

The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effects

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This article develops a model of the upstairs market where order size, beliefs, and prices are determined endogenously. We test the model's predictions using unique data for 5,625 equity trades during the period 1985 to 1992 that are known to be upstairs transactions and are identified as either buyer or seller initiated. We find that price movements prior to the trade date are significantly positively related to trade size, consistent with information leakage as the block is "shopped" upstairs. Further, the temporary price impact or liquidity effect is a concave function of order size, which may result from upstairs intermediation.

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Large-block transactions now account for a substantial fraction of the volume of trading in common stocks.¹ Many of these transactions originate in the so-called upstairs market. In upstairs markets, large transactions are accomplished through a search-brokerage mechanism where an intermediary or broker locates counterparties to a trade before sending it to the downstairs market for execution.² By contrast, downstairs markets (such as the NYSE) rely on market makers, floor traders, and limit orders to provide liquidity on demand. Markets resembling the upstairs mechanism exist for other assets and in other countries. Yet despite their importance as a source of liquidity, relatively little is known about how prices in upstairs markets are determined. This article's objective is to increase our understanding of the effects of large transactions facilitated in the upstairs market for common stock.

We develop a theoretical model of the upstairs market where order size, beliefs, and prices are formed endogenously. The model yields testable hypotheses that formalize and extend previously articulated predictions about the price effects associated with a large trade [see, e.g., Burdett and O'Hara (1987), Grossman (1992), and Seppi (1990)]. For example, in contrast to previous models, our model predicts that the temporary price impact, the liquidity component of the trade, is a concave function of order size. Intuitively the number of counterparties located by the block broker is an increasing function of order size, and spreading the order among more traders lowers the liquidity cost, producing the concave relation. Also, our model allows for information leakage prior to the trade as the block is "shopped," resulting in a measure of the permanent component of price impact that includes the period prior to the trade. Finally, a formal description of this important, yet relatively unstudied, market mechanism is of independent interest.

We investigate the model's hypotheses with unique data on the upstairs trades of an investment management firm. Our data differ from those employed in previous empirical analyses of the price impacts associated with block trades [see, e.g., Ball and Finn (1989), Choe, McInish, and Wood (1991), Holthausen, Leftwich, and Mayers (1987,

¹ A block trade is often defined as a trade of 10,000 or more shares. In 1993, block trades represented almost 54 percent of New York Stock Exchange (NYSE) share volume; in 1965 the corresponding figure was just 3 percent.

² Under NYSE Rule 76, it is generally illegal to prenegotiate trades on the NYSE; the order must be exposed to the public in accordance with auction principles of price and time priority for possible price improvements. See Hasbrouck, Sofianos, and Sosebee (1993) for further details. Thus, when we describe a block trade as being negotiated or arranged upstairs, we refer to the process of upstairs intermediation (or facilitation) by which a block trader finds counterparties to accommodate a large trade.

1990), Kraus and Stoll (1972), Mikkelsen and Partch (1985), Scholes (1972), and Seppi (1992a)] in several important respects. First, the transactions in our sample are all upstairs trades, whereas those used in previous studies are identified by their size and consequently consist of a mixture of upstairs and downstairs trades. The inability to identify the mechanism of origin of a large trade is a problem since the majority of block trades of 10,000 or more shares are downstairs trades.³ Second, the investment firm providing the data has a policy of accepting only those trades that are not fragmented.⁴ The trades examined in previous studies, however, may represent only parts of larger orders that are broken up for easier execution in the downstairs market. Order fragmentation can potentially bias the measured price impacts associated with upstairs-negotiated trades. Third, trades in our sample are identified as either buyer or seller initiated. In most previous studies, by contrast, trade initiation must be inferred indirectly from tick tests based on the direction of the price movement. This procedure may result in biases because some trades are incorrectly classified. Finally, whereas most previous studies of block transactions in U.S. markets examine only trades on the NYSE and AMEX, the transactions examined here are for stocks that reside in the bottom half of market capitalization on the NYSE and are traded on the NYSE, AMEX, and NASDAQ.

Although our data are uniquely suited to an analysis of the upstairs market, there is an important caveat to keep in mind. Since the investment firm providing the data (a passive, small-cap stock manager) is a party to all trades in the sample, idiosyncratic aspects of the firm's trading style may affect our empirical results, even though the transactions represent a broad cross-section of stocks. Consequently, caution is required in generalizing our results to the upstairs market as a whole.

The empirical results provide support for the model's predictions about price movements around upstairs-facilitated trades. We find that price movements up to 4 weeks prior to the trade date are significantly related to trade size. This is consistent with the model, where information leakage occurs as the block is shopped prior to the trade

³ The New York Stock Exchange (1993) reports that only 27 percent of NYSE block volume in 1993 was facilitated upstairs by member firms. Similar figures are reported for the Dow Jones 30 firms by Cheng and Madhavan (1995). For active stocks it is not unusual for downstairs market makers to accommodate trades well in excess of 10,000 shares from inventory. See, for example, Madhavan and Smidt (1993) and Hasbrouck and Sofianos (1993).

⁴ It is possible, of course, that the broker knowingly or unknowingly arranges a trade that is part of an ongoing series of transactions. However, anecdotal evidence suggests that these occurrences are rare, possibly because they can easily be detected *ex post* in the thin markets in which the firm trades and block brokers wishing to protect their reputational capital may avoid dealing with initiators who pursue such actions.

date. Thus, the standard measure of the permanent price impact, estimated using trade-day price movements, can seriously understate the information contained in the block trade. This may explain why in the previous literature the permanent impacts measured on the block trade day are not related to trade size. Indeed, using the traditional definition we find that permanent impacts are significant but unrelated to trade size. The temporary price impact (which captures the price-pressure effect of the trade) is a concave function of order size, as predicted by our model. Finally, the temporary price impacts of seller-initiated block trades (which make up almost 80 percent of our sample) are substantially larger than found in previous studies, partly because the trades are larger and in smaller capitalization stocks than those used in most previous studies of price impacts of block trades. However, even when the price impacts reported here are compared to results in recent studies that examine similar-sized trades in stocks of similar market capitalization [e.g., Chan and Lakonishok (1993a)], the price impacts of large trades in small stocks reported here are larger, suggesting more attention be paid to the lack of liquidity in these markets.

The article proceeds as follows. Section 1 develops a theoretical model of the upstairs market. Section 2 describes the data and provides summary results for our sample of block trades. Section 3 reports our results and the corresponding implications for assessing the implicit costs of trading. Section 4 summarizes the article.

1. A Model of the Upstairs Market for Block Trades

1.1 The basic framework

We begin our analysis with a theoretical examination of the operation of the upstairs market. Consider a risky security whose full-information value at time T in the future, denoted by $\tilde{v}$, is distributed normally with mean μ and variance σ_v^2 . Our analysis focuses on the price path of the security around an upstairs-negotiated transaction that occurs at calendar time t_b . Let t_d represent the day when the trade initiator decides to trade a large block, t_0 represent the day preceding the actual execution of the block, and t_1 represent the day immediately after the block is executed, 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 (end-of-day) market prices. Downstairs market prices are assumed to equal the expected value of the stock given the public information at that time and are determined by an auction mechanism with atomistic traders.

At the decision date t_d , the block trade is not public so that p_d is the unconditional expectation of the liquidation value, that is, $p_d = E_{t_d}[\tilde{v}] = \mu$. The intermediate or pretrade downstairs price p_0 may differ from μ because information about the size of the block trade has become public through “leakage” in the upstairs market. This information is valuable because there is a possibility the trade is initiated by a trader with private information about the liquidation value of the asset, as we show below. When the block trade is arranged at time t_b , the block traders and counterparties are assumed to condition their beliefs on the size of the trade, so that for one of these agents, $E_{t_b}[\tilde{v}] = E[\tilde{v}|Q]$.⁵ At date t_1 after the trade is public, the post-trade price is equal to the expectation of the asset’s value conditioned on order size, that is, $p_1 = E_{t_1}[\tilde{v}] = E[\tilde{v}|Q]$.

It is useful at this stage to distinguish between the *permanent* and *temporary* components of the price changes around a block trade. These distinctions, first used by Kraus and Stoll (1972), are commonly used in the empirical literature on block trading. The permanent component represents the change in the market’s perception of the security’s value due to the block transaction. In previous empirical work, the permanent component is defined as the difference between the stock’s price before and after the block, that is, by $p_1 - p_0$. We argue below that this definition may understate the true revision in beliefs as a result of the trade. Intuitively, the inevitable leakage of information about order size as the trade is negotiated in the upstairs market may be reflected in the pretrade price. Our approach is to define a new measure of a permanent impact with reference to the price at the time the trade was initiated. Accordingly, we define the permanent impact as

$$\pi = p_1 - p_d. \quad (1)$$

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 on the day following the block where

$$\tau = p_b - p_1. \quad (2)$$

The total price impact associated with the block trade is the sum of the two components, that is, $p_b - p_d = \pi + \tau$. Our objective is to obtain closed-form solutions for the two price components. This is

⁵ The observed block price will not equal the conditional expectation because counterparties must be compensated for their services in bearing risk (i.e., the temporary price impact). This liquidity or price pressure effect is particular to the block trade, and is dissipated by the end of the day following the trade.

complicated by the fact that the price components are determined endogenously; the revision in beliefs and the price pressure effects depend on the optimal behavior of the initiator, which in turn is conditioned on expectations of the price effects of the trade.

