Trading and Pricing in Upstairs and Downstairs Stock Markets

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We provide empirical evidence on the economic benefits of negotiating trades in the upstairs trading room of brokerage firms relative to the downstairs market. Using Helsinki Stock Exchange data, we find that upstairs trades tend to have lower information content and lower price impacts than downstairs trades. This is consistent with the hypotheses that the upstairs market is better at pricing uninformed liquidity trades and that upstairs brokers can give better prices to their customers if they know the unexpressed demands of other customers. We find that these economic benefits depend on price discovery occurring in the downstairs market.

It is common for an individual stock to be traded in more than one market. One way for this to occur is for a stock to be traded not only in its main (home) market, but also in one or more regional or foreign markets. Another way is for a stock to be traded in upstairs and downstairs markets. The upstairs market is an off-exchange market where buyers and sellers negotiate in the "upstairs" trading rooms of brokerage firms. The downstairs market is the exchange floor or its electronic counterpart. In the latter venue, the trades take place anonymously.

The nature of the relationships among multiple markets has recently attracted the attention of practitioners and academicians. Examples of studies examining main versus other markets include Harris et al. (1995), Hasbrouck (1995), and Easley, Kiefer, and O'Hara (1996), to name but a few. Studies that explicitly investigate the relationships between upstairs and downstairs markets, however, are virtually nonexistent, with Madhavan and Cheng (1997)

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being a notable exception. They use the Consolidated Audit Trail Data (CAUD) files maintained by the NYSE and an indirect algorithm to classify upstairs and downstairs trades. Analyzing block trades of the Dow Jones stocks for a 30-day period, Madhavan and Cheng (1997) report that the expected price impacts for orders of more than roughly 20,000 shares are smaller for upstairs than for downstairs trades. Their results are consistent with Seppi (1990), who hypothesizes that directly negotiated upstairs trades have lower adverse information costs than downstairs trades, and with Grossman's (1992) conjecture that an upstairs broker/dealer can give a selling customer a better price than prevails downstairs if he knows an interested buyer.

The purpose of this study is to provide new evidence on trading activities and pricing mechanisms of upstairs and downstairs markets. The Helsinki Stock Exchange (HSE) is analyzed because its upstairs market is formally organized and details (including the market in which a trade originated) for all trades must be reported to the HSE in a timely manner. The HSE downstairs market is electronic and trade information is reported in real time. These transaction data permit us to investigate the permanent and temporary price effects of trades on upstairs and downstairs markets. They also permit us to examine each market's contribution to price discovery. This is accomplished using common factor autoregression, a framework that explicitly recognizes that a stock's upstairs and downstairs prices share its fundamentals.

We add to the literature in three ways. First, for the 20 highest-volume HSE stocks, we examine the permanent and temporary price effects of all upstairs and downstairs trades. Similar to the U.S. findings by Madhavan and Cheng (1997), we find that upstairs trades are typically larger than the downstairs trades and that the former tend to have lower permanent and total price effects. Second, we show that the benefit of upstairs uninformed trading is associated with price discovery in the downstairs market. Our findings suggest that brokers tend to use the downstairs price as the basis for pricing upstairs trades and that the upstairs price has little effect on the pricing of downstairs trades. Third, because the HSE data allow us to identify the brokers on both sides of the transaction, we can provide a more detailed analysis of upstairs trades than previous empirical studies. The results suggest that brokers tend to internalize upstairs trades, which is consistent with Grossman's (1992) notion that upstairs brokers are aware of the unexpressed demands of their own customers. Internalized trading may also be due to upstairs traders not wanting to contact other brokers because doing so exposes them to front running.

This study is organized as follows. Section 1 briefly describes the operations of the HSE upstairs and downstairs markets. Section 2 discusses the sample data used in the study. Section 3 presents the empirical evidence on the price impact differences between upstairs and downstairs trades. Section 4 examines the price discovery process linking the upstairs and downstairs markets. Section 5 offers concluding remarks.

