In Search of Liquidity: Block Trades in the Upstairs and Downstairs Markets

Ananth Madhavan
University of Southern California

Minder Cheng
Salomon Brothers Asia

We analyze the ability of various market mechanisms to provide liquidity for large equity trades. Using data on 21,077 block transactions in Dow Jones stocks, we find that the "downstairs" NYSE floor market is a significant source of liquidity. Although negotiation in the informal "upstairs" market provides better execution than the downstairs market for large trades, these differences are economically small. We find, however, that upstairs markets are used by traders who can credibly signal that their trades are liquidity motivated. Thus, upstairs markets allow trades that may not otherwise occur.

Liquidity is an essential attribute for equity markets to function as a source of capital for corporations and provide investment and diversification opportunities

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for the public. A liquid market is characterized by its ability to absorb large trading volumes without substantial price movements. This aspect of liquidity has attracted considerable attention because of the growing importance of large-block transactions.[1]

There are two economically distinct trading mechanisms for large-block transactions. First, a block can be sent directly to the "downstairs" markets. These markets in turn comprise the continuous intraday markets, such as the NYSE floor, and batch auction markets, such as openings and the after-hours session on the NYSE. Second, a block trade may be directed to the "upstairs" market where a block broker facilitates the trading process by locating counterparties to the trade. The upstairs market operates as a search-brokerage mechanism where prices are determined through negotiation. By contrast, downstairs markets are characterized by their ability to provide immediate execution at quoted prices. This article examines empirically the role of upstairs and downstairs markets in providing liquidity for large-block trades.

This topic is important for both practical and academic reasons. From a practical viewpoint, an examination of the magnitude and determinants of the price movements associated with large transactions is of obvious importance for equity traders, policymakers, and regulators. From an academic viewpoint, we know relatively little about price formation in the upstairs market and the relation between upstairs and downstairs markets, factors which determine the observed prices and volumes.

Theoretical analyses of upstairs intermediation focus on its role in mitigating the adverse selection costs faced by large traders. Burdett and O'Hara (1987) provide the first model of upstairs intermediation, focusing on the search process by which trade counterparties are located. Seppi (1990) develops an intertemporal model where an investor has the choice between trading upstairs or downstairs. Seppi shows that a liquidity trader may trade a block rather than place a sequence of small transactions by credibly signaling to the block trader that he or she is uninformed. In Seppi's model, this signal takes the form of a commitment not to "bag the street" by trading after the block. Similar results would obtain from reputational signals or other implicit commitments. Thus the upstairs market serves as a screening device,

[1] See, among others, Bagwell, Breen, and Korajczyk (1995), Ball and Finn (1989), Choe, McInish and Wood (1991), Holthausen, Leftwich, and Mayers (1987, 1990), Keim and Madhavan (1996b), Kraus and Stoll (1972), Mikkelson and Partch (1985), Scholes (1972), Seppi (1992a, 1992b), and Stoll (1993). In 1994, block trades of 10,000 shares or more amounted to 55.5 percent of New York Stock Exchange (NYSE) share volume.

mitigating the adverse selection costs facing large liquidity traders.[2] Seppi's (1990) results are important because they demonstrate that the upstairs and downstairs markets can coexist in equilibrium by serving different clienteles.

Although there is an extensive empirical literature on the price impacts associated with large-block trades, it is difficult to test hypotheses concerning price formation in different trading mechanisms. For example, we expect that the price impact of a trade is an increasing function of its size. However, as noted by Seppi (1990), this relation may be obscured in the available data which represents a mixture of upstairs and downstairs trades. Intuitively, traders who can credibly signal that they are liquidity motivated can trade large blocks in the upstairs markets with minimal price impacts. By contrast, traders who cannot credibly signal their motivations will trade anonymously downstairs, possibly facing large price impacts even for small trades, thereby confounding empirical estimation of the price-size relation.

Unfortunately, publicly available databases do not provide a way to determine whether a particular block trade was first facilitated upstairs or was directly routed to the downstairs market.[3] As a result, even the most fundamental questions about the extent and determinants of upstairs market activity remain unresolved. We know of no empirical studies that compare and contrast price formation in the upstairs and the downstairs markets. The objective of this article is to shed light on these issues.

We use unique data on 21,077 block trades in the 30 stocks comprising the Dow Jones Industrial Average to determine whether a block trade was first facilitated upstairs (and then sent downstairs) or was sent directly downstairs. This permits a direct comparison of price formation and liquidity between the upstairs and the downstairs markets. The Dow Jones stocks are of particular interest because they account for a substantial fraction of NYSE trading volume and market capitalization. These stocks also provide an interesting contrast to the small stocks examined by Keim and Madhavan (1996b).

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[2] Similarly, Grossman (1992) argues that upstairs markets aggregate information about investor's latent demands. Keim and Madhavan (1996b) model the upstairs market as a mechanism to aggregate traders and dampen the price impacts associated with a block trade by risk sharing. Luskin (1989) provides a historical overview of the development of upstairs trading.

[3] An exception is Keim and Madhavan (1996b), who analyze data obtained from an upstairs trader who specializes in low market capitalization stocks. Although all the transactions in their sample are upstairs trades, they cannot distinguish between upstairs and downstairs trades in a particular stock.

Our results show that downstairs markets are a major source of degree of liquidity for large-block transactions in the sample stocks. Indeed, about 80% of total dollar volume of the block trades in our data are executed in the intraday downstairs market without upstairs facilitation. Contrary to popular perception, this is also true for the largest transactions. Although our sample consists of large stocks, there is evidence to suggest that our results are consistent with the general pattern for all NYSE stocks. Hasbrouck, Sofianos, and Sosebee (1993) report that 27% of the block volume in *all* NYSE-listed stocks was upstairs-facilitated for a randomly chosen day in 1993. This figure is somewhat larger than our estimates for the sample stocks, but nonetheless is consistent with our findings that downstairs markets are important sources of liquidity for large trades.

We develop an endogenous switching regression model to explain the observed price movements in the upstairs and downstairs markets based on the choices of individual traders. The results provide strong support for theoretical models of price formation in upstairs markets. In particular, we find evidence for Seppi's (1990) hypothesis that upstairs markets are used by traders who can credibly signal that their trades are not information motivated. Further, correcting for the selectivity bias arising from the endogenous choice of market mechanism, we find that the marginal price impacts for large-block trades are lower in upstairs markets, as predicted by theoretical models. However, the differences in price impacts between upstairs and downstairs intraday markets are economically small for the average trade. When the other costs of upstairs intermediation are considered, the downstairs market may be a viable alternative to the upstairs market even for large traders.

The small differences between the expected costs in both markets raises questions about the primary functions of the upstairs markets. Certainly, for the sample stocks, our evidence suggests that the existence of upstairs trades conveys only small benefits to the average initiator. A possible explanation is that liquidity providers, especially institutional traders, are reluctant to submit large limit orders and thus offer free options to the market. Upstairs markets allow these traders to selectively participate in trades screened by brokers who have strong reputational reasons to avoid trades that may originate from traders with private information. Thus the upstairs market permits transactions that would not otherwise occur in the downstairs market.

The article proceeds as follows. Section 1 describes the functioning of upstairs trading and the data and methodology employed in the article; Section 2 provides summary results of the price movements associated with upstairs and downstairs block trades. Section 3 examines the determinants of these price movements in the context of an endogenous switching regression model. Section 4 concludes.

1. Institutions, Data Sources, and Procedures

1.1 Trading arrangements for large-block transactions

We begin by describing briefly the procedures and regulations that govern large-block transactions since these rules are important for our subsequent empirical analyses.

In a typical upstairs trade, a large investor contacts an upstairs brokerage firm or block trader who then locates potential counterparties to the trade. Once the block trader has secured an agreement to cross a certain number of shares at a particular price, a floor broker at the NYSE is usually asked to represent the upstairs brokerage firm on both the buy and sell side of the cross.[4] Since the cross is handled by a floor broker, the upstairs brokerage firm cannot submit the order via a computerized execution system such as SuperDot that routes customer orders from the Exchange member directly to the specialist.