1.2 Upstairs market participants

There are three types of agents in the model: a trader who initiates the block trade, a block trader (or upstairs market maker) who facilitates the trade by locating potential counterparties to take the opposite side of the block transaction, and the counterparty traders themselves. Traders maximize their utility given their conjectures regarding the strategic behavior of other agents and their beliefs about the value of the security. In 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 counterparty traders who eventually take the opposite side of the block, then considering the block trader's choice of the number of counterparties to locate, and finally closing the model by analyzing the strategy of the initiator of the trade.

1.2.1 Potential traders. 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 locates potential traders. A representative potential trader (indexed by i) has a mean-variance utility function over final period wealth of the form

$$E[\tilde{W}_i] - \left(\frac{\rho}{2}\right) \sigma^2[\tilde{W}_i], \quad (3)$$

where $\tilde{W}_i$ is the (random) wealth at time T , ρ_i is trader i 's coefficient of absolute risk aversion, and $E[\cdot]$ and $\sigma^2[\cdot]$ represent the mean and variance operators, given the trader's information at time t_b . Wealth $\tilde{W}_i$ is a random variable given by

$$\tilde{W}_i = (\tilde{v} - p_b)q_i + z_i, \quad (4)$$

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, z_i is trader i 's initial cash holding, and p_b is the price at which the shares are traded.

We assume that the counterparties know the total size of the order. The assumption that order size is inferred by potential traders is

consistent with the absence of anonymity in the upstairs market. Alternatively, this assumption can be motivated by reputational considerations including the block trader's desire to maintain long-term relationships with potential customers. For simplicity, we assume traders have homogeneous expectations and consider a representative counterparty.⁶ Thus, the counterparty's expectation of asset value is equal (on average) to the posttrade price, p_1 .

Assuming that counterparties are price takers, we can derive the demand function for the representative counterparty by substituting Equation (4) into Equation (3), and maximizing utility with respect to q_i .⁷ This yields the demand function:

$$q_i(p_b; Q) = \frac{E_{t_b}[\tilde{v}|Q] - p_b}{\rho\sigma^2[\tilde{v}|Q]}. \quad (5)$$

The demand function depends on Q because the counterparty's expectation of asset value, $E_{t_b}[\tilde{v}|Q]$, is conditioned on the signal conveyed by the initiator's order size.

1.2.2 The block trader. We assume the block trader is a competitive broker who does not hold inventory but facilitates the trade by locating counterparties to take the opposite side.⁸ The brokerage function involves costly search, and the block trader charges commissions to offset these costs. 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 counterparties. We assume that the 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.

Burdett and O'Hara (1987) provide a model of the block market based on sequential search. In their model, marginal search costs are

⁶ It is straightforward to extend the model to incorporate heterogeneous expectations without altering our conclusions.

⁷ This assumption is reasonable if there are many potential traders present in the market or if block traders do not negotiate with counterparties. The analysis could be extended to allow counterparties to possess market power, as may be the case for small stocks, without significantly altering our qualitative results.

⁸ Many block traders do not take principal positions, possibly reflecting capital constraints, inventory holding costs, or agency problems. Our model can be extended to allow the block trader to act as a dealer who positions part of the block by treating the block trader as another counterparty. It is also straightforward to incorporate a broker who possesses market power.

interpreted as the marginal permanent price impact from revealing the impending trade to an increasingly large group of traders. Hence, Burdett and O'Hara (1987) find that more intensive searches increase the probability of execution, but result in larger permanent impacts. By contrast, the transaction price in our model reflects the trade size irrespective of when this information is revealed. Indeed, if it were possible for a block trader to deceive counterparties about the trade size by limiting the number of searches, he/she would soon develop a reputation for such actions. Potential counterparties with rational expectations would make inferences about the true size of the order from the portion they observe or simply deal with other block traders. Thus, we do not treat the permanent price impact as an economic cost.

Let $\phi(n)$ represent the total costs of locating n potential counterparty traders. Search costs in our model represent both explicit and implicit costs associated with locating counterparties. As noted above, the marginal permanent impact of an additional search is not a component of this cost function as this is a pecuniary cost. While the explicit costs of locating a potential trader are likely to be relatively small, the implicit costs associated with search may be significant. Implicit costs include the costs to the broker associated with failing to arrange the trade in a timely manner, and the potential reputational costs to the block trader if the trade later appears to have been informationally motivated. Reputational costs may arise even if counterparties understand and rationally price adverse selection risk. Intuitively, suppose there are differences among block brokers in their ability to screen informed traders. If a trade subsequently results in losses to the counterparties, these agents (particularly those counterparties with whom the block trader has had few prior dealings) may be reluctant to participate in future trades arranged by the broker. The problem is exacerbated if, as is likely, there are agency costs (which may cause brokers to misrepresent the adverse selection risk for less-favored clients) or if it is not possible for a broker to fully disclose trade-specific information. It is reasonable to model these costs as an increasing function of the number of counterparties located.⁹

In what follows, we consider cost functions of the form $\phi(n) = \delta n^\gamma$, where to assure an interior solution we assume that $\delta > 0$ and $\gamma \geq 1$. The constant δ is inversely related to the probability of locating willing counterparties; γ reflects the returns to the search process, with higher values implying diminishing returns to search. Suppose the block trader contacts n counterparties to absorb the block. The

⁹ In addition, the time spent locating counterparties may be costly to the initiator. Our results concerning block pricing are unaffected in this case, but we need to reinterpret the commission schedule since these costs are not borne by the block broker.

equilibrium price of the block solves the equation

$$\sum_{i=1}^n q_i(p_b; Q) = -Q, \quad (6)$$

where $q_i(p_b; Q)$ is the potential trader's demand function given by Equation (5). Let $p_b(Q; n)$ denote the block price solving this equation as a function of order size, Q , given the number of counterparties, n .

A competitive block broker facilitates the upstairs trade in such a way as to maximize the net revenue of the initiator. More intensive search decreases the overall price impact by increasing the number of counterparties but also increases commission costs. As shown in the Appendix, this trade-off implicitly defines the optimal search intensity as a function of order size Q , denoted by $n(Q)$. Let $C(Q) = \phi(n(Q))$ denote the corresponding function relating *total* commission costs to order size. Thus, the block price p_b can be expressed as a function of order size alone, that is, $p_b(Q) = p_b(Q; n(Q))$.¹⁰ Note that $p_b(Q)$ captures not only the temporary price concession demanded by counterparties to accommodate the block trade, but also their perceptions of the postblock price as a result of information conveyed by order size. Finally, we close the model by describing the initiator's choice of order size.

1.2.3 The initiator. Given the strategies adopted by the traders and the block broker, the initiator (indexed as agent 0) faces a price schedule, denoted by $p_b(Q)$. In a rational expectations equilibrium, the initiator's choice of order size takes into account the expected price impact of the trade, and the trade price in turn is consistent with public beliefs about the initiator's strategy and private information signals. In other words, equilibrium is a fixed point in the space of continuous functions such that the functionals describing the temporary and permanent price impacts are consistent with the rational beliefs and actions of all optimizing agents in the model.

To formalize this, suppose the initiator observes a private signal regarding the value of the risky asset at time T . Let y denote the realization of this signal, where we assume that y is drawn from a normal distribution with mean equal to the realized liquidation value v and variance σ_y^2 . Then, using the properties of the normal distribution, the expected value of the security from the initiator's viewpoint is

¹⁰ We can handle the case where the block trader can act as a broker-dealer by positioning a part of the block by treating the block trader as a counterparty that can be contacted at zero cost; this benefits the initiator by reducing execution costs but does not affect the main elements of the analysis.

a weighted average of the prior mean and signal, $E_0[\tilde{v}|y] \equiv \mu_0 = (1 - u_0)\mu + u_0y$, where the weight placed on the signal, u_0 , is the ratio of the variance of the prior distribution to the sum of the variance of the prior and the variance of the private information signal, that is, $u_0 = \sigma_v^2/(\sigma_v^2 + \sigma_y^2)$ [see, e.g., DeGroot (1970)].

Like counterparties, the initiator has a utility function of the form given by Equation (3). Let x denote the initiator's (unobservable) holdings of the risky asset, where (unconditionally) x is distributed normally with a mean normalized to zero. The existence of initial endowments creates portfolio hedging motives for trade in addition to the information motives discussed above.

Let $\tilde{W}_0$ denote the future wealth of the initiator, where $\tilde{W}_0 = \tilde{v}(Q + x) + z_0 - p_b(Q)Q - C(Q)$. Substituting this into Equation (3) and simplifying, the initiator's maximization problem is

$$\max_Q \mu_0(Q + x) + z_0 - p_b(Q)Q - C(Q) - \left(\frac{\rho}{2}\right)\sigma_0^2(Q + x)^2, \quad (7)$$

where σ_0^2 denotes the conditional variance of the asset's value.

The initiator's optimal order quantity is found by differentiating Equation (7), which yields

$$\mu_0 - Qp'_b(Q) - p_b(Q) - C'(Q) - \rho\sigma_0^2(Q + x) = 0. \quad (8)$$

The initiator's equilibrium order thus reflects a mix of information and portfolio hedging motivations for trade. Consequently, order quantity conveys a noisy signal to outsiders (the block trader and counterparties) about the initiator's private information signal.

