close to Next Day Close), and Pre- and Post-Block Price Changes for NYSE, AMEX and OTC NMS Firms, July 1985–December 1990.

Block Size[c]	Mean Price Impact: Day of Block (%)[a]			Mean Price Change (%)[b]	
	Total	Temporary	Permanent	$t-21$ to $t-1$	$t+2$ to $t+21$
A. Seller-Initiated Blocks					
0.01–0.14	−2.92	−1.32	−1.66	−2.85	1.59
	(0.11)	(0.15)	(0.16)	(0.46)	(0.55)
0.14–0.26	−3.51	−2.09	−1.54	−3.89	0.81
	(0.11)	(0.18)	(0.18)	(0.52)	(0.55)
0.26–0.47	−3.80	−3.04	−0.94	−4.31	1.32
	(0.13)	(0.20)	(0.19)	(0.47)	(0.53)
0.47–0.95	−4.47	−3.51	−1.18	−4.76	−0.89
	(0.14)	(0.20)	(0.19)	(0.49)	(0.56)
0.96–7.86	−5.83	−4.84	−1.42	−6.47	−0.61
	(0.17)	(0.24)	(0.20)	(0.49)	(0.56)
B. Buyer-Initiated Blocks					
0.01–0.07	1.26	−0.73	0.52	1.10	2.93
	(0.17)	(0.20)	(0.23)	(0.93)	(1.08)
0.08–0.14	1.47	−0.12	1.36	0.48	0.07
	(0.15)	(0.23)	(0.31)	(0.99)	(0.93)
0.14–0.24	1.22	—	1.06	3.56	0.27
	(0.27)		(0.31)	(0.97)	(1.20)
0.24–0.46	1.74	—	2.01	3.46	−0.15
	(0.14)		(0.29)	(0.99)	(0.96)
0.46–5.48	1.53	—	2.30	2.93	1.48
	(0.13)		(0.31)	(0.90)	(0.98)

Note: Each classification category represents a quintile based on a sort of the data based on block size. Each category contains 678 observations in panel A and 170 observations in panel B.

[a]The numbers in parentheses are standard errors.

[b]Day t is the day of the block trade.

[c]Block size is defined as the number of shares traded as a percentage of the total number of outstanding shares.

Table 4

The Determinants of the Price Impacts for Block Trades

The parameter estimates in the table are for the following model[a] estimated over the period July 1985 to December 1990:

$$\begin{aligned} y_i = \beta_0 + \beta_1 D_i^{\mathrm{OTC}} + \beta_2 \mathrm{PINV}_i + \beta_3 Q_i &+ \beta_4 (Q_i - Q^{50\mathrm{th}}) \cdot D_i^{50\mathrm{th}} \\ &+ \beta_5 (Q_i - Q^{75\mathrm{th}}) \cdot D_i^{75\mathrm{th}} \\ &+ \beta_6 D_i^{3\mathrm{rd}} \\ &+ \beta_7 Q_i \cdot D_i^{3\mathrm{rd}} + e_i \, . \end{aligned}$$

β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adjusted R-Squared
A. Temporary Impact ($y_i = \tau_i$)								
Seller-Initiated								
0.0124	−0.0042	−0.1418	−0.0480	0.0327	0.0088	0.0018	0.0008	.205
(4.38)[b]	(−2.14)	(−24.60)	(−4.21)	(2.51)	(2.01)	(0.77)	(0.36)	
Buyer-Initiated								
0.0053	0.0024	0.0679	−0.0668	0.0529	0.0090	−0.0061	0.0088	.058
(1.19)	(1.03)	(5.40)	(−1.74)	(1.28)	(1.12)	(−2.18)	(1.94)	
B. Permanent Impact								
Seller-Initiated								
−0.0113	0.0046	−0.0725	−0.0677	0.0464	0.0224	−0.0147	0.0056	.015
(−1.47)	(0.87)	(−4.65)	(−2.20)	(1.32)	(1.88)	(−2.31)	(0.89)	
Buyer-Initiated								
−0.0086	0.0233	−0.1156	0.2097	−0.1847	−0.0293	0.0125	−0.0072	.013
(−0.48)	(2.45)	(−2.29)	(1.36)	(−1.11)	(−0.90)	(1.11)	(−0.39)	

[a]The variables in the model are:

D_i^{OTC} = 1 if block trade i is an OTC stock
= 0 otherwise

PINV_i = $1/P_{ib}$

Q_i = [(number of shares traded)/(total shares outstanding)]·100 (absolute value)

$Q^{50\mathrm{th}}$ = Median of Distribution of Q

$Q^{75\mathrm{th}}$ = 75th Percentile of Distribution of Q

$D_i^{50\mathrm{th}}$ = 1 if trade i > median trade size
= 0 otherwise

$D_i^{75\mathrm{th}}$ = 1 if trade i > 75th percentile trade size
= 0 otherwise

$D_i^{3\mathrm{rd}}$ = 1 if block trade i was done by a 3rd market broker
= 0 otherwise

[b]The numbers in parentheses are t-values.