The floor broker proposes a price ("crossing price") to the trading crowd on the floor at which he intends to execute the block. Before the cross can be accomplished, the floor broker must fill, at the proposed crossing price, all the orders either in the specialist's limit order book or held by other brokers present on the floor at the time of the cross that represent a willingness to buy (sell) at the crossing price or higher (lower). In such cases, the intended cross may be partially broken up, with the floor traders or limit orders obtaining better prices.[5] The cross can also be broken up by some other traders willing to offer better prices to either side of the cross.[6]

By contrast, a downstairs trade is usually the result of a buy order meeting a sell order on the floor, each represented by a different broker or alternatively, with the specialist participating as principal. This distinction is the key to identifying upstairs trades.

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[4] NYSE Rule 390 specifies that for stocks initially listed on a U.S. exchange on or before April 26, 1979, an exchange member cannot effect principal trades and two-sided crosses off an organized exchange. Many large upstairs traders are exchange members, but even if Rule 390 applies, the trade can be sent to a regional exchange instead of the NYSE.

[5] When multiple parties are involved, the trade is printed as single transaction on the consolidated tape, with the reported volume equal to that of the entire amount of the transaction.

[6] See Hasbrouck, Sofianos, and Sosebee (1993) for further explanations on NYSE Rules 72, 76, and 127 that specifically enforce the auction market's order priority, order exposure, and price improvement principles in the case of crossing orders, and other related rules.

Table 1
Consolidated tape print of a sample trade

Symbol	Date	Time	Price	Size	Sequence number
IBM	940331	11:43:30	52.625	19000	533860

A sample trade of 19,000 shares in IBM at 11:43:30 A.M. on March 31, 1994, reported to the consolidated tape and taken from the TAQ database. The trade price is $52.625. The sequence number is assigned automatically by the Market Data System of the NYSE and uniquely identifies each NYSE trade reported to the tape.

1.2 Identifying upstairs and downstairs trades

As noted above, it is generally not possible to identify from publicly available databases [e.g., the Trades and Quotes (TAQ) or ISSM databases] whether a trade was directly routed to the downstairs market or was upstairs facilitated.[7] However, this distinction is possible with the Consolidated Audit Trail Data (CAUD) files maintained by the NYSE. Three months of the CAUD files for a sample of 144 NYSE stocks form the basis for the TORQ database, but these files are generally not released publicly. We use a procedure developed by the NYSE's Research and Planning Group (based on conversations with market participants) to identify upstairs and downstairs trades from data in the CAUD and TAQ files.

It is easiest to explain the NYSE's procedure to identify upstairs trades with a particular example. Table 1 presents the details of a consolidated tape print for a trade of 19,000 shares of IBM at a price of $52.625 at 11:43:30 A.M. on March 31, 1994. The table presents the information on this trade that is also recorded on the publicly available TAQ database. In particular, the TAQ data contain, among other variables, the symbol, trade date, trade time, trade price, trade size, and the unique sequence number for the trade.[8]

Table 2 illustrates the audit trail records corresponding to the single consolidated print, where several additional fields have been omitted for simplicity. There are four audit trail records reflecting the allocation of the 19,000 shares among four pairs of buying and selling brokers, as indicated by the subsequence number. In addition to the fields included in the consolidated tape record, the audit trail records contain augmented information on the numeric codes (badge numbers) identifying the brokers representing the buyers and the sellers and their respective transacting share quantities. On the sell side, broker 0764 is involved in two transactions for 5,000 and 4,000 shares separately,

[7] The TAQ database, like the ISSM database, contains all trade and quote records for stocks listed on the NYSE, AMEX, and regional exchanges, as well as NASDAQ NMS securities.

[8] The sequence number is automatically assigned by the Market Data System of the NYSE and uniquely identifies each NYSE trade reported to the consolidated tape.

Table 2
Sample audit trail records

Symbol	Date	Time	Price	Size	Buyer badge	Seller badge	B/S qty.	Sequence number	Subseq. number
IBM	940331	11:43:30	52.625	19000	0807	0764	5000	533860	1
IBM	940331	11:43:30	52.625	19000	0807	0764	4000	533860	2
IBM	940331	11:43:30	52.625	19000	0807	0807	5000	533860	3
IBM	940331	11:43:30	52.625	19000	0807	0861	5000	533860	4

Four audit trail records corresponding to the trade presented in Table 1. These records are obtained from the NYSE Consolidated Audit Trail (CAUD) files for March 31, 1994. The CAUD files contain the result of trade matching comparison and market data. All buy/sell trades matched to a given tape print have the same sequence number.

possibly for one customer. Note though that only one trade for 19,000 shares of IBM is reported to the ticker tape and recorded in the TAQ database.

The additional information contained in the audit trail data on the allocation of shares among buyers and sellers enables us to infer the mechanism of origin for the trade. To see this, recall that in a typical upstairs transaction the upstairs broker searches and matches buyers and sellers and then exposes the order for (possible) price improvement through the public auction process on the floor of the NYSE. As a result, the same floor broker must represent both the buyer and the seller for at least part of the overall trade volume. The sample trade illustrated in Table 2 has this characteristic.

Observe that in the third record of Table 2, broker number 0807 represents both the buy and the sell sides of the order, indicating that the entire order was possibly facilitated in the upstairs market first before being executed at NYSE. Moreover, the portion successfully crossed by the floor broker does not involve the specialist and does not reach the floor through electronic order submission systems such as SuperDot. In this case, we can check that these additional requirements are satisfied using audit trail information not reported in Table 2.[9]

The sample audit trail record also illustrates another interesting feature of upstairs trades. Observe that the amount actually crossed by the upstairs trader using broker 0807 was only 5,000 shares, or 26% of the total order size of 19,000 shares. Crosses are often broken up because the upstairs trade has to be exposed to the public, offering an opportunity for other sellers (represented by brokers 0764 and 0861) to trade in accordance with auction principles of price and time priority, and for either side of the cross to obtain possible price im-

[9] It is also possible that broker 0807, by coincidence, received buy and sell orders, and the floor filled the balance. As we discuss below, this occurrence is unlikely for large-block trades.

provement. Thus, competition from other traders may explain the low crossing rate.

1.3 Screening algorithm

The screening algorithm used here is a formalization of the intuitive classification scheme described above. Specifically, for a trade print to count as facilitated in the upstairs market, at least one of its corresponding audit trail records must satisfy all the following five conditions:

1. The buyer and the seller must be represented by the same broker for at least a portion of a consolidated tape print. The representing broker is neither a specialist nor a relief specialist.[10]
2. The *matching* buyer and the seller cannot have reached the floor through electronic systems such as SuperDot. The trade must be crowd-to-crowd with no system participation.
3. Neither the *matching* buy or sell order is from the limit order book.
4. The trade must be good, that is, no cancellation or error.
5. The trade must have a corresponding print on the consolidated tape, that is, it must have a nonzero trade sequence number.

As explained above, conditions (1) and (2) are required for a trade to be upstairs facilitated since a floor broker is needed to represent all cross-participating parties in executing an upstairs trade on the floor. Condition (3) states that the order type used by the matching broker (i.e., the broker who is on both the buy and sell side) cannot be a limit order. This screen is needed because a simultaneous crossing attempt by the matching broker must involve a floor order. However, the orders other than the matching order can be (and often are) limit orders. Conditions (4) and (5) act as checks on possible data errors, ruling out cases where the trade was canceled or was not reported on the consolidated tape.

An application of the procedure described above will classify all block trades in our sample as upstairs or downstairs trades. In addition, some trades on the NYSE are executed at the opening auctions, the reopenings after trading halts, or in the two after-hours crossing sessions. These markets are batch-auction markets, where multiple buyers and sellers trade simultaneously at a single price, as opposed to the continuous market operating during the day. Both the TAQ and CAUD files contain the information (condition codes and time) neces-

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[10] A relief specialist is a floor broker who is assigned to be a specialist on a temporary basis. Since relief specialists change frequently, we checked this requirement on a daily basis. This task is complicated by the fact that, unlike the regular specialist, the numeric identification code varies over time and across stocks and must be gathered by hand from exchange records.

sary to determine whether a trade occurred in a batch or continuous mechanism.