As the block trader and counterparties observe Q (but not y or x) they cannot infer completely the private signal of the initiator. However, since $\mu_0 = (1 - u_0)\mu + u_0y$, these agents can form the statistic s where

$$s = \frac{Qp'_b(Q) + p_b(Q) + C'(Q) + \rho\sigma_0^2Q - (1 - u_0)\mu}{u_0}. \quad (9)$$

Substituting Equation (8) into Equation (9), we see that the signal has the form $s = y + \zeta x$, where $\zeta = -\rho\sigma_0^2/u_0$ is a constant. From the perspective of an agent who cannot observe the initiator's holdings, x , the signal s is an unbiased estimate of the true value v with variance $\sigma_y^2 + \zeta^2\sigma_x^2$, where σ_x^2 is the unconditional variance of the initiator's holdings.¹¹

¹¹ The initiator's problem is similar to that of Glosten (1989) in that he has rational expectations about how his order will be priced by the block trader. It differs in that the price schedule arises from the optimization by the block trader on behalf of the initiator.

The posttrade price is equal to the expectation of asset value conditioned upon prior beliefs and the noisy estimate (inferred from the observed order size) of the initiator's private signal. Thus, $p_1 = E_{t_1}[\tilde{v}] = E_{t_b}[\tilde{v}|Q]$.

Under our assumptions, the expected value of the asset, given the order size, is given by

$$E[\tilde{v}|Q] = p_1(Q) = (1 - w)\mu + ws = \mu + w(s - \mu), \quad (10)$$

where $w = \sigma_v^2 / (\sigma_v^2 + \sigma_s^2)$ is the weight placed on the information content of the signal and [following DeGroot (1970)] σ_s^2 is the conditional variance of the signal about v conveyed by order size.

Recall that the total price impact of the trade is the sum of the temporary price effect (which represents the price pressure associated with the block trade) and the permanent effect (which represents the revision in public beliefs as a result of the block trade), that is, $p_b(Q) = p_1(Q) + \tau(Q)$. Further, the permanent impact can be expressed as $\pi(Q) = p_1(Q) - \mu$. Then, using Equations (9) and (10), we obtain the following differential equation:

$$\pi(Q) = \frac{w}{u_0} (Q(\tau'(Q) + \pi'(Q)) + \tau(Q) + \pi(Q) + C'(Q) + \rho\sigma_0^2 Q). \quad (11)$$

The equilibrium price functionals $\tau(Q)$ and $\pi(Q)$ and commission schedule $C(Q)$ must satisfy Equation (11) subject to the initial condition $\pi(0) = 0$, that is, that there is no information revelation without trade. The solutions completely characterize the equilibrium price movements around an upstairs-negotiated block trade.

We show below that an equilibrium exists if the perceived need for portfolio hedging is sufficiently large relative to the degree of asymmetric information.

1.3 Equilibrium price paths

The following proposition characterizes the temporary price effects of a block trade.

Proposition 1. *In equilibrium, the temporary price component of an upstairs-negotiated block trade is*

$$\tau(Q) = K_1 \text{sign}(Q)|Q|^{\frac{\gamma-1}{\gamma+1}}, \quad (12)$$

where $K_1 > 0$ is a constant.

The temporary impact is positive for buys and negative for sells, but the proposition also demonstrates that the absolute equilibrium temporary impact is an increasing and strictly concave function of trade

size. The only exception occurs when marginal search costs are constant, so that the number of counterparties located is proportional to trade size and the price impact is a constant. Intuitively, when the number of counterparties is constant, the temporary impact is linear in quantity because the aggregate inverse demand function is also linear. With constant search costs, the optimal number of searches is a linear function of the quantity traded, so that the temporary impact is constant. With increasing search costs, the block trader will add more counterparties if the reduction in the total dollar price impact exceeds the marginal cost. Thus, as quantity rises, the optimal number of counterparties increases, reducing the price impact on the entire amount of the trade, producing the concave relation. The search-brokerage aspect of the upstairs market mitigates the price impact of the trade by intensifying the search for counterparties as trade size increases, even if there are diminishing marginal returns to search.

The following result provides comparative statics results on the temporary impact:

Proposition 2. *For a given order size, the temporary price component is positively related to the cost of locating counterparties, δ , the degree of risk aversion, ρ , and the variance of the risky asset's return, σ_v^2 .*

Proposition 2 is important for our subsequent empirical analysis of the empirical determinants of the temporary impact. The temporary impact, adjusted for trade size, will be larger for trades arranged through brokers with high search costs or for securities where uncertainty is large. The proposition may also help shed some light on the stylized fact that the great majority of block trades are sells. The model admits the possibility that the costs of locating counterparties for buyer-initiated trades are larger than for seller-initiated trades. This case is realistic because of short-sale constraints and the difficulty in locating traders who have large holdings of a particular asset. Indeed, it has been argued that many financial intermediaries earn rents because it is more costly to locate counterparties for buyer-initiated transactions rather than seller-initiated transactions. If this is indeed the case, the price effects of buyer- and seller-initiated transactions may be asymmetric, possibly explaining some previous empirical findings.

The temporary impact is an implicit trading cost for the initiator, who must also bear explicit commission costs. Commission costs in our model are endogenously determined. The following proposition characterizes these costs.

Proposition 3. *Total commission costs are an increasing function of order size*

$$C(Q) = K_2 |Q|^{\frac{2\gamma}{\gamma+1}} \quad (13)$$

where $K_2 > 0$ is a constant that is positively related to search costs, risk aversion, and the variability of the asset's return.

Since commissions per share are given by $C(Q)/|Q|$, it follows directly that per share commissions are constant when $\gamma = 1$ and increase with trade size when $\gamma > 1$. Proposition 3 shows that commissions per share are positively related to search costs, risk aversion, and the variability of the asset's return.

Proposition 3 has an important implication for empirical studies of execution costs because it implies a systematic relation between explicit (i.e., commissions) and implicit (i.e., price impact) costs. This relation is not intuitive. For example, it is natural to hypothesize that there is a trade-off between commissions paid and the resulting price impact of the trade; a trader can pay high commissions to obtain better execution and hence lower implicit costs in the form of reduced price impact. Indeed, such a trade-off drives our theoretical model of the upstairs market. However, the *equilibrium* relation between commissions and price impact need not be negative. To see this, observe from Propositions 1 and 3 that when $\gamma > 1$, larger orders result in larger commissions per share and higher temporary impacts. In this case, the sample correlation between these variables is positive, not negative as one might expect. When $\gamma = 1$, both commissions per share and the temporary price impact are constants independent of size.¹²

The total price impact is the sum of the permanent and temporary impacts. The following proposition characterizes the permanent price impact of the trade.

Proposition 4. *There exists a rational expectations equilibrium if the unconditional variance of the initiator's asset holdings is sufficiently large relative to the precision of the private information signal. In equilibrium, the permanent impact measured relative to the decision price, $\pi(Q)$, is given by*

$$\pi(Q) = \lambda_1 Q + \lambda_2 \text{sign}(Q) |Q|^{\frac{\gamma-1}{\gamma+1}}, \quad (14)$$

where λ_1 and λ_2 are positive constants.

Proposition 4 shows that the permanent component, measured relative to the decision date, is an increasing (decreasing) and concave (convex) function of order size for buys (sells). The permanent impact is a linear function of trade size only in the special case with

¹² If $\phi(n)$ represents implicit costs to the initiator arising from time-consuming search, the results reflecting the pricing of the block are unaffected but the commission schedule reflects only those costs incurred by the block broker.

constant returns to search. The nonlinearity in the permanent impact arises from the nonlinear form of the temporary impact. In turn, the nonlinearity in the temporary impact arises from the search-brokerage nature of the upstairs market.

Proposition 4 has some additional implications for empirical studies which measure the permanent impact relative to the pretrade price instead of the decision price. As the process of negotiating an upstairs trade is time consuming, information on the impending block trade may leak to the market between times t_d and t_b , affecting p_0 and hence biasing the traditional estimate of the permanent impact. To investigate this intuition more formally, suppose outside agents receive noisy signals about the size of the block trade before time t_0 . On the basis of these signals, suppose that public information concerning the size of the impending block is summarized by a distribution function, denoted by $F(\cdot)$. Using our definition of the permanent impact, $E[\tilde{v}|Q] = \pi(Q) + p_d$, so that $p_0 = E_{t_0}[\tilde{v}] = \int \pi(z) dF(z) + \mu$. Let $\pi^0 = p_1 - p_0$ denote the usual measure of the permanent impact so that

$$\pi^0 = \pi(Q) - \int \pi(z) dF(z). \quad (15)$$

This representation shows that the permanent impact measured relative to the pretrade date, π^0 , will generally understate the true revision in beliefs induced by the block trade. Only when the block is completely unanticipated will the bias be zero, but this appears unlikely since the block facilitation process may result in information leakage. The extent of this mismeasurement is an empirical question, one we address below.

Together, Propositions 1 and 4 provide a complete description of the price impact of an upstairs trade. The price functionals described are equilibrium responses when the degree of information asymmetry is not unduly severe, that is, when there are sufficient noninformational motives for trade. This condition is consistent with the observation that upstairs intermediaries avoid dealing with traders who may possess private information while cultivating relationships with traders who have portfolio reasons for trading. In the remainder of this article, we investigate the hypotheses suggested by Propositions 1 through 4 using data on block transactions arranged in the upstairs market.