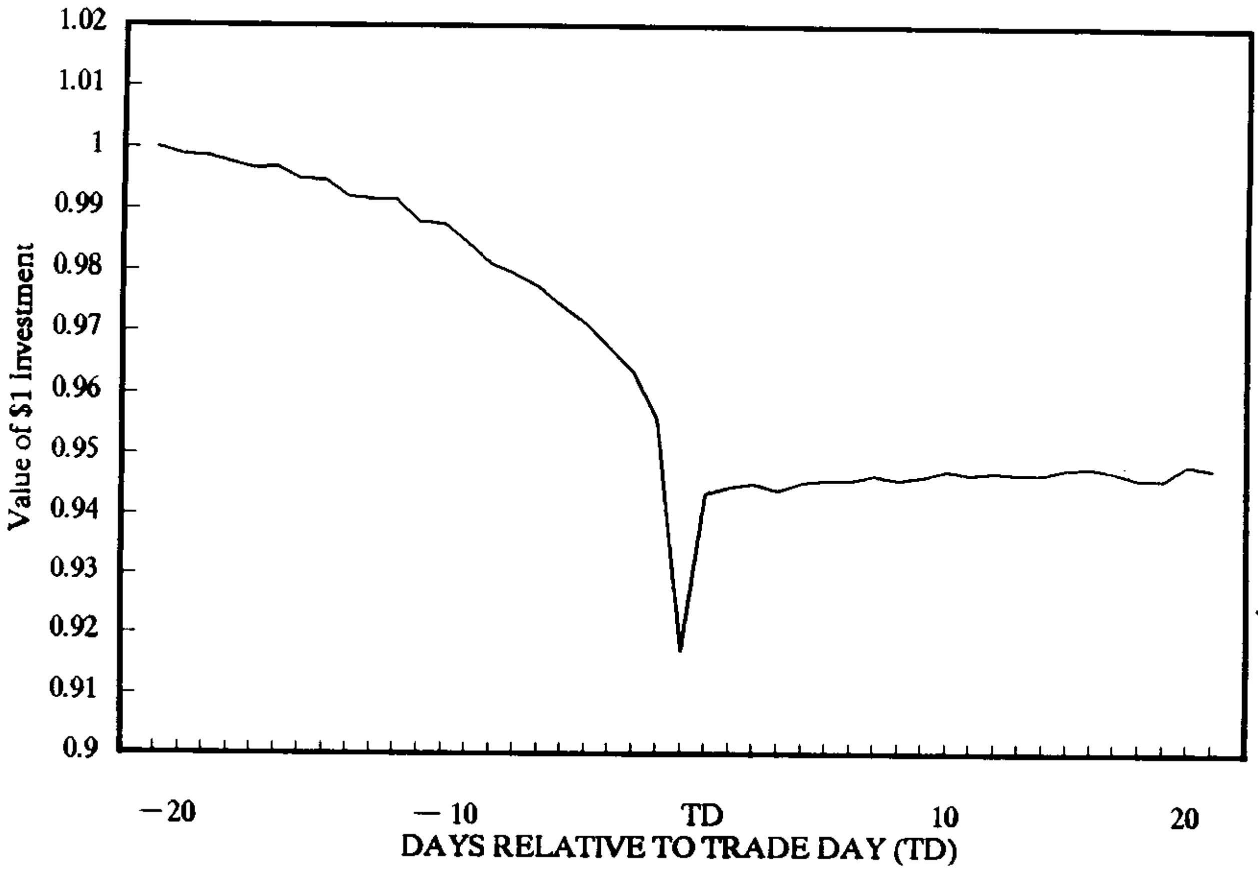

Fig. 1. Price behavior associated with seller-initiated blocks for two months (42 trading days) surrounding the trade day for the period July 1985 to December 1990.