1.4 Possible classification problems

Although the classification scheme described above appears straightforward, there are some important caveats that should be noted. First, the screening conditions cannot eliminate cases where a broker receives a block buy for execution while in the process of brokering a block sell order on the floor. In this case, a trade classified as upstairs may in fact be a downstairs trade. However, conversations with floor brokers suggest that this is not a common event for block trades. When a large order is "worked" by a floor broker, it is generally broken up into smaller trades and executed over a period of time. Consequently, it is unlikely that a broker will simultaneously participate on the buy and sell sides of a downstairs large-block trade. Any misclassifications will result in an overstatement of the upstairs market activity, but this does not appear to be the case here.

Second, it is possible that a trade that was upstairs facilitated is completely broken up, with the floor taking the whole of the opposite side. In this case, the procedure will classify the trade as a downstairs trade when it actually originated in the upstairs market. There is, unfortunately, no way to identify such trades. However, it could be argued that such trades are, in fact, downstairs trades since the counterparties located through upstairs intermediation play no role in providing the liquidity necessary to complete the transaction. Consequently, we do not feel that these occurrences represent a serious problem in our data.

Third, the interpretation of trades in batch markets with a matching broker on both the buy and sell sides is troublesome. Such trades may, in theory, reflect a crossing attempt by an upstairs broker who is simultaneously presenting buy and sell orders in the same stock. However, this may simply reflect the random matching of independent buy and sell orders placed by large brokers, an occurrence that is likely in a multilateral trading system. There is, unfortunately, no way to distinguish these two possibilities. However, since there are only 64 batch trades where the same broker is represented, in part, on both the buy and sell sides in our sample of 21,077 trades, the quantitative impact of this problem is small. A more serious problem is that some large downstairs trades in batch markets may be the result of a consolidation of small retail orders, making it difficult to make inferences about the liquidity of these markets. As a result, we focus primarily on price formation in the continuous intraday markets.

1.5 The data

Our data set is drawn from a file of all 21,077 block trades in the 30 stocks that comprise the Dow Jones Industrial Average for the 30 trading days from December 17, 1993, through January 28, 1994. These stocks are of interest because they represent a major fraction of average daily trading volume and the only previous empirical study of upstairs trades [by Keim and Madhavan (1996b)] focused on small capitalization stocks.[11]

We used the NYSE's audit trail data to identify upstairs facilitated block trades. The block trades identified through the procedure above are then merged with the TAQ database to determine the prices and quotations surrounding each upstairs facilitated block trade. All NYSE trades of 10,000 shares or more in the TAQ database that have no matching records in the pool of trades identified as upstairs facilitated are identified as downstairs block trades. The prices and quotations surrounding each downstairs block trade are identified accordingly. Each consolidated tape print corresponds to one or more pairs of matched buy/sell orders in the audit trail file. The whole print size, rather than the quantity of the crossed buy/sell orders that satisfies the above conditions, is included in the analysis.[12]

For some of our analyses, it is important to determine whether a trade is buyer or seller initiated. We use the TAQ consolidated quotation data to infer trade initiation, following a procedure similar to that adopted by Lee and Ready (1991). We checked the accuracy of this procedure using data on upstairs trades where there was a clear dominant party and found it to be highly accurate. In the case of midquote transactions, trade initiation is unclear so we treat these trades separately.

2. Empirical Results

2.1 Trading activity in upstairs and downstairs markets

Table 3 presents summary statistics on share size and dollar volume for upstairs and downstairs block trades for the sample stocks. All trades occurred in the continuous (intraday) market. Batch markets trades (including the opening auction, reopenings following trading halts, and after-hours crossing sessions) are excluded. Of the 21,077

[11] It would be interesting to broaden the sample to include smaller capitalization stocks, but this was not feasible because such stocks have only a few upstairs transactions in a month.

[12] Filter (1), the requirement that there be a matching broker identification number on both buy and sell sides, excluded approximately 85% of the trades. The remaining filters (2)–(4) collectively account for less than 4% of the exclusions, leaving a total of 2,284 trades identified as upstairs trades.

Table 3
Summary statistics of share size and dollar volume

Variables	Size (thousands)	Dollar volume ($ millions)
Panel A: Downstairs		
Mean	19.52	0.94
Standard deviation	18.38	0.86
95% percentile	50.00	2.28
75% quantile	21.00	1.09
Median	14.60	0.70
25% quantile	10.00	0.53
Number of observations	16,951	
Panel B: Upstairs		
Mean	38.60	1.82
Standard deviation	45.26	2.24
95% percentile	100.00	5.56
75% quantile	46.55	2.07
Median	23.60	1.11
25% quantile	14.00	0.64
Number of observations	2,220	

This table reports, for upstairs and downstairs block trades, the number of observations, the mean, the standard deviation, the quantiles, and the 95% percentile for the share size and the dollar volume. Trades in batch markets (including openings, reopenings after trading halts, market-on-close orders, and after-hours crossing sessions) are excluded. The sample consists of all NYSE trades in Dow Jones 30 stocks of 10,000 shares or more for the 30 trading days from December 17, 1993, to January 28, 1994.

block trades in the sample, 19,171 were executed in the continuous intraday market. Of these, 16,951 trades (80.4%) were executed in the downstairs market and the remaining 2,220 trades (19.6%) were executed in upstairs markets. Excluding batch markets transactions, the downstairs market still accounts for 79.8% of the total dollar volume of large-block trades. When batch market transactions are considered, this figure rises to 83%. Downstairs markets are thus an important source of liquidity for the sample portfolio.

There is evidence that this finding applies beyond the sample stocks used here. Hasbrouck, Sofianos, and Sosebee (1993) report that downstairs markets account for 73% of the block volume (and 86% of total volume) in all NYSE listed stocks.[13] Our results for continuous markets are also consistent with Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993). They find that downstairs specialists are willing to accommodate relatively large trades out of inventory, even though the stocks in their samples are traded much less frequently than the stocks we consider.

Intuition suggests that upstairs trades are larger than downstairs trades. The data supports this hypothesis both in terms of share vol-

[13] These figures are based on a classification of trades on January 12, 1993, using a procedure very similar to that described above.

ume and dollar volume. The mean size for the downstairs sample is 19,520 shares (with a mean value of $0.94 million) as opposed to 38,600 shares ($1.82 million in value) for the upstairs trades.[14] Similar remarks apply to the quantiles of share size and dollar volume. Not only are upstairs trades larger than downstairs trades, they also exhibit more heterogeneity, as measured by the standard deviation of size.

Table 4 reports, for both upstairs and downstairs block trades in the continuous market, the number of trades, the percentage of trades in each market, the dollar volume, and the percentage of dollar volume in each market, broken down for three size ranges and for buyer-initiated trades, seller-initiated trades, and midquote trades. In all three panels, the percentage of downstairs transactions and value (for that panel) declines monotonically with size. Conversely, the percentage of trades facilitated upstairs increases monotonically with size, with the only exception being midquote trades. This pattern is consistent with our conjectures about upstairs intermediation.

The table confirms our findings that the downstairs markets are highly liquid, for even the largest transactions. Indeed, in trades larger than 50,000 shares, the downstairs market accounts for about 42% of block sells, 56% of block buys, and 62% of midquote transactions by dollar volume.[15] These results suggest that the downstairs market can accommodate relatively large trades without the need for upstairs facilitation.

Another aspect of the interaction between the upstairs and downstairs markets concerns the extent to which floor traders participate in upstairs trades, as shown in Tables 1 and 2. To examine this issue, we computed the mean percentage of the ratio of the shares traded by the upstairs broker representing both sides of an order to the total size of the order, broken down by order size range and trade initiation. This ratio is, on average, about 58%, with the remaining representing participation by downstairs traders. This figure is much higher (67%) for crosses between the quotes, since the possibility for outside participation in these orders is much smaller.

Downstairs participation may reflect the order exposure requirements imposed on floor brokers in accordance with auction principles. It is also possible that upstairs facilitated trades act as catalysts, providing buyers and sellers in the downstairs market with the impe-

[14] Hasbrouck, Sofianos, and Sosebee (1993) report that the average size of an upstairs trade in all NYSE stocks was 43,000 shares.