2. Empirical Evidence on Upstairs Trade

2.1 The data

The data file used is constructed from the trading history of a passive investment management firm, Dimensional Fund Advisors, Inc. (DFA).

The file contains trade dates, trade prices, number of shares traded, and commissions paid for all upstairs-negotiated trades in which the firm participated during the period July 1985 to December 1992. The firm selectively takes the opposite side of large trades initiated by others in the upstairs market, trading stocks that are on their buy or sell list. In this respect, the firm is a counterparty, not a block trader, in the terms of our model. DFA's buy list consists of all stocks that reside in the smallest half of market capitalization. The cutoff is determined by the median market capitalization for stocks trading on the NYSE, but the list also includes AMEX and OTC National Market System (NMS) stocks that fall into this category. The trades are not time-stamped (within the day), although given the normal volume of trading in these shares the block transactions are easily identifiable on intraday transactions tapes. The sample used here consists of 4,688 seller-initiated blocks and 937 buyer-initiated blocks.

It is worth emphasizing the unique aspects of these data. First, all the trades in our sample are upstairs trades. In particular, we do not need to use an arbitrary definition based on order size to infer the mechanism in which trades originate. Second, the firm has a policy of taking the entire amount of the block, so that order fragmentation is not an issue. However, this policy does require the firm to pay or receive the potential prices offered by other traders who would break up the block to reduce the impact. Essentially, DFA must match the competitively determined price schedule (based on multiparty search) derived above to obtain the trade. Paying such a premium may make sense for this firm because it follows a simple passive trading strategy and can time its trades. Third, the data employed here identify the trade as either buyer- or seller-initiated so that there is no possibility of systematic errors from incorrect inferences about trade initiation. Finally, whereas previous studies of price effects of block transactions in U.S. markets generally examine only block trades on the NYSE, the blocks examined here are from the NYSE, AMEX, and NASDAQ NMS.

To examine the price effects associated with our sample of block trades, we use closing prices from the CRSP daily stock files to compute the temporary and permanent impacts. 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 postblock 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, indicating that they represent the last (and, perhaps, only) trade of the day. For this reason, we measure the temporary and permanent impacts using the closing price on the trading day after the block. For our sample of 5,625 block trades, less than one-half of 1 percent of the stocks

did not trade on the day following the block trade.¹³ Specifically, the temporary price impact is defined as $-\ln(P_{t+1}/P_{\text{trade}})$, where P_{t+1} is the closing price on the day following the block, P_{trade} is the negotiated trade price, and date t is the block trade date. The permanent price impact is defined as $\ln(P_{t+1}/P_{t-n})$, where P_{t-n} is the closing price on the n th trading day before the trade date. All non-trade-date price movements are adjusted for market movements by subtracting the equal-weighted CRSP NYSE-AMEX market index for the NYSE and AMEX stock trades, and subtracting the CRSP NASDAQ index return for the NASDAQ stock trades, without any adjustment for the stock's market beta in either case.

Recall that the block price effects described in Propositions 1 and 4 are stated in dollar price changes, whereas the empirical analysis below is conducted with returns. 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 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: the empirical hypotheses suggested by the model relate to a particular stock, whereas our empirical analysis is cross-sectional. However, the stocks in our sample are relatively homogeneous since they are all smaller NYSE stocks or comparably sized AMEX or OTC-NMS stocks. Further, to the extent that there is cross-stock heterogeneity, the model's predictions are tested in such a way as to minimize these distortions, for example, by scaling trade size by shares outstanding. Third, we performed tests for subsamples of the data sorted by size and price to check the robustness of the results; there was not a significant difference in using finer portfolios of stocks for analysis.

2.2 Summary results: seller-initiated trades

Tables 1 and 2 contain summary statistics for the sample of block trades used here. Table 1 reports results for the seller-initiated blocks, Table 2 for the buyer-initiated blocks. The tables contain estimated means (standard errors) of temporary and permanent price impacts for the sample. Also included are the sample medians for the trade

¹³ 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.

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. Panel B reports statistics separately for listed (NYSE and AMEX) and NASDAQ trades, and also across all markets for the entire period. Consistent with previous research, there appears to be a large temporary price effect (−2.84 percent) associated with the block trade. This block-day price change is more dramatic than documented previously because of the illiquid markets in which the stocks in our study trade. The median price of the blocks here is \$8.38 for firms with a median market capitalization of \$77 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 extremely large trade.

There is not much year-to-year variation in the estimated temporary impacts, although there does appear to be a tendency for the blocks in 1985 and 1986 to display smaller temporary price effects—about 1.0 to 1.5 percent compared to almost 3.0 percent in the last 6 years in our sample. The results for the separate markets, reported in panel B, tell basically the same story. Interestingly, the NASDAQ blocks display larger temporary effects (−3.28 percent) than the NYSE and AMEX blocks (−1.86 percent), although the market capitalizations of the NASDAQ firms in our sample are generally smaller and the size of the NASDAQ blocks are larger when computed as a percentage of total outstanding shares. These differences in liquidity may reflect the differences in trading arrangements between exchanges and the NASDAQ. In particular, blocks executed on exchanges must be exposed to the public for possible price improvement through the auction process, but this is not the case with NASDAQ stocks. Since outside participation increases the potential number of counterparties to the block, the price impacts may be lower on exchanges than on NASDAQ for comparable trades. We estimate regressions below that test for differences across market mechanisms while controlling for price and trade size.

To detect the possible influence of information leakage prior to the trade on the measurement of the permanent impact, we report three estimates of the permanent price impact that incorporate different amounts of pretrade price movement. Recall that the permanent price impact for trade i is defined as $\ln(P_{i,t+1}/P_{i,t-n})$, where $P_{i,t-n}$ is the closing price for stock i on the n th trading day before the trade date, and that all non-trade-date price movements are adjusted for market movements by subtracting the market return over the same interval

Table 1
Summary Statistics for Seller-Initiated Block Trades for NYSE, AMEX, and NASDAQ NMS Stocks for the Period July 1985 to December 1992

	Temporary impact	Permanent impact measured over the period		Number of blocks	Median price	Median market cap (\$ million)	Median no. of shares traded ('000s)	Median trade size (%)
		$(t - 1 \text{ to } t + 1)$	$(t - 6 \text{ to } t + 1)$					
A. All markets								
1985	-1.05 (0.36)	-1.99 (0.41)	-4.45 (0.56)	-8.42 (0.96)	\$ 7.50	\$ 46	16	0.32
1986	-1.50 (0.19)	-1.72 (0.22)	-3.94 (0.34)	-6.53 (0.63)	10.38	67	15	0.22
1987	-2.95 (0.19)	-1.46 (0.23)	-4.50 (0.33)	-8.77 (0.57)	8.50	58	23	0.37
1988	-2.99 (0.18)	-1.26 (0.15)	-4.09 (0.22)	-6.67 (0.40)	6.88	48	30	0.42
1989	-2.94 (0.18)	-1.66 (0.16)	-4.43 (0.24)	-8.02 (0.43)	8.00	55	33	0.50
1990	-2.71 (0.23)	-1.82 (0.22)	-4.66 (0.31)	-7.52 (0.69)	9.13	146	44	0.27
1991	-2.67 (0.22)	-1.18 (0.23)	-3.70 (0.37)	-6.05 (0.58)	9.63	153	50	0.31
1992	-3.73 (0.24)	-1.47 (0.19)	-4.77 (0.30)	-7.64 (0.52)	8.50	135	54	0.34
B. All years								
All Markets	-2.84 (0.08)	-1.50 (0.07)	-4.32 (0.11)	-7.40 (0.20)	\$ 8.38	\$ 77	33	0.34
NYSE and AMEX	-1.86 (0.12)	-1.80 (0.12)	-4.69 (0.18)	-8.19 (0.35)	9.88	124	36	0.30
NASDAQ/NMS	-3.28 (0.10)	-1.37 (0.09)	-4.17 (0.14)	-7.05 (0.24)	7.63	64	30	0.38

The table provides summary information on upstairs-negotiated block trades. The temporary price impact is defined as $-\ln(P_{t+1}/P_{trade})$, where P_{t+1} is the closing price on the day following the block, P_{trade} is the negotiated trade price, and date t is the block trade date. The permanent price impact is defined as $\ln(P_{t+1}/P_{t-n})$, where P_{t-n} is the closing price on the n th day before the trade date. All non-trade-date price movements are adjusted for market movements. The equal-weighted CRSP NYSE-AMEX market index is used to adjust the NYSE and AMEX stock trades, and the CRSP NASDAQ index is used to adjust the NASDAQ stock trades. The adjustment is made by subtracting the relevant market index return from the stock's return, without any adjustment for the stock's market beta. These impacts are stated in percent, and standard errors are reported in parentheses. Also reported are the median values for share price, market capitalization (millions of dollars), number of shares traded (thousands of shares), and trade size (number of shares traded/total shares outstanding) * 100 for the traded stocks in the particular (sub)sample.