1. The Helsinki Stock Exchange

The HSE is a small market that expanded rapidly subsequent to its adoption of an automated trading and information system, HETI (Helsinki Stock Exchange Automated Trading and Information Systems).[1] Established in 1989 and fully operational by April 1990, HETI resembles with some minor differences the Continuous Automated Trading System (CATS) used in many markets, including the Toronto, Paris, Brussels, and Barcelona exchanges. HETI is an electronic network without designated market makers. Limit order traders specify bid and offer prices through authorized brokerage firms, and these orders are continuously and anonymously matched during the free-trading session from 10:00 A.M. to 4:00 P.M.[2] The tick size is determined by a step function scheme that categorizes stocks into four price bins. For all but the few stocks in the highest price category, the relative tick size evaluated at the price midpoint is 0.18%.[3]

Orders can also be matched upstairs in the office of an authorized brokerage firm (20 at the end of 1995), which then reports the trades to HETI in a timely manner. For these orders, the brokerage firm searches for counterparties and negotiates prices. Usually when a broker gets a large order (almost always by phone), it is not immediately put into HETI. Rather, all other brokers in the room are informed that an order has been received. These brokers may either actively try to find counterparties among their own customers or passively wait for counterparties to arrive so that a transaction can be done in house. One reason for keeping the order in house is that submitting a large order to HETI can create an order imbalance and result in a large price impact in the downstairs market. Another reason is that because of potential front running, the brokerage firm does not want to inform its competitors and, in turn, their customers that it has a large order. Nevertheless, if the downstairs market's depth is substantial and the customer's desired price is close to the best prevailing bid or ask prices, the broker may send the large order directly to the downstairs market.

[1] For instance, from 1991 to 1995 trading volume increased 13.3 times to FIM 83.0 billion ($17.3 billion). The growth from 1993 to 1995 was 86%.

[2] Before the free-trading session, there is a pretrading session. In the first phase of pretrading from 8:30 A.M. to 9:50 A.M., traders submit bid and offer prices. In the second phase, from 9:50 A.M. to 10:00 A.M., HETI matches suitable orders into transactions and transfers the remaining orders to the free-trading session. The purpose of pretrading is to determine the quotation and trading level for each stock exchange security for free trading. After the free-trading session, there are two after-market trading sessions: 5:05 P.M.–6:00 P.M. and 8:00 A.M.–8:25 A.M. the next day. In these sessions, trades must be executed inside the maximum price range bounded by the continuous trading session's closing bid-ask spread such that if the trading day's high (low) transactions price is above (below) the closing ask (bid), that transactions price defines the upper (lower) bound.

[3] The tick sizes are as follows: (1) 10 markkas for stocks priced at or above FIM 1,000, (2) 1 markka for stocks priced under FIM 1,000 and at or above FIM 100, (3) 10 pennies for stocks priced under FIM 100 and at or above FIM 10, and (4) 1 penni for stocks under FIM 10. Angel (1997) documents that this step function approach is not uncommon throughout the world. See Booth et al. (2000) for additional detail.

Customers can choose their trading venue. Traders with large orders, who fear their orders may have a significant impact on prices in the downstairs market, may request that their orders be processed in the upstairs market. Conversely, traders who prefer a prompt and anonymous transaction may request their orders be matched in the downstairs market. When brokers receive orders from customers not specifying the market to be used, brokers have the discretion to send the orders downstairs or to process them upstairs. However, according to the rules set up by the Financial Supervision Authority, which functions as an independent body and together with the Bank of Finland oversees the operation of the HSE, brokers are not allowed to make an upstairs trade at a price that would not be the best price for the customer. This price is the broker's estimate of the best price available for the trade in any marketplace.[4] The broker's commission depends on the size of the trade, not its location.