[15] Similar patterns are reported by Hasbrouck, Sofianos, and Sosebee (1993). They find that only 10% of block trades between 10,000 and 25,000 shares were upstairs facilitated; for trades between 25,000 and 100,000, the corresponding figure is 32%; and for trades above 100,000 shares, the figure is 57%.

Table 4
Upstairs and downstairs block trades in Dow Jones 30 stocks

		Block size ranges (thousands)			
Market	Variables	10–20	20–50	Over 50	All
Panel A: Sells					
Upstairs	Number of trades	383	279	180	842
	Number of trades/(1)	7.81%	16.48%	47.24%	12.07%
	Dollar volume ($ millions)	279.09	455.11	994.15	1728.34
	Dollar volume/(2)	8.63%	18.89%	57.59%	23.45%
Downstairs	Number of trades	4519	1414	201	6134
	Number of trades/(1)	92.19%	83.52%	52.76%	87.93%
	Dollar volume ($ millions)	2954.76	1954.22	732.15	5641.12
	Dollar volume/(2)	91.37%	81.11%	42.41%	76.55%
All	(1) Total number of trades	4902	1693	381	6976
	(2) Total dollar volume	3233.85	2409.33	1726.30	7369.46
Panel B: Buys					
Upstairs	Number of trades	506	414	166	1086
	Number of trades/(1)	7.64%	18.14%	35.85%	11.59%
	Dollar volume ($ millions)	355.52	690.33	805.51	1851.37
	Dollar volume/(2)	8.11%	20.22%	44.10%	19.23%
Downstairs	Number of trades	6116	1868	297	8281
	Number of trades/(1)	92.36%	81.86%	64.15%	88.41%
	Dollar volume ($ millions)	4028.48	2724.52	1021.19	7774.19
	Dollar volume/(2)	91.89%	79.78%	55.90%	80.77%
All	Total number of trades	6622	2282	463	9367
	Total dollar volume	4384.00	3414.85	1826.70	9625.56
Panel C: Midquote Trades					
Upstairs	Number of trades	151	107	34	292
	Number of trades/(1)	7.28%	16.16%	37.36%	10.33%
	Dollar volume ($ millions)	114.35	203.34	151.22	468.92
	Dollar volume/(2)	7.66%	19.35%	37.97%	15.94%
Downstairs	Number of trades	1924	555	57	2536
	Number of trades/(1)	92.72%	83.84%	62.64%	89.67%
	Dollar volume ($ millions)	1379.06	847.26	247.09	2473.41
	Dollar volume/(2)	92.34%	80.65%	62.03%	84.06%
All	Total number of trades	2075	662	91	2828
	Total dollar volume	1493.41	1050.6	398.31	2942.33

This table reports, for both upstairs and downstairs block trades, the number of trades, the percentage of trades in each market, the dollar volume, and the percentage of dollar volume in each market broken down for three size ranges, and buyer-initiated trades, seller-initiated trades, and midquote trades. Batch market trades (openings, reopenings after trading halts, market-on-close orders, and after-hours crossing sessions) are excluded. The sample consists of all NYSE trades in Dow Jones 30 stocks of 10,000 shares or more for the 30 trading days from December 17, 1993, to January 28, 1994.

tus to trade, resulting in a lower crossing ratio. There is some evidence for this hypothesis; in 7.2% of upstairs trades, the reported trade size is *larger* than the active party's trade size measured by the maximum of the buy-side or sell-side size.[16] The additional amount of trading

[16] We thank the anonymous referee for suggesting this to us.

for these trades is an average of 23,025 shares, a nontrivial amount.[17] However, without detailed information on the order submission process for upstairs trades, this hypothesis is somewhat speculative.

2.2 Price movements associated with block trades

The above results suggest that for the sample portfolio, both upstairs and the downstairs markets have the liquidity to absorb large-block trades. We turn now to an analysis of the price movements surrounding large-block trades.

Following Kraus and Stoll (1972), we distinguish between the *permanent* and *temporary* components of the price changes surrounding a block trade. The permanent component represents the change in the market's perception of the security's value due to the block transaction, while the temporary component represents the transitory price movement necessary to provide the liquidity to absorb the block. Let S_t denote the stock price t trades after (before when $t < 0$) the block trade and let S_0 be the block trade price. Consistent with previous research, we measure the permanent price impact, denoted by P_{+20}, as the logarithmic return from the trade before the block to the 20th trade after the block, that is, $P_{+20} = \ln(S_{+20}) - \ln(S_{-1})$. This measure allows for a delay in the market's speed of adjustment to the block trade. Similarly, we define the temporary price impact, denoted T_{+20}, as the logarithmic return from the 20th trade after the block to the block, that is, $T_{+20} = \ln(S_0) - \ln(S_{+20})$. For a "typical" seller-initiated trade where the posttrade price is below the pretrade price and where the trade price is below both the pre- and posttrade prices, the permanent and temporary components are negative. The opposite is the case for the "typical" buyer-initiated trade.

The usual definition of the permanent impact may understate the true revision in beliefs as a result of the trade because of information leakage as the trade is negotiated in the upstairs market. This leakage may be reflected in the pretrade price [see, e.g., Burdett and O'Hara (1987), Keim and Madhavan (1996b), Nelling (1992), and Seppi (1992a)], possibly biasing the measure. Accordingly, we also compute two measures of the pretrade price movement: R_c, the preblock trade return, defined as the logarithmic return from the previous day's close to the trade before the block, and R_{-20}, the logarithmic return measured from the 20th trade before the block to

[17] This computation excludes 131 trades where the maximum exceeded the trade size reported on the consolidated tape. These trades probably reflect instances where the size shown on the consolidated tape is adjusted for reporting errors without a corresponding adjustment to the buy or sell quantities.

Table 5
Price movements surrounding block trades in the downstairs market

Variables	Block size ranges (thousands) 10–20	20–50	Over 50	All
Panel A: Sells				
R_c	0.12 (2.58)	−11.18 (5.02)	−26.77 (14.56)	−3.37 (2.28)
R_{-20}	−4.09 (0.49)	−3.58 (0.95)	0.52 (2.35)	−3.82 (0.43)
T_{+20}	−4.88 (0.46)	−6.36 (0.90)	−6.74 (2.22)	−5.28 (0.40)
P_{+20}	−5.63 (0.51)	−8.77 (0.99)	−15.09 (2.80)	−6.66 (0.45)
R_b	−14.60 (0.45)	−18.71 (0.89)	−21.31 (2.38)	−15.77 (0.40)
Panel B: Buys				
R_c	26.94 (1.96)	27.69 (4.48)	40.86 (10.14)	27.61 (1.80)
R_{-20}	7.41 (0.40)	6.55 (0.76)	4.91 (1.95)	7.13 (0.35)
T_{+20}	3.37 (0.38)	2.83 (0.72)	3.74 (2.05)	3.27 (0.34)
P_{+20}	7.08 (0.42)	9.99 (0.82)	18.36 (2.44)	8.14 (0.37)
R_b	17.86 (0.39)	19.38 (0.70)	27.01 (2.01)	18.53 (0.34)

This table reports returns surrounding block trades of 10,000 shares or more executed on the NYSE floor in Dow Jones 30 stocks for the period December 17, 1993, to January 28, 1994, broken down by trade initiation. Batch market trades (openings, reopenings after trading halts, market-on-close orders, and crossing sessions) and midquote trades are excluded from the sample. Five measures are reported: (1) R_c is the preblock trade return, defined as the logarithmic return from the previous day's close to the trade before the block; (2) R_{-20} is the logarithmic return measured from the 20th trade before the block to the trade prior to the block; (3) T_{+20} is the temporary price impact, defined as the logarithmic return from the 20th trade after the block to the block; (4) P_{+20} is the permanent price impact, defined as the logarithmic return from the trade before the block to the 20th trade after the block; and (5) R_b is the total price impact, defined as the logarithmic return from the 20th trade before the block to the block. All numbers are denominated in basis points. (Standard errors are reported in parentheses.)

the trade prior to the block.[18] Specifically, $R_c = \ln(S_{-1}) - \ln(S_c)$ and $R_{-20} = \ln(S_{-1}) - \ln(S_{-20})$, where S_c denotes the previous day's closing price. Again, for the typical sell (buy), both measures are negative (positive) if there is leakage.