Table 2
Summary Statistics for Buyer-Initiated Block Trades for NYSE, AMEX, and NASDAQ NMS Stocks for the Period July 1985 to December 1992

	Temporary impact	Permanent impact measured over the period		Number of blocks	Median price	Median market cap (\$ million)	Median no. of shares traded ('000s)	Median trade size (%)
		$(t - 1 \text{ to } t + 1)$	$(t - 6 \text{ to } t + 1)$					
A. All markets								
1985	-0.66 (0.41)	1.86 (0.52)	3.28 (1.09)	7.64 (1.35)	35	\$25.00	21	0.19
1986	-0.17 (0.26)	1.83 (0.32)	2.72 (0.61)	5.26 (1.16)	90	25.25	18	0.16
1987	-0.32 (0.28)	1.59 (0.33)	2.56 (0.53)	3.43 (0.87)	139	22.50	34	0.32
1988	-0.01 (0.94)	1.85 (0.72)	3.50 (0.94)	3.02 (1.40)	42	19.38	40	0.37
1989	-0.10 (0.21)	1.45 (0.23)	2.93 (0.42)	3.91 (0.69)	153	23.00	29	0.22
1990	-0.35 (0.19)	2.20 (0.25)	3.58 (0.64)	6.48 (1.14)	223	19.00	20	0.12
1991	0.23 (0.30)	0.89 (0.37)	1.22 (0.69)	0.23 (0.99)	78	23.63	18	0.12
1992	0.10 (0.22)	1.09 (0.28)	2.50 (0.57)	5.44 (1.06)	180	21.38	20	0.13
B. All years								
All markets	-0.15 (0.10)	1.60 (0.12)	2.82 (0.24)	4.66 (0.41)	937	\$22.13	24	0.16
NYSE and AMEX	-0.24 (0.13)	1.52 (0.14)	2.57 (0.30)	3.38 (0.47)	582	22.38	25	0.17
NASDAQ/NMS	-0.00 (0.16)	1.73 (0.20)	3.24 (0.39)	6.76 (0.77)	355	19.88	20	0.13

The table provides summary information on upstairs-negotiated block trades. The temporary price impact is defined as $-\ln(P_{t+1}/P_{trade})$, where P_{t+1} is the closing price on the day following the block, P_{trade} is the negotiated trade price, and date t is the block trade date. The permanent price impact is defined as $\ln(P_{t+1}/P_{t-n})$, where P_{t-n} is the closing price on the n th day before the trade date. All non-trade-date price movements are adjusted for market movements. The equal-weighted CRSP NYSE-AMEX market index is used to adjust the NYSE and AMEX stock trades, and the CRSP NASDAQ index is used to adjust the NASDAQ stock trades. The adjustment is made by subtracting the relevant market index return from the stock's return, without any adjustment for the stock's market beta. These impacts are stated in percent, and standard errors are reported in parentheses. Also reported are the median values for share price, market capitalization (millions of dollars), number of shares traded (thousands of shares), and trade size [(number of shares traded/total shares outstanding) * 100] for the traded stocks in the particular (sub)sample.

from the return for stock i . We report the trade-date permanent impact which incorporates no pretrade information (identified in the table as covering the period $t-1$ to $t+1$), a permanent impact that incorporates 1 week of pretrade price movements ($t-6$ to $t+1$), and one that incorporates 4 weeks of pretrade price movements ($t-22$ to $t+1$).

The estimates of the trade-date permanent impact are negative and significant, -1.50 percent when averaged over all markets and years, but substantially smaller than the corresponding temporary impact. These findings are consistent with previous research. In contrast to the results for the temporary impacts, the permanent impacts are larger for NYSE and AMEX trades (-1.86 percent) than for the NASDAQ trades (-1.37 percent), suggesting that the listed block trades in our sample tend to be more informationally motivated than the NASDAQ trades.

Adjusted for market movements, the 1-week permanent impact is -4.32 percent and the 4-week permanent impact is -7.40 percent. These estimates are both statistically and economically significant. The differences in the 1-week and 4-week permanent impacts are consistent with the notion that the market incorporates some of the information associated with the block prior to the actual transaction as it is shopped upstairs. This is also consistent with Seppi (1992a), who finds that block price changes reflect the revelation of private information about surprises in earnings announcements. 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. However, such information leakage may be less of a problem for the larger, more liquid stocks examined in most previous studies. It is also possible that the differences in the 1-week and 4-week excess returns reflects price pressure from block trades in related stocks or from sales of smaller blocks to other upstairs traders.

An alternative explanation for the pretrade price movement is that traders, on average, place buy (sell) orders following positive (negative) returns. Nelling (1992) uses our data described above, and additional information on how long each block was “shopped” (i.e., when the initiator first announced an intention to trade by submitting indications to an electronic bulletin board), to distinguish these hypotheses. Nelling finds strong support for the hypothesis that the pretrade price movement reflects leakage in the upstairs market.¹⁴

¹⁴ See also Seppi (1992b) who develops a regression measure to capture the permanent price impact associated with large trades and addresses the issue of leakage in the context of this measure.

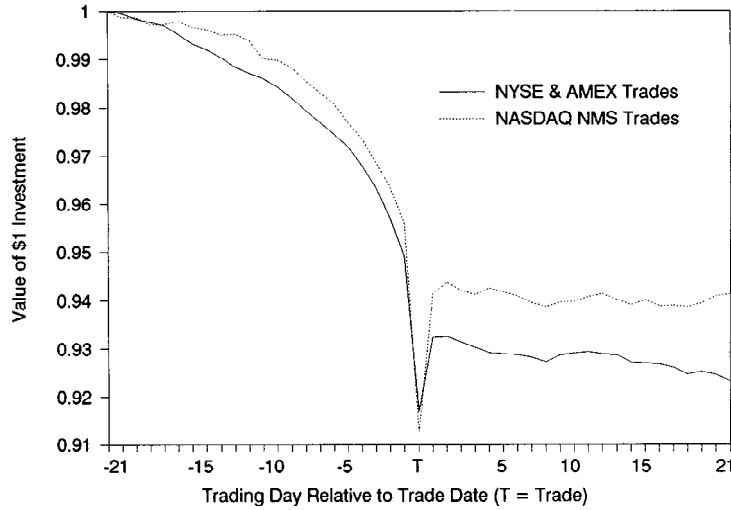


Figure 1
Price behavior associated with seller-initiated blocks

The price path is plotted for 2 months (42 trading days) surrounding the trade day for the period July 1985 to December 1992. The series represent the average price behavior for the separate samples of NYSE-AMEX and NASDAQ NMS blocks trades. We compute each series using the following steps: (1) align 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 $V_{-22} = 1$, as $V_t = V_{t-1}(1 + r_t^{vw})$.

These findings for the temporary and permanent price effects are illustrated graphically in Figure 1, which contains the average price behavior for the seller-initiated blocks for the 2 months surrounding the block trade date. To compute the series, we first computed market-adjusted daily returns for each block-firm's stock for the 2 months surrounding the block day. Value-weighted market-adjusted returns were then computed across all stocks for each day in the 2-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. After the block trade, there is no obvious trend in the returns of the seller-initiated blocks.

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 339 seller-initiated trades (about 7.2 percent of the sample) not being correctly classified. The average total price impact for the 4,349 seller-initiated blocks that would have been correctly classified by this tick rule is 4.76

percent, a significant 41 basis points greater than the 4.35 percent total impact for the entire sample of seller-initiated trades.

2.3 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 percent 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. Third, the permanent price effects are in the hypothesized direction, but the estimates that incorporate longer pretrade periods tend to be smaller in magnitude than the permanent effects for the seller-initiated trades in Table 1. Finally, only after 1990 is the temporary impact the right sign for this sample of buyer-initiated blocks, but the magnitudes of the temporary impacts are very small and statistically insignificant.

The asymmetry in the temporary components of buyer- versus seller-initiated trades is puzzling. Ball and Finn (1989), Chan and Lakonishok (1993b), Holthausen, Leftwich, and Mayers (1987), Kraus and Stoll (1972), and Scholes (1972) also find evidence suggesting asymmetric responses. However, it should be noted that the temporary impacts for trades identified as buyer initiated in these studies are positive. The fact that the temporary impacts had the wrong sign in the 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 DFA may sell to buying initiators 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. This may occur because the firm is eager to sell a stock that exits its universe for liquidity reasons, and this passive strategy is known to potential buyers. This option is also present for a potential seller of a small capitalization stock, but if the firm already has a position in a stock, it may not elect to purchase more stock when the seller wishes to trade. By contrast, potential traders can compute when a particular stock reaches the firm's sell list using public information. Thus, the temporary impact is subsumed into the permanent impact for buyer-initiated transactions. The persistent upward postblock price movement for nearly 3 weeks for the buyer-initiated blocks documented

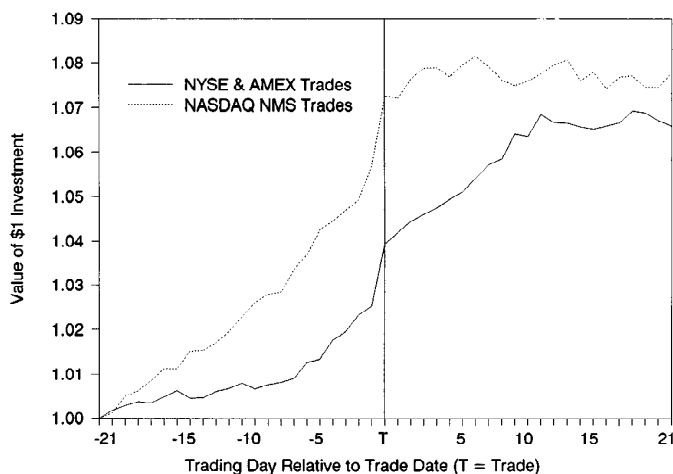


Figure 2
Price behavior associated with buyer-initiated blocks

The price path is plotted for 2 months (42 trading days) surrounding the trade day for the period July 1985 to December 1992. The series represent the average price behavior for the separate samples of NYSE-AMEX and NASDAQ NMS blocks trades. We compute each series using the following steps: (1) align 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 $V_{-22} = 1$, as $V_t = V_{t-1}(1 + r_t^{vw})$.

in Figure 2 reinforces the notion that the buyers may have been informationally motivated. These results demonstrate the difficulty in assessing the true desired trade quantity of a buyer: the initiator may continue to purchase stock, despite providing assurances to the contrary.