The series represents the average price behavior for our combined sample of NYSE, AMEX and OTC block trades. We compute the series using the following steps: (1) allign the daily returns for each of the block firms around the block trade day; (2) compute a value weighted return r_t^{vw}, across all firms, for each day t; (3) Create a wealth series, with initial value $V_{-21} = 1$, as

$$V_t = \Sigma V_{t-1} (1+r_t^{vw}).$$

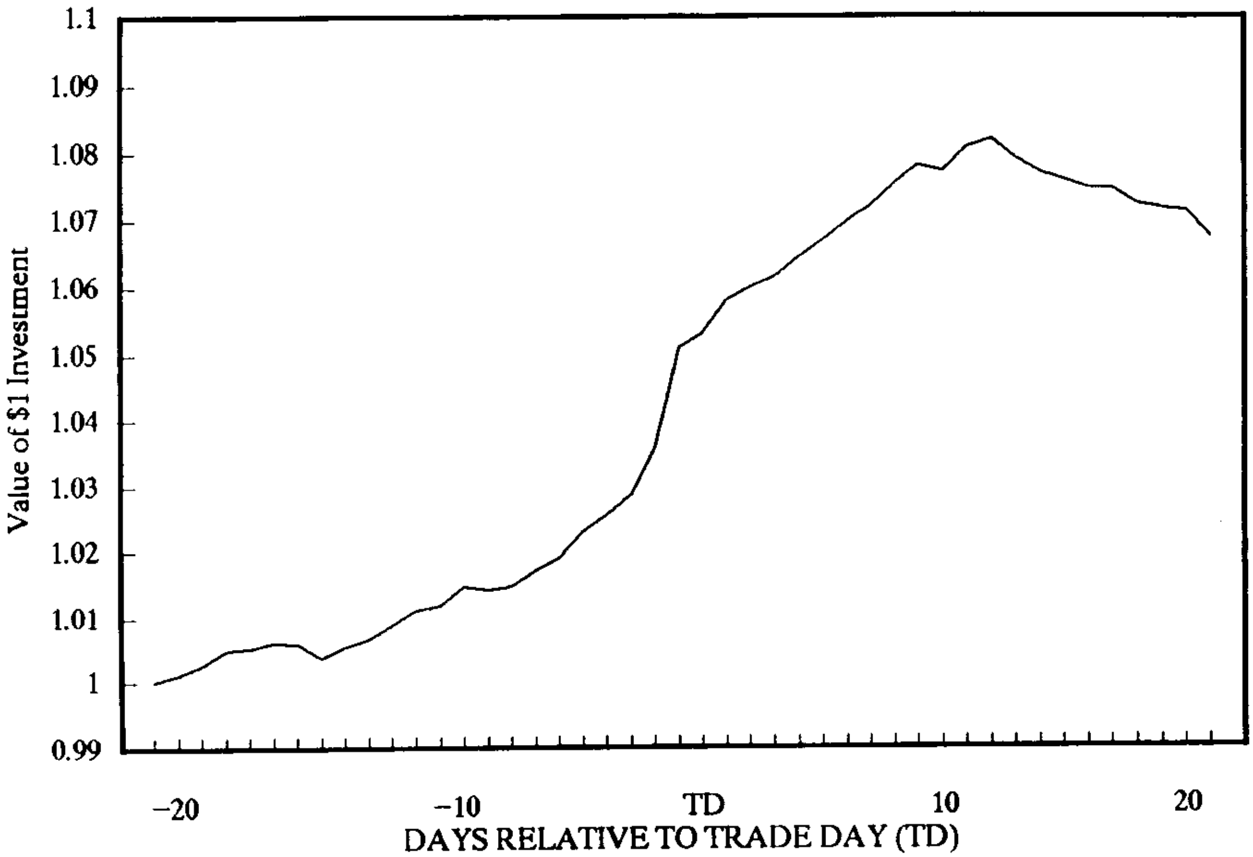

Fig. 2. Price behavior associated with buyer-initiated blocks for two months (42 trading days) surrounding the trade day for the period July 1985 to December 1990.

The series represents the average price behavior for our combined sample of NYSE, AMEX and OTC block trades. We compute the series using the following steps: (1) allign the daily returns for each of the block firms around the block trade day; (2) compute a value weighted return r_t^{vw}, across all firms, for each day t; (3) Create a wealth series, with initial value $V_{-21} = 1$, as

$$V_t = \Sigma V_{t-1} (1 + r_t^{vw}).$$