It is straightforward to use these returns to compute more meaningful measures of the information content of the trade. For example, the permanent impact measured using the prevailing price 20 trades around the block is then simply $R_{-20} + P_{+20}$. We define the total price impact, R_b, as the logarithmic return from the 20th trade before the block to the block, that is, $R_b = R_{-20} + P_{+20} + T_{+20}$.

Tables 5 and 6 report the mean values for the five return measures, broken down by trade initiation, for the downstairs and upstairs markets. We exclude midquote trades since the price impacts cannot be meaningfully interpreted without knowing the direction of the trade. The average price impacts in both markets are negative for sells and positive for buys, as expected, but are relatively small in percent-

[18] We compute two measures because the duration over which leakage may occur is difficult to ascertain. If blocks are not extensively shopped, a short transaction time measure will capture most of the information leakage in the few minutes prior to the trade. By contrast, if leakage is more extensive, a calendar time measure is more appropriate.

Table 6
Price movements surrounding block trades in the upstairs market

Variables	Block size ranges (thousands) 10–20	20–50	Over 50	All
Panel A: Sells				
R_c	−13.00 (10.74)	−14.25 (11.94)	−13.72 (23.51)	−13.57 (8.04)
R_{-20}	−5.68 (1.56)	2.53 (1.89)	0.96 (2.30)	−1.54 (1.08)
T_{+20}	−5.06 (1.52)	−9.39 (1.78)	−1.88 (2.02)	−5.81 (1.01)
P_{+20}	−4.36 (1.66)	−4.07 (1.87)	−19.93 (2.51)	−7.59 (1.13)
R_b	−15.10 (1.44)	−10.93 (1.67)	−20.85 (2.62)	−14.95 (1.03)
Panel B: Buys				
R_c	41.29 (7.95)	40.64 (7.40)	36.50 (19.89)	40.31 (5.56)
R_{-20}	7.02 (1.27)	5.56 (1.49)	3.68 (2.60)	5.95 (0.91)
T_{+20}	5.37 (1.26)	6.90 (1.81)	0.08 (2.41)	5.15 (0.98)
P_{+20}	3.95 (1.38)	4.84 (1.94)	21.81 (3.11)	7.02 (1.10)
R_b	16.35 (1.19)	17.30 (1.28)	25.57 (2.63)	18.12 (0.84)

This table reports returns surrounding upstairs facilitated block trades of 10,000 shares or more in Dow Jones 30 stocks for the period December 17, 1993, to January 28, 1994, broken down by trade initiation. Batch market trades (openings, reopenings after trading halts, market-on-close orders, and after-hours crossing sessions) and midquote trades are excluded from the sample. Five measures are reported: (1) R_c is the preblock trade return, defined as the logarithmic return from the previous day's close to the trade before the block; (2) R_{-20} is the logarithmic return measured from the 20th trade before the block to the trade prior to the block; (3) T_{+20} is the temporary price impact, defined as the logarithmic return from the 20th trade after the block to the block; (4) P_{+20} is the permanent price impact, defined as the logarithmic return from the trade before the block to the 20th trade after the block; and (5) R_b is the total price impact, defined as the logarithmic return from the 20th trade before the block to the block. All numbers are denominated in basis points. (Standard errors are reported in parentheses.)

age terms. Although the total price impacts for both buys and sells are roughly similar, it should be kept in mind that the average trade size in the upstairs market is about twice as large as in the downstairs market. Even so, it is apparent that for the sample portfolio, the downstairs intraday market appears to accommodate large-block trades with minimal price movements.

Consistent with previous research, the total price impact in both markets increases in absolute value as order size increases. Further, the relative importance of the permanent component increases with size in both markets, indicating that asymmetric information is a major component of the price impact. This is consistent with Seppi (1992b), who develops a procedure to quantify the contribution of a block to price discovery and shows that large trades are more informative than small trades. The pretrade price movements are also an important element of the impact. On average, the pretrade movements associated with upstairs trades are larger in magnitude than in downstairs markets, which is consistent with the leakage hypothesis. It is also evident that the overnight measure R_c captures more leakage than the more immediate transaction time measure R_{-20}.

Finally, although leakage is increasing in trade size in the downstairs market, no such pattern is evident in the upstairs market. We would expect such a relation in downstairs markets because large blocks are typically "worked" by floor brokers, resulting in leakage. The puzzle is why there is no such relation in the upstairs market. One possibility is that leakage in upstairs markets is more unsystematic, obscuring the relation to order size. Alternatively, if very large upstairs trades occur only because the initiator can credibly signal [as in Seppi (1990)] that the trade is liquidity motivated, trade size may have little impact on the pretrade price movement.

3. An Analysis of Upstairs and Downstairs Markets

We turn now to an analysis of the determinants of the price movements associated with large-block trades. The previous results suggest that upstairs and downstairs markets are highly liquid and offer similar costs of trading. However, this inference requires closer scrutiny because traders self-select the market mechanism that offers them the lowest cost of trading. In this section we develop a model to explain the decision of traders, and then test the model using a two-stage econometric procedure that explicitly corrects for possible selection bias.

3.1 An economic model of the selection mechanism

To deal with possible selection biases, it is first necessary to develop a behavioral model of the selection mechanism that determines whether a trade is upstairs facilitated or is sent directly to the downstairs market. Clearly, traders will choose the market mechanism that provides execution at the least cost. Thus, to model the economic decisions of traders, we must first describe how the markets differ in their execution costs.

Theoretical models [e.g., Easley and O'Hara (1987)] suggest the price impact of a trade in downstairs markets is an increasing function of order size. We model the realized trading cost in the downstairs market as

$$y_i^d = \beta_d' X_i + \epsilon_i^d, \tag{1}$$

where y_i^d is the price impact of the trade, X_i is a $k \times 1$ vector of variables (e.g., a constant and order size), and ϵ_i^d is a disturbance term that captures idiosyncratic factors affecting the price impact of the trade.

Similarly, studies of upstairs intermediation by Burdett and O'Hara (1987), Keim and Madhavan (1996b), and Seppi (1990) suggest the price impact of a trade in the upstairs markets is also increasing in order size. Unlike downstairs markets, however, the identity of the initiator is revealed to the upstairs block broker through the negotiation process. Seppi (1990) shows that traders who can credibly signal to a block broker that they are not information motivated will obtain lower costs of trading in the upstairs market. Thus we model the realized trading cost in the upstairs market as

$$y_i^u = \beta_u' X_i - \theta_i + \epsilon_i^u, \tag{2}$$

where y_i^u denotes the price impact of trade i in the upstairs market, θ_i is a reputation signal, ϵ_i^u is a stochastic disturbance term that captures the impact of trader-specific shocks, and β_u is a $(k \times 1)$ vector of coefficients.

The signal θ_i summarizes the broker's information regarding the initiator's identity, investment style, and reputation. Seppi's (1990) model suggests that, other things being equal, the price impact of the trade decreases with the probability that the trade is liquidity motivated. For this reason, θ_i is assumed to enter Equation (2) negatively. It is important to note that trader i knows his reputation, θ_i, but that this variable is not observed by the econometrician. Thus, from the viewpoint of an econometrician, Equation (2) can be expressed as $y_i^u = \beta_u' X_i + \xi_i^u$, where $\xi_i^u \equiv -\theta_i + \epsilon_i^u$ represents the regression error term.

Having specified the trading costs in the respective markets, we now return to the trader's decision problem. Let Ω_i denote the information set of trader i. Trader i will trade in the market that offers the best expected execution. Part of this decision depends on the expected price impacts in the two markets. In addition, there may be other factors that affect the costs of execution in both markets. The difference between the expected costs of trading in downstairs relative to upstairs for trader i can be expressed as

$$u_i^* = \alpha' W_i + E[y_i^d - y_i^u \mid \Omega_i], \tag{3}$$

where α is a vector of constants and W_i is a vector of state variables that capture other cost differentials relevant to the trading decision.