The direction of the temporary impacts suggests the use of the tick test to identify trades as buyer-initiated transactions may produce biases; indeed, we find that 191 buyer-initiated trades (about 20.4 percent of the sample) would not be correctly classified with this methodology. The average total price impact for the 746 buyer-initiated blocks that would have been identified by the tick rule is 2.01 percent, 56 basis points greater than the 1.45 percent total price impact for the entire sample of buyer-initiated trades.¹⁵

¹⁵ 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 percent of their trades; Robinson and White (1991) and Chan and Lakonishok (1993b), using data that identifies buyer- and seller-initiated transactions, report very similar results.

Table 3
The Relation between Percentage Price Changes and Block Size

Trade size ¹	Temporary impact	Permanent impact measured over the period:			Postblock price change ($t + 2$ to $t + 21$)
		($t - 1$ to $t + 1$)	($t - 6$ to $t + 1$)	($t - 22$ to $t + 1$)	
A. Seller-initiated blocks					
0.01–0.15	–1.48 (0.13)	–1.56 (0.14)	–3.58 (0.29)	–3.72 (0.70)	0.19 (0.41)
0.15–0.27	–2.21 (0.14)	–1.51 (0.15)	–4.38 (0.22)	–5.99 (0.54)	–1.02 (0.43)
0.27–0.46	–2.76 (0.15)	–1.28 (0.16)	–3.91 (0.23)	–6.84 (0.45)	–1.15 (0.43)
0.46–0.82	–3.31 (0.17)	–1.54 (0.17)	–4.67 (0.26)	–7.97 (0.43)	–1.90 (0.44)
0.82–7.86	–4.57 (0.20)	–1.64 (0.19)	–4.78 (0.28)	–9.08 (0.47)	–1.76 (0.46)
B. Buyer-initiated blocks					
0.01–0.07	0.23 (0.19)	1.22 (0.26)	2.70 (0.45)	4.96 (1.36)	–1.89 (1.48)
0.07–0.13	0.28 (0.19)	1.19 (0.22)	2.47 (0.41)	5.04 (0.93)	–2.18 (1.28)
0.13–0.19	–0.38 (0.22)	1.85 (0.29)	2.99 (0.54)	6.18 (1.05)	0.32 (0.87)
0.19–0.35	–0.42 (0.27)	1.94 (0.26)	3.26 (0.70)	6.46 (1.30)	0.48 (0.85)
0.35–5.48	–0.43 (0.23)	1.77 (0.27)	2.78 (0.50)	3.26 (0.70)	1.68 (0.79)

The table presents mean temporary, permanent and postblock percentage price changes for upstairs-negotiated block trades for NYSE, AMEX, and NASDAQ stocks for the period July 1985 to December 1992. The temporary price impact is defined as $-\ln(P_{t+1}/P_{\text{trade}})$, where P_{t+1} is the closing price on the day following the block, P_{trade} is the negotiated block price, and date t is the block trade date. The permanent price impact is defined as $\ln(P_{t+1}/P_{t-n})$, where P_{t-n} is the closing price on the n th day before the trade date. All non-trade-date price movements are adjusted for market movements. The equal-weighted CRSP NYSE-AMEX market index is used to adjust the NYSE and AMEX stock trades, and the CRSP NASDAQ index is used to adjust the NASDAQ stock trades. The adjustment is made by subtracting the relevant market index return from the stock's return, without any adjustment for the stock's market beta. These impacts are stated in percent, and standard errors are reported in parentheses. Block size is defined as the number of shares traded stated as a percentage of the total number of shares outstanding.

¹ Each classification category represents a quintile based on a sort of the data based on trade size. Each category contains 937 observations in panel A and 187 observations in panel B.

3. The Determinants of Block Price Effects

3.1 Descriptive 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 temporary and permanent 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 show that the 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.¹⁶ Proposition 4 predicts 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 trade-day permanent impact ($t - 1$ to $t + 1$) and trade size for the seller-initiated blocks. This finding is consistent with most results in the literature.¹⁷

Proposition 4 also 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 preblock price behavior, and the permanent effect measured relative to the decision price is an increasing function of trade size. Since we don't know precisely when the initiators made the decision to sell the blocks in our sample, we report two additional estimates of the permanent impact: one that incorporates 1 week of pretrade price movements ($t - 6$ to $t + 1$) and one that incorporates 4 weeks of pretrade price movements ($t - 22$ to $t + 1$). While we don't observe much of a relation between the 1-week permanent impact and trade size, the 4-week permanent impacts are strongly related to trade size, suggesting that the larger 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 pretrade price change on the stock price and trade size (measured as a percentage of outstanding shares), the coefficient on trade size is -0.0112 with a t -value of -3.77 . Intuitively, the very fact that a block trade is impending conveys information to the market (the so-called overhang), and the larger the block, the greater the information contained in that signal. Consistent with this conjecture, Nelling (1992) finds strong support for the hypothesis that

¹⁶ Although the temporary price impacts reported in this study reflect in part the bid-ask spread, the estimates contain much more information about the costs of large trades than the spread alone conveys, for several reasons. First, we find a significant relation between trade size and temporary impacts. While a relation between reported spreads and market capitalization has been widely documented, there is no reason to believe that reported spreads are related to the size of individual trades, and there is no relation between trade size and market capitalization in our sample. Table 4 contains regression results where we explicitly control for share price, a proxy for market cap, when estimating a significant relation between trade size and temporary impact. Second, for stocks with similar market capitalizations as the stocks in our sample, reported bid-ask spreads are small in comparison to our estimates of temporary impacts. For example, Keim (1989) reports that half of the median reported bid-ask spread for NYSE, AMEX, and NASDAQ stocks in the ninth decile of size (the average market cap of \$77 million for our sample falls in this decile) ranges from 0.9 to 1.4 percent, less than the temporary impacts we report in Table 3 for the smallest trades in our sample. Further, effective bid-ask spreads are known to be considerably smaller than reported spreads.

¹⁷ The exception is Kraus and Stoll (1972).

the relation between trade size and pretrade returns reflects leakage in the upstairs market.

The results for the buyer-initiated blocks, given in Table 3B, are less clear. As discussed above in Table 2, we find no evidence of significant temporary impacts for the buyer-initiated blocks and, as a result, no relation between trade size and temporary impacts. Although the trade-day permanent impacts appear to be strongly related to trade size, the 1-week and 4-week permanent impacts exhibit no such relation. 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 pretrade 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 posttrade price was at or above the block price. In addition, there is evidence of a significant relation between posttrade market-adjusted price movements and trade size, suggesting that much information contained in the trade was not incorporated into the price until after the trade, and that this posttrade “information component” is related to trade size. As we noted above, this finding can be explained if DFA underestimated 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.

3.2 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:

$$\tau_i = \beta_0 + \beta_1 D_i^{OTC} + \beta_2 PINV_i + \beta_3 q_i + \beta_4 q_i^2 + \beta_5 q_i^3 + \beta_6 D_i^{3rd} + \epsilon_i, \quad (16)$$

where $\tau_i = -\ln(P_{i,t+1}/P_{i,trade})$ is the temporary impact measured in (decimal) return form, 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 inverse of the trade price, q_i is the (absolute) number of shares traded divided by the number of shares outstanding, and D_i^{3rd} equals one if block trade i was done by a third market broker and zero otherwise.

The regression, Equation (16), is motivated by our model. The coefficient β_1 allows us to test for systematic differences in the price impacts of listed versus NASDAQ 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 that the absolute value of the temporary impact is an increasing and concave function of trade size. By including trade size and higher powers of trade size, we can examine this hypothesis in a general way. In the case of a seller-initiated trade, for example, we expect $\beta_3 < 0$, $\beta_4 > 0$, and $\beta_5 < 0$. We can distinguish trades executed in the upstairs market through exchange-member brokers from those executed by third-market (nonexchange member) brokers. Any differences in the ability of exchange and nonexchange brokers to provide upstairs intermediation will be captured in the coefficient β_6 .