Substituting the price impact equations [Equations (1) and (2)] into Equation (3), and assuming for simplicity that $E[\epsilon_i^d \mid \Omega_i] = E[\epsilon_i^u \mid \Omega_i]$, we obtain

$$u_i^* = \alpha' W_i + (\beta_d' - \beta_u')X_i + \theta_i. \tag{4}$$

Equation (4) is the criterion function for trader i. We can write this as

$$u_i^* = \gamma' Z_i + \theta_i, \tag{5}$$

where $Z_i = (W_i, X_i)$ and γ is a vector of coefficients. Note that θ_i is a random variable from the econometrician's viewpoint because the trader's reputation is not observed. We assume that (unconditionally) θ_i, ϵ_i^u, and ϵ_i^d are jointly normally distributed with mean 0 and variance-covariance matrix Σ.

Let u_i represent the trader's choice of venue, where u_i takes the value 1 if trader i selects upstairs intermediation and 0 otherwise. The trader's decision rule is

$$u_i = \begin{cases} 1 & \text{if } u_i^* > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

The econometrician observes $u_i = 1$ if $u_i^* > 0$ and $u_i = 0$ if $u_i^* \leq 0$.

The model consists of the price impact equations in the downstairs and upstairs markets [Equations (1) and (2)], the criterion function [Equation (4)], and the decision rule [Equation (6)].

3.2 An endogenous switching regression model

Estimation of the model is complicated by the fact that trading venue is endogenous, so that simple regressions of y_i^u and y_i^d on X_i will yield inconsistent estimates of the price impact equations. Intuitively, the error term in the price impact equation [Equation (2)] is correlated with the error term in the criterion function [Equation (4)]. To see this, note that the trader's unobserved reputation θ_i affects both the price impact in the upstairs market and the choice of market. The cross-equation correlation arising from the omitted reputation variable θ_i implies that OLS estimates will be inconsistent.

Since we observe upstairs trades only when $u_i^* > 0$, the error term ϵ_i^u does not have a zero mean conditional on there being an upstairs trade. Using the properties of the normal distribution (and normalizing the variance of θ_i to be 1), the expected price impact conditional on observing an upstairs trade is

$$E[y_i^u \mid u_i = 1] = \beta'_u X_i + \sigma_u \left[\frac{\phi(\gamma' Z_i)}{\Phi(\gamma' Z_i)} \right], \tag{7}$$

where $\phi(\cdot)$ denotes the standard normal density function, $\Phi(\cdot)$ denotes the cumulative standard normal distribution, and σ_u is the covariance between the composite disturbance term ξ_i^u (recall that $\xi_i^u = -\theta_i + \epsilon_i^u$) in the upstairs market price impact regression equation and the term θ_i in the criterion function. Similarly,

$$E[y_i^d \mid u_i = 0] = \beta'_d X_i + \sigma_d \left[\frac{-\phi(\gamma' Z_i)}{(1 - \Phi(\gamma' Z_i))} \right], \tag{8}$$

where σ_d is the covariance between the disturbance terms θ_i and ϵ_i^d.

The model places restrictions on the covariances in the above expressions. These restrictions can be used to test theories about upstairs markets, as we will see shortly. Using the definitions above, we have

$$\sigma_u = \text{cov}[-\theta_i + \epsilon_i^u, \theta_i] = -\text{var}[\theta_i] + \text{cov}[\epsilon_i^u, \theta_i]. \quad (9)$$

The first term in Equation (9) is unambiguously negative, and intuition suggests that the second term will also be negative. Specifically, Keim and Madhavan (1995, 1996a) show that traders using technical or momentum-based strategies trade more aggressively and incur higher trading costs than value traders who use passive investment strategies. So a trader who can signal that his trade is liquidity motivated (i.e., $\theta_i > 0$) is unlikely to need to trade quickly, instead using passive order submission strategies to obtain better execution so that $\epsilon_i^u < 0$. Conversely, an informed trader who cannot credibly signal that his trade is liquidity motivated is likely to trade aggressively, so that $\epsilon_i^u > 0$. It follows that $\text{cov}[\epsilon_i^u, \theta_i] < 0$, and hence that $\sigma_u < 0$. In Equation (7), this implies that the expected price impact in the upstairs market, conditional upon a trader selecting this mechanism, is smaller than the unconditional expected price impact using Equation (2), that is, $E[y_i^u \mid u_i = 1] < E[y_i^u]$. This has a natural economic interpretation — the *observed* price impact in the upstairs market is lower than the expected impact because traders with above-average reputational signals self-select upstairs intermediation. Similarly, $\sigma_d = \text{cov}[\epsilon_i^d, \theta_i] < 0$, so that $E[y_i^d \mid u_i = 0] > E[y_i^d]$.

Lee, Maddala, and Trost (1979) propose a two-stage procedure that produces consistent parameter estimates when faced with selectivity bias. The idea is straightforward. Observe that $\Pr[u_i = 1] = \Pr[u_i^* > 0] = \Pr[\theta_i > -\gamma' Z_i] = 1 - \Phi(-\gamma' Z_i) = \Phi(\gamma' Z_i)$. Since the continuous response variable u_i^* is not observed, we can estimate γ from observations of u_i using the probit method.[19] Let $\hat{\gamma}$ denote the maximum likelihood estimates of γ from this first-stage estimation.

In the second stage, we use the maximum likelihood estimates from the first-stage structural probit model to estimate the price impact equations [Equations (1) and (2)] simultaneously, using all observations of y_i. To implement the second stage, observe that the expected price impact is

$$\begin{aligned} E[y_i] &= E[y_i \mid u_i = 1]\Pr[u_i = 1] + E[y_i \mid u_i = 0]\Pr[u_i = 0] \\ &= \beta_d' X_i + (\beta_u' - \beta_d') X_i \Phi_i + \phi_i(\sigma_u - \sigma_d), \end{aligned} \quad (10)$$

where X_i is the vector of explanatory variables in Equations (2) and (1) and σ_d and σ_u are the cross-covariance terms between the error term in the criterion function and those in the upstairs and downstairs price

[19] Since the variance of θ_i is normalized to 1, γ can be estimated only up to a proportionality factor.

impact equations. The second-stage procedure consists of estimating Equation (10) using the estimated probabilities $\hat{\Phi}_i = \Phi(\hat{\gamma}' Z_i)$ and $\hat{\phi}_i = \phi(\hat{\gamma}' Z_i)$ for each observation based on the structural probit estimates. This yields consistent estimates of the parameters of the price impact equations, as well as the covariances among the residual terms, which also have economic interest.

3.3 Estimation of the model

3.3.1 Stage I estimation. To estimate the model, we must specify the variables in the criterion function [Equation (4)]. Previous studies show that the price impact of a trade in both upstairs and downstairs markets is an increasing function of trade size. Thus we write the variable X_i in Equations (1) and (2) as $X_i = [1, q_i]$, where q_i is a measure of trade size. The expected price impacts in the upstairs and downstairs markets, from the viewpoint of an econometrician who does not observe the reputation signal, take the form $\beta_0^u + \beta_1^u q_i$ and $\beta_0^d + \beta_1^d q_i$, respectively. Economic theory imposes restrictions on these coefficients.

Specifically, upstairs intermediation may reduce the marginal impact of order size relative to the downstairs market by mitigating adverse selection problems [Seppi (1990)], risk sharing [Keim and Madhavan (1996b)], or locating potential trade counterparties [Burdett and O'Hara (1987), Grossman (1992)], so that $\beta_1^u < \beta_1^d$. In addition, we hypothesize that the constant component of the price impact is higher under upstairs intermediation, that is, $\beta_0^u > \beta_0^d$. This is reasonable because part of the price impact of the trade is compensation for the costly search and negotiation required by upstairs intermediation. In addition, downstairs trades may not be feasible at times when the market is illiquid or the limit order book is thin, proxied for by the prevailing bid-ask spread. Finally, there may be other costs associated with the use of downstairs markets (relative to upstairs markets) that are related to the level of the stock price. For example, the relative cost of using upstairs intermediaries will decline with the value of the trade, and hence price, when there are fixed costs of negotiation. To control for possible effects of this sort, we include a measure of the stock's value.