Table 4A reports estimates of Equation (16). The first regression in panel A is for seller-initiated transactions, which comprise almost 80 percent of our sample. The coefficient of the NASDAQ dummy variable, β_1 , is significantly negative, suggesting that temporary costs are higher (for seller-initiated transactions, the temporary impact is negative) for nonlisted stock trades. The results show that there is a significant inverse relation between the temporary impact and the price level. This finding is consistent with our hypotheses since higher priced stocks tend to be associated with larger market capitalizations, making it easier and cheaper to find a counterparty for the trade. Further, more information may be available for higher priced stocks, implying counterparties 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 the negative and significant estimate of β_3 . Additionally, β_4 is significantly positive, consistent with the prediction of Proposition 1 in which the relation between temporary impacts and trade size is nonlinear. Although β_5 is negative as predicted, it is insignificant. The bounded concave relation implied by the regression estimates in Table 4A is graphically depicted in Figure 3 for the relevant range of trade size for our sample. Finally, the coefficient on the third-market broker variable is insignificant, indicating that the magnitude of the temporary impact is not affected by the choice of the broker.¹⁸

The second regression in panel A contains results for the temporary

¹⁸ We also tested for interactions between order size and broker type, but these results merely confirmed that the choice of broker has little effect on liquidity costs.

Table 4
The Determinants of the Price Impacts for Block Trades

The parameter estimates in the table are for the following model¹ estimated over the period July 1985 to December 1992:

$$y_i = \beta_0 + \beta_1 D_i^{\text{OTC}} + \beta_2 \text{PINV}_i + \beta_3 q_i + \beta_4 q_i^2 + \beta_5 q_i^3 + \beta_6 D_i^{\text{3rd}} + \beta_7 R_i^{\text{Post}} + e_i.$$

β_0	β_1	β_2	β_3	β_4	β_5	β_6	β_7	Adjusted R^2
A. Temporary impact ($y_i = \tau_i$)²								
<i>Seller-initiated</i>								
0.0081 (0.0021) ³	-0.0081 (0.0016)	-0.1354 (0.0126)	-0.0201 (0.0037)	0.0041 (0.0019)	-0.0003 (0.0002)	-0.0022 (0.0016)	—	.163
<i>Buyer-initiated</i>								
0.0012 (0.0029)	0.0007 (0.0021)	0.0420 (0.0341)	-0.0252 (0.0072)	0.0156 (0.0046)	-0.0023 (0.0008)	-0.0019 (0.0021)	—	.009
B. Permanent impact ($y_i = \pi_i$)²								
<i>Seller-initiated</i>								
-0.0590 (0.0052)	0.0167 (0.0044)	-0.0928 (0.0182)	-0.0230 (0.0101)	0.0019 (0.0051)	0.0003 (0.0006)	-0.0029 (0.0042)	-0.0471 (0.0135)	.020
<i>Buyer-initiated</i>								
0.0299 (0.0113)	0.0366 (0.0096)	-0.0967 (0.1055)	0.0187 (0.0268)	-0.0182 (0.0158)	0.0030 (0.0025)	0.0117 (0.0087)	-0.0142 (0.0208)	.014

¹ The variables in the model are:

$$\begin{aligned} \tau_i &= -\ln(P_{i,t+1}/P_{i,\text{trade}}) \\ \pi_i &= \ln(P_{i,t+1}/P_{i,t-22}) \\ D_i^{\text{OTC}} &= 1 \text{ if block trade } i \text{ is a NASDAQ stock} \\ &= 0 \text{ otherwise} \\ \text{PINV}_i &= 1/P_{ib} \\ q_i &= [(\text{number of shares traded})/(\text{total shares outstanding})] \cdot 100 \quad (\text{absolute value}) \\ D_i^{\text{3rd}} &= 1 \text{ if block trade } i \text{ was done by a 3rd market broker} \\ &= 0 \text{ otherwise} \\ R_i^{\text{Post}} &= \ln(P_{i,t+21}/P_{i,t+2}) \end{aligned}$$

² All non-trade-date price movements are adjusted for market movements. The equal-weighted CRSP NYSE-AMEX market index is used to adjust the NYSE and AMEX stock trades, and the CRSP NASDAQ index is used to adjust the NASDAQ stock trades.

³ The numbers in parentheses are heteroscedasticity-consistent standard errors.

impacts for buyer-initiated trades. Unlike the sample of seller-initiated blocks, the coefficients on both the NASDAQ and price variables are insignificantly different from zero, possibly because of the smaller sample size. The coefficient on the third-market broker variable is also insignificant, again suggesting that the broker type has little effect

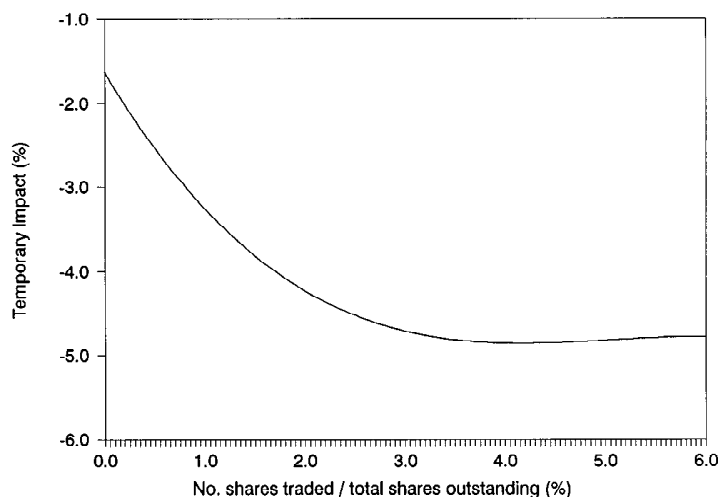


Figure 3

Relation between temporary price impacts of seller-initiated blocks and trade size

The plot is generated using the estimated coefficients from Equation (10) over the relevant range of trade size for our sample of block trades for NASDAQ block trades ($D^{OTC} = 1$) arranged by exchange-member brokers ($D^{3rd} = 0$). Trade size is defined as the number of shares traded divided by the total outstanding shares, stated in percent. The median share price for our sample (\$8.375) is used in the calculations. The time period is July 1985 to December 1992.

on liquidity. Finally, the coefficients on the trade size variables are significantly different from zero, but are exactly the reverse in sign of our predictions.

Larger trade sizes appear to reduce the temporary price impact. There are two possible explanations for this finding. First, the finding is possibly due to our confounding the identity of the initiator for these trades. Participants in the upstairs market know the identity and trading strategy of the investment 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. Indeed, blocks of the same size may have very different price impacts if outsiders can infer part of the motivations for trade. For example, a large order placed by a pension fund that frequently rebalances its portfolio may have small price effects. Second, as noted earlier, this finding is also consistent with the firm incorrectly

assessing the probability that a buyer-initiated trade was informationally motivated. That is, the estimated relation may be confounding the temporary and permanent components of the trade impact.¹⁹

Figure 1 suggests that using the date $t - 1$ 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, in our test of the information component of the trade, we measure the permanent impact using the price that prevailed 22 days before the block was traded. Table 4B contains results from estimating the following equation:

$$\begin{aligned} \pi_i = & \beta_0 + \beta_1 D_i^{OTC} + \beta_2 PIN V_i + \beta_3 q_i + \beta_4 q_i^2 + \beta_5 q_i^3 \\ & + \beta_6 D_i^{3rd} + \beta_7 R_i^{Post} + \epsilon_i, \end{aligned} \quad (17)$$

where the dependent variable is the permanent impact in return (decimal) form, i.e., $\pi_i = \ln(P_{t+1}/P_{t-22})$, and the posttrade return R_i^{Post} is equal to $\ln(P_{t+21}/P_{t+2})$, where P_{t+n} is the closing price on the n th trading day before or after the trade date. Recall that all non-trade-date price movements are adjusted for market movements by subtracting the relevant market price index from the stock's return.

The results in panel B show that the magnitude of the seller-initiated permanent impact is significantly greater for exchange-listed stocks (see also Figure 1) and inversely related to the price of the security. We find evidence that larger trade sizes imply higher permanent impacts for the seller-initiated trades, but although our model predicts a nonlinear response, the coefficients β_4 and β_5 are insignificant.²⁰ The coefficient on the third-market broker variable β_6 is again statistically insignificant. Interestingly, the coefficient on the posttrade return variable is negative and significant, indicating that a significant portion of the negative pretrade price movement for some trades is reversed after the trade. This finding suggests that some of the pretrade price movement reflects price pressure effects that are temporary in nature.

¹⁹ When we estimate the regression for buyer-initiated temporary impacts using only those impacts with the correct sign, the coefficients on all trades size variables are insignificantly different from zero.

²⁰ 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 finding is consistent with our earlier claim that studies of price impacts that ignore the effect of the pretrade "overhang" may seriously understate the permanent impacts of the trade.

The estimates for the permanent impact regression for the buyer-initiated trades indicate that permanent effects are significantly larger for NASDAQ trades, but the remaining coefficients are all insignificantly different from zero. The lack of statistical significance of trade size is consistent with the buyer-initiated trades being perceived as largely liquidity motivated.²¹

To summarize, the results for seller-initiated trades provide strong support for our conjectures. 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. The implications of our results for large upstairs trades may be useful for empirical studies of price impacts in dealer markets. Specifically, researchers need to be careful about assumptions of linearity of the relation between temporary 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.²²

4. Conclusions

A significant fraction of large-block trades in U.S. equities is accomplished through the upstairs market. Yet despite its importance as a source of liquidity in equity markets, the upstairs mechanism has been largely overlooked in previous studies. Further, previous empirical studies of large transactions identify trades by their size, not by the mechanism in which they originate.