Then the continuous value of the criterion function u_i^* is given by

$$u_i^* = \gamma' Z_i = \gamma_0 + \gamma_1 q_i + \gamma_2 s_i + \gamma_3 m_i, \tag{11}$$

where q_i is the volume of block i divided by the average block volume in the stock (to control for possible heteroskedasticity), s_i denotes the percentage spread at the time of the trade prior to the block, defined as the ratio of the bid-ask spread to the quotation midpoint times 100,

Table 7
Stage I estimates of structural probit model

Coefficient	Estimate	χ^2	P value	Log likelihood
Panel A: Unrestricted Model				−5524.548
γ_0	−1.616 (0.233)	47.860	0.0001	
γ_1	0.301 (0.0112)	715.219	0.0001	
γ_2	−0.131 (0.120)	1.194	0.275	
γ_3	0.034 (0.053)	0.407	0.524	
Panel B: $\beta_1 = \beta_2 = \beta_3 = 0$				−5930.266

The table reports the coefficient estimates (with asymptotic standard errors in parentheses) of a structural probit model for stage I of the endogenous switching regression model. Batch market trades (openings, reopenings after trading halts, market-on-close orders, and after-hours crossing sessions) and midquote trades are excluded from the sample, which consists of 16,294 NYSE block trades in Dow Jones 30 stocks for the 30 trading days from December 17, 1993, to January 28, 1994. The probit model estimated is

$$\Pr[u_i = 1 \mid Z_i] = \Phi(\gamma' Z_i),$$

where $\Phi(.)$ is the cumulative standard normal distribution, u_i is an indicator variable taking the value 1 if the ith trade was upstairs facilitated and 0 otherwise, Z_i is a vector of independent variables, and γ is a vector of unknown coefficients. The linear combination $\gamma' Z_i$ is given by

$$\gamma' Z_i = \gamma_0 + \gamma_1 q_i + \gamma_2 s_i + \gamma_3 m_i,$$

where q_i is the volume of block i divided by the average block volume in the stock (to control for possible heteroskedasticity), s_i denotes the percentage spread at the time of the trade prior to the block, defined as the ratio of the bid-ask spread to the quotation midpoint times 100, and m_i is the log of the midquote prevailing 20 trades prior to the block. Panel B presents the value of log likelihood under the restriction $\gamma_1 = \gamma_2 = \gamma_3 = 0$.

and m_i is the log of the midquote prevailing 20 trades prior to the block. From Equation (4), we have $\gamma_1 = (\beta_1^d - \beta_1^u) > 0$.[20] As upstairs intermediation may be preferred to downstairs trading in times of temporary market illiquidity, we expect that $\gamma_2 > 0$. Finally, if upstairs intermediation is preferred for higher-priced stocks, we expect that $\gamma_3 > 0$.

Table 7 presents the coefficient estimates (with asymptotic standard errors in parentheses) of the model $E[u_i = 1] = \Phi(\gamma' Z_i)$. The sample size consists of 16,294 blocks; batch market and midquote transactions are excluded from the analysis. The size coefficient γ_1 is positive and significant at the 1% level using the Wald chi-square test. This is consistent with our hypothesis that upstairs intermediation is more likely to be used for larger trades. The coefficients γ_2 and γ_3, however, are relatively small and are not statistically significantly different from zero. One possibility for this finding is that these variables are correlated so that their standard errors are high although they help explain the observed choice of market mechanism. Indeed, a likeli-

[20] Any size-related differences in explicit costs between the two markets will also be reflected in γ_1.

hood ratio test strongly rejects the hypothesis that the explanatory variables have zero coefficients.

The estimated structural probit model provides some insights into the choice of market. A trader will select the upstairs market if the value of the continuous response $u_i^* > 0$. Recall that the impact of a trader's reputation on prices in the upstairs market is summarized by the term θ_i in Equation (2). Denote by $u^*(q_i; \theta_i)$ the expected value of the criterion function [Equation (4)] as a function of trade size q_i given the trader's reputation, θ_i. Let $q^*(\theta_i)$ denote the trade size at which a trader of type θ_i is indifferent between the choice of market, where $q^*(\theta_i)$ solves $u^*(q_i; \theta_i) = 0$.

The estimates in Table 7 imply that for the average stock, the indifference level for a trader with $\theta_i = 0$ is $q^*(0) = 5.07$, about five times the average block trade. The indifference levels fall rapidly as θ_i rises. For example, a similar computation yields $q^*(1) = 1.74$. Since the average upstairs trade is approximately twice the size of the average downstairs trade, these computations indicate that traders using upstairs intermediation have reputational signals that are well above average. We turn now to the second-stage estimation.

3.3.2 Stage II estimation. Given $X_i = [1, q_i]$, $\beta_d' = (\beta_0^d, \beta_1^d)$, and $\beta_u' = (\beta_0^u, \beta_1^u)$, substitution into Equation (10) yields the reduced-form regression equation

$$y_i = \beta_0 + \beta_1 q_i + \beta_2 \hat{\Phi}_i + \beta_3 q_i \hat{\Phi}_i + \beta_4 \phi_i + \epsilon_i. \tag{12}$$

The model provides the following interpretations of the variable coefficients and restrictions on their signs: $\beta_1 = \beta_1^d > 0$, $\beta_2 = (\beta_0^u - \beta_0^d) > 0$, $\beta_3 = (\beta_1^u - \beta_1^d) < 0$, and $\beta_4 = (\sigma_u - \sigma_d)$. It is reasonable to assume that the covariance of the trader's unobserved signal with their idiosyncratic price impact shocks is the same in both markets (i.e., $\text{cov}[\epsilon_i^d, \theta_i] = \text{cov}[\epsilon_i^u, \theta_i]$) so that $\beta_4 = -\text{var}[\theta_i] < 0$. Note that the error term ϵ_i is known to be heteroskedastic because of the adjustment for selectivity bias. Accordingly, we use White's procedure to obtain heteroskedastic-consistent standard errors.

Table 8 reports the coefficient estimates (with White heteroskedastic-consistent standard errors in parentheses) of the stage II endogenous switching regression model of the price impacts of block trades. Batch market trades (openings, reopenings after trading halts, market-on-close orders, and crossing sessions) and midquote trades are excluded, leaving 16,294 observations. The dependent variable is the percentage price impact, measured for trades classified as buys, as the return from the midquote prevailing 20 trades prior to the block

Table 8
Stage II endogenous switching regression

Coefficient	Estimate	Standard error
β_0	0.725	(0.044)
β_1	0.494	(0.032)
β_2	1.556	(0.408)
β_3	−0.613	(0.060)
β_4	−5.985	(0.543)

The table reports the coefficient estimates (with heteroskedastic-consistent standard errors in parentheses) of the stage II endogenous switching regression model of the price impacts of block trades. Batch market trades (openings, reopenings after trading halts, market-on-close orders, and crossing sessions) and midquote trades are excluded from the sample, which consists of all NYSE block trades in Dow Jones 30 stocks for the 30 trading days from December 17, 1993, to January 28, 1994. There are 16,294 observations in the sample. The dependent variable is y_i, the price impact in percent. For trades classified as buys (sells), y_i is the (negative) return from the midquote prevailing 20 trades prior to the block to the block price. The model estimated is

$$y_i = \beta_0 + \beta_1 q_i + \beta_2 \hat{\Phi}_i + \beta_3 q_i \hat{\Phi}_i + \beta_4 \phi_i,$$

where q_i is trade size (the ratio of trading volume to average block size in the corresponding stock), $\hat{\Phi}_i = \Phi(\hat{\gamma}' Z_i)$, and $\hat{\phi}_i = \phi(\hat{\gamma}' Z_i)$, where $\hat{\gamma}' Z_i$ denotes the estimated value of the continuous response variable u_i^* based on the structural probit estimates.

to the block price. For sells, the impact is measured as the negative of this return.

The estimated coefficients provide strong support for the model. All coefficients have the expected sign and are highly significant. Although the adjusted R^2 is low (3.8%), the F value is 160.03, and we strongly reject the hypothesis that the independent variables have no explanatory power. The coefficient estimates provide several insights into the process of price formation in the upstairs and downstairs markets.

Of particular interest, the coefficient on trade size, β_1, is the slope of the price impact function in the downstairs market. This is positive and highly significant, as expected. The coefficient β_2 represents the differences between the intercepts of the price functions in the upstairs and downstairs markets. This is positive, suggesting the upstairs market has higher fixed costs, as expected. The coefficient β_3 is interpreted as the difference between the slopes of the price functions in the upstairs and downstairs markets, that is, as $(\beta_1^u - \beta_1^d)$. This coefficient is negative, showing that the marginal cost of trading in the upstairs market is significantly lower than the marginal cost in the downstairs market. Finally, β_4 is negative, as expected, and is highly significant. This result provides strong evidence for the presence of an omitted variable for a trader's reputation in the upstairs market, and is consistent with Seppi's (1990) hypotheses.

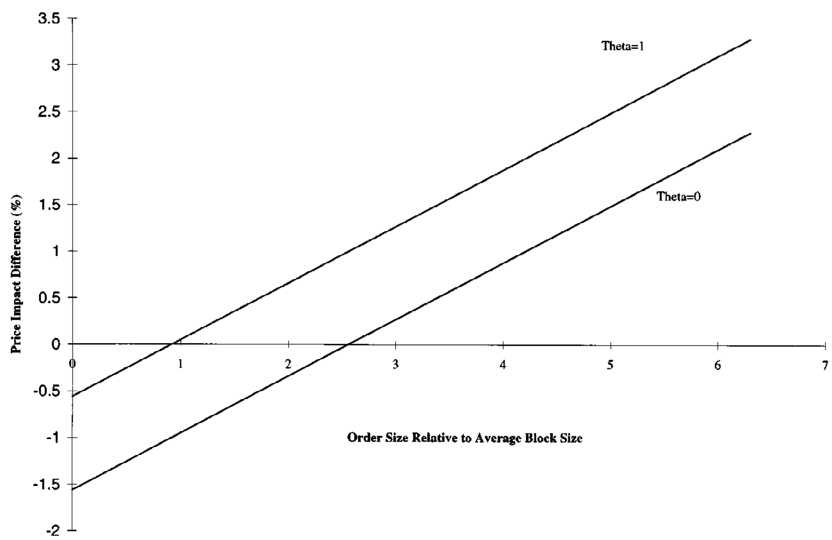

Figure 1
The figure shows the difference between the expected price impact in the downstairs and upstairs market as a function of order size divided by average block size for two possible realizations of the unobserved reputational signal θ. Higher signal realizations (i.e., $\theta = 1$) convey a greater likelihood of the trader being liquidity motivated, and hence a greater cost differential to using the downstairs market.

It is important to note that the price functionals in the upstairs and downstairs markets are specific to each trader. For traders who can credibly signal their reputations, the range of order sizes over which the upstairs market dominates the downstairs market may be quite large. The opposite may be true for traders who do not have established relationships with upstairs brokers or who cannot credibly signal their trading motivations. To see this, we used the parameter estimates reported in Table 8 to compute the difference in the unconditional expected price impacts in the downstairs and upstairs markets for a trader with a reputational effect summarized by θ_i.

Figure 1 plots this difference (i.e., $E[y_i^d - y_i^u \mid \theta_i]$) as a function of trade size q_i for $\theta_i = 0$ and $\theta_i = 1$. Recall that θ_i measures trader i's reputation in terms of the percentage price concession granted through upstairs intermediation. Let $q^c(\theta_i)$ denote the trade size at which the difference in expected price impacts is zero for a trader with reputation θ_i. It is clear that $q^c(\theta_i)$ is a decreasing function of the reputational signal. From Figure 1 we see that $q^c(0) = 2.56$ and $q^c(1) = 0.93$, suggesting that the difference in predicted price impacts between the two market mechanisms is relatively modest for the average-size trade. This is not the case for the larger order sizes.

For example, when $\theta_i = 0$, the difference between the expected price impact in the downstairs market and the upstairs market is 1.49% when $q_i = 5$.

It is important to note that the critical bounds at which the difference in the unconditional expected price impacts is zero need not correspond to the indifference levels computed in the previous section. This is because the indifference bound $q^*(\theta_i)$ based on the estimated structural probit model takes into account all the factors affecting the choice of market. By contrast, the critical bound $q^c(\theta_i)$ reflects just one dimension of this decision, that is, the price impact. Indeed, for a given trader type θ_i, it is evident that $q^*(\theta_i) > q^c(\theta_i)$. In other words, the indifference level between the two markets taking into account all possible cost factors is higher than that implied by just the difference in expected price impacts. This is intuitively clear because upstairs intermediation may involve additional costs in the form of higher commissions or the lack of immediacy.

We performed a number of specification tests to assess the robustness of our results. First, we transformed order size using the square-root transform given evidence that the price impacts of large trades is bounded above. The results are very similar to those discussed above and are not reported here. Second, we estimated an ordered probit model to correct for the effects of possible price discreteness. Since our impact measure is based on a benchmark 20 trades prior to the actual block trade, discreteness is not a significant problem. Third, the theoretical results of Seppi (1990) suggest that the reputation variables would be especially important in determining the permanent impact of the trade. To test this hypothesis, we reestimated the model with the permanent impact as the dependent variable. While the signs of the coefficients remain unchanged, the coefficient estimates are lower and the explanatory power of the model drops. This suggests that the effects of reputation are not confined to the permanent component of the price impact. This seems reasonable since the investor's choice of mechanism depends on the sum of the two components.

Finally, to test for the possibility that there are asymmetries between buyer- and seller-initiated trades, we reestimated the structural probit model by replacing the single volume variable q_i with separate buy and sell volume variables. The estimated coefficients on buy and sell volume, however, were virtually identical, and a formal likelihood ratio test cannot reject the hypothesis that they are the same. In the second-stage estimation, the coefficients on the buy and sell volume variables are also very similar. Again, we reject the hypothesis that buyer- and seller-initiated trades have different price impacts. This finding is somewhat surprising given previous studies which find asymmetries. It is possible that the correction for selectivity bias explains these differences, but this is a topic for future research.

4. Conclusions

Our findings demonstrate that (1) downstairs markets are a significant source of liquidity for large-block trades; (2) the observed price movements associated with large-block trades in both mechanisms are relatively small; (3) there is strong evidence to support the hypothesis advanced by Seppi (1990) that upstairs markets are preferred by traders who can credibly signal that their trades are not information motivated; (4) as predicted by theoretical models, upstairs intermediation reduces the marginal costs of trading; (5) the expected price functionals depend on reputation and hence are trader specific; and (6) correcting for selectivity biases, the difference in expected price impacts between the two mechanisms are relatively small for the average block trade.

In summary, both upstairs and downstairs markets are highly liquid. Considering the other costs of upstairs intermediation, downstairs markets may provide competitive pricing for most trades. Downstairs markets may offer so much liquidity because floor brokers can "work" a large order (much as upstairs brokers do) or because the specialist-auction system provides a large crowd of potential counterparties. But if the expected cost differentials between upstairs and downstairs markets are small on average, why does the upstairs market exist in the first place?

As described above, the upstairs market has been viewed in the literature primarily from the initiator's viewpoint. Upstairs intermediation can reduce trading costs by mitigating adverse selection costs [Seppi (1990)], locating trade counterparties [Burdett and O'Hara (1987), Grossman (1992)], and risk sharing [Keim and Madhavan (1996b)]. We find, however, that the economic benefits of upstairs intermediation is small for the average-size block trade. However, every block trade involves willing participants on both sides of the transaction. Thus the primary benefit offered by the existence of an upstairs market may not be to the initiator, but rather to the counterparties to the transaction. Liquidity providers, especially institutional traders, are reluctant to submit large limit orders and thus offer free options to the market. Upstairs markets allow these traders to selectively participate in trades screened by block brokers who avoid trades that may originate from traders with private information. Thus the upstairs market's major role may be to enable transactions that would not otherwise occur in the downstairs market.

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