As the majority of block trades occur in the downstairs market, the inability to distinguish trades facilitated in the upstairs market limits our understanding of this mechanism. This problem is compounded by the fact that the data used in previous studies generally do not identify a trade as buyer or seller initiated, and the trades examined may be parts of still larger orders. Given these deficiencies, even basic empirical questions about the upstairs market remain unanswered. This article's objective is to analyze, both theoretically and empirically,

²¹ It is possible that the magnitude of the permanent impact 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.

²² For example, Hausman, Lo, and MacKinlay (1992) use an ordered probit model to analyze intraday price movements. They report that in order 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, for example, Glosten and Harris (1988), have noted that the estimated effect of quantity on price is lower than expected.

the effect of large transactions arranged in the upstairs market on stock prices.

We develop a model of the upstairs market that provides theoretical representations of the price effects around an upstairs trade. We investigate the model's predictions with unique data obtained from a trader of small, illiquid stocks in the upstairs market. The data cover 5,625 block trades during the period 1985 to 1992. Unlike previous studies, all the trades in our database are negotiated upstairs and are identified as buyer or seller initiated. As a result, we view our findings as a more accurate characterization of the operation of the upstairs market and its effect on the costs of trading large blocks of stock.

We find that the temporary price impact for seller-initiated trades is positively and significantly related to trade size, and negatively related to price. The impacts for NASDAQ trades are significantly larger than the impacts for comparable trades on exchanges where block trades on exchanges must be exposed to the floor for possible price improvement. There is also evidence that the temporary price impact of block trades is a concave function of order size, as predicted by the model. This finding suggests that we exercise care in modeling the relation between price impact and trade size when trades include large-block trades that were likely to have been negotiated in the upstairs market. We also find significant pretrade (net-of-market) price movements that are related to the size of the trade. We attribute these price movements to the search-brokerage nature of the upstairs market, where information contained in the trade may be leaked to the market before the actual consummation of the trade. Thus, the standard measure of the permanent price impact, estimated using trade-day price movements, probably provides a lower bound for information actually contained in a block trade.

The analysis raises several new issues. It would be valuable to extend the model to incorporate more complicated trading strategies involving trades over a long horizon. For example, how does order breakup affect price dynamics and information revelation over time? It would also be interesting to compare the operation of the upstairs and downstairs markets in terms of their ability to provide liquidity. This would be especially relevant for stocks with low market capitalization. Finally, do the results documented here apply more generally and to other markets? These, however, are topics for future research.

Appendix

Proof of Proposition 1. Substituting Equation (5) into Equation (6) and solving, we can express the equilibrium block price as a function of

Q , given n , which we denote by

$$p_b(Q; n) = E_{t_b}[\tilde{v}|Q] + \frac{\alpha Q}{n}, \quad (\text{A.1})$$

where $\alpha = \rho\sigma^2[\tilde{v}|Q]$. The size of the trade becomes public at time t_1 , so that the posttrade price in the downstairs market p_1 (which equals the expected value of the security given the size of the trade) is equal to the conditional expectation of the representative counterparty who observes the trade size, that is, $p_1 = E_{t_1}[\tilde{v}] = E_{t_b}[\tilde{v}|Q]$. Using Equation (A.1) and Equation (2), the temporary effect can be expressed as

$$\tau = p_b - p_1 = \frac{\alpha Q}{n}. \quad (\text{A.2})$$

The number of counterparties is selected by the block trader. A competitive block trader arranges the trade to maximize the trading revenue (or minimize the cost) for a block sale (buy). For a purchase, the block trader chooses the search intensity n to solve

$$\min_n \{Qp_b(Q; n) + \phi(n)\}. \quad (\text{A.3})$$

For a sell, the corresponding problem is to maximize net revenues given by $-Qp_b(Q; n) - \phi(n)$. Equating expected marginal revenues and costs (and ignoring integer constraints²³), the optimal number of traders identified through the search process solves

$$\frac{\alpha Q^2}{n^2} = \gamma \delta n^{\gamma-1}. \quad (\text{A.4})$$

Solving, we obtain the optimal number of contacts as a function of trade size,

$$n(Q) = \left(\frac{\alpha}{\gamma \delta} \right)^{\frac{1}{\gamma+1}} |Q|^{\frac{2}{\gamma+1}}. \quad (\text{A.5})$$

Substituting Equation (A.5) into Equation (A.2) yields Equation (12), where

$$K_1 = \alpha^{\frac{\gamma}{\gamma+1}} (\gamma \delta)^{\frac{1}{\gamma+1}}. \quad (\text{A.6})$$

Note that when $\gamma > 1$, $\tau(Q)$ is an increasing (decreasing) and concave (convex) function of trade size for buys (sells.) When $\gamma = 1$, the temporary impact is a constant independent of size.

²³ Treating n as a continuous variable simplifies the exposition considerably, and may be more in keeping with reality where several counterparties are contacted (although very few may respond) by the block trader.

Proof of Proposition 2. Fix order size, Q , and consider Equation (A.6). As K_1 is increasing in δ and α , it follows that the temporary impact is increasing with the cost of search, degree of risk aversion, and the conditional variance of the asset's liquidation value.

Proof of Proposition 3. Denote by $C(Q)$ the *total* commission costs as a function of order size. As n is a function of trade size, $|Q|$, the commission costs are also a function of size and

$$C(Q) = \phi(n(Q)) = K_2|Q|^b, \quad (\text{A.7})$$

where $K_2 = \delta^{\frac{1}{\gamma+1}}(\alpha/\gamma)^{\frac{\gamma}{\gamma+1}}$ and $b = \frac{2\gamma}{\gamma+1}$. For a given order size, K_2 is increasing in α and δ , that is, commissions increase with cost of search, degree of risk aversion, and the conditional variance of the asset's liquidation value. Per share commissions are given by $C(Q)/|Q| = K_2|Q|^{b-1}$.

Proof of Proposition 4. Consider a buy order; the price response for sell orders is determined in a corresponding manner. Recall that $\tau(Q) = K_1 \text{sign}(Q)|Q|^a$ and $C(Q) = K_2|Q|^b$, where K_1 and K_2 are positive constants, $a = \frac{\gamma-1}{\gamma+1}$ and $b = a + 1 = \frac{2\gamma}{\gamma+1}$. Using these relations, Equation (11) can be expressed in the form

$$\pi(Q) = A[b(K_1 + K_2)Q^a + \pi(Q) + Q\pi'(Q) + BQ], \quad (\text{A.8})$$

where $A = w/u_0$ and $B = \rho\sigma_0^2$. Observe that $A < 1$. Intuitively, s is a noisy signal of y , which in turn is a noisy signal of v , so the variance of s is greater than the variance of y . Accordingly, the initiator places more weight on the direct signal than the counterparty places on the indirect signal conveyed by order size. The following price functional is a solution to Equation (A.8):

$$\pi(Q) = \lambda_1 Q + \lambda_2 Q^a, \quad (\text{A.9})$$

where (when $\gamma > 1$) $\lambda_1 = \frac{AB}{1-2A}$ and $\lambda_2 = \frac{Ab(K_1+K_2)}{1-Ab}$.²⁴ Note that the initial condition $\pi(0) = 0$ is also satisfied by Equation (A.9).

For λ_1 to be positive, the constant A must be less than $\frac{1}{2}$. If this condition holds, then λ_2 is also positive (since $b < 2$ and, thus, $Ab < 1$), and the second order condition of the block initiator's problem [Equation (7)] is satisfied. Recall that $A = \frac{w}{u_0}$, the ratio of the weight placed by the public on the information signal conveyed by the initiator's order to the weight placed by the initiator on the private signal. Us-

²⁴ When $\gamma = 1$, τ is a constant and both $\pi(Q)$ and $C(Q)$ are linear functions.

ing the definitions of these weights, we obtain $A = \frac{\sigma_v^2 + \sigma_y^2}{\sigma_v^2 + \sigma_s^2}$. Recall that $\sigma_s^2 = \sigma_y^2 + \zeta^2 \sigma_x^2$, where $\zeta = -\rho \sigma_0^2 / w_0$. Now, from DeGroot (1970), the conditional variance of the initiator is given by $\sigma_0^2 = \sigma_v^2 \sigma_y^2 / (\sigma_v^2 + \sigma_y^2)$. Using this expression and the definitions of ζ and w_0 , the restriction $A < \frac{1}{2}$ reduces to

$$\frac{1+r}{\sigma_y^2} < \rho^2 \sigma_x^2, \quad (\text{A.10})$$

where $r = \sigma_v^2 / \sigma_y^2$ is a measure of information asymmetry given by the ratio of the variance of public information to the variance of private information. Thus, existence requires that portfolio hedging motivation for trade (measured by $\rho^2 \sigma_x^2$) be sufficiently large relative to the degree of information asymmetry. This is a familiar requirement in trading models [see, for example, Glosten (1989) and Madhavan (1992)]. The analysis for a sell is symmetric. In the general case, the permanent impact is $\pi(Q) = \lambda_1 Q + \lambda_2 \text{sign}(Q)|Q|^a$. The price functional is a concave (convex) function of order size for buys (sells).

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