2. The Sample Data

At the end of 1995, 73 firms were listed on the HSE, with a market value of FIM (Finnish markka) 191 billion. Since the HSE is a relatively thinly traded market, we select the HEX-20 stocks (as of the end of 1995) to ensure enough upstairs and downstairs observations for analysis in the three-year sample period from January 1993 through December 1995. The HEX-20 index is constructed by the HSE and consists of the 20 most actively traded stocks in terms of markka. The index comes up for review twice a year (January and July), although its composition did not change during the sample period. The sample includes all downstairs round-lot trades and upstairs trades in the free-trading session.[5]

Table 1 contains summary statistics of the 20 sample firms. The average trade price ranges from FIM 8.96 to 520.29, with a mean of FIM 130.76 and a median of FIM 94.18. On average there are about 23 trades in a day per firm, about 22% of which take place in the upstairs market. However, on average the upstairs market accounts for about 51% of the total trading volume. The mean upstairs trade size, 6,914 shares, is 3.3 times as large as the mean downstairs trade size, 2,072 shares.

Table 2 provides a detailed distribution of trades by markka volume and share volume. For each firm we classify trades into five groups: trade size

[4] Achievement of the best price is monitored by legal recourse. Prima facie evidence that this requirement is met is for the trade to be executed within the downstairs market's inside spread. For large trades, however, such execution may not be possible. In these cases, prima facie evidence is provided by executing the maximum volume possible using the extant limit orders. Using both the upstairs and downstairs markets is required if the customer makes this request.

[5] Downstairs odd-lot trades are excluded because their prices are automatically determined by the prices of the previous round-lot trade. Also, after-hours trades are excluded because the after-hours trading prices are based on the price range set in the free-trading session.

Table 1
Summary statistics of the 20 sample stocks

Ticker symbol	Mean price (FIM)	Mean trading volume (shares)	Mean daily number of trades	Upstairs trades as a % of the total number of trades	Upstairs trades as a % of total trading volume	Mean upstairs trade size (shares)	Mean downstairs trade size (shares)
Amer	102.45	30,797	21	22.4	50.7	3,298	927
Cultor	135.44	14,339	9	19.9	51.4	4,076	958
Enso	37.09	266,124	35	20.6	61.5	22,583	3,665
Huhtamaki	169.77	22,432	19	19.9	50.0	2,890	719
Instru	189.12	7,607	9	24.0	60.4	2,110	437
Kesko	46.75	74,236	18	22.4	52.2	9,749	2,577
Kone	520.29	4,368	11	20.4	49.7	968	252
KOP	8.96	442,208	41	28.1	41.7	16,150	8,820
Kymmene	108.65	110,601	42	25.0	48.1	5,049	1,817
Metra	163.69	21,048	17	21.1	48.7	2,787	785
Metsa-Serla	193.98	32,773	21	23.1	55.1	3,802	928
Nokia	355.54	71,253	45	23.2	51.8	3,516	985
OKO	48.00	7,236	4	20.3	42.8	3,915	1,336
Outokumpu	73.48	76,046	26	22.0	46.2	6,244	2,054
Partek	55.72	19,437	10	19.8	49.0	4,961	1,275
Pohjola	65.49	39,486	16	19.1	46.1	5,844	1,612
Rautaruukki	37.50	75,752	19	18.9	48.1	10,098	2,537
Repola	85.90	172,106	50	25.1	55.1	7,578	2,039
Stockmann	204.08	5,347	7	24.0	59.2	1,921	420
Unitas	13.24	323,466	31	23.2	46.1	20,748	7,315
Mean	130.76	90,833	23	22.1	50.7	6,914	2,072
Median	94.18	36,129	19	22.2	49.9	4,518	1,305

The 20 sample stocks are the stocks in the HEX-20 index in 1995. The summary statistics are based on trades occurring in the freetrading session during the sample period from January 1993 through December 1995.

Table 2
Distribution of trades by trade size, market type, and broker

Trade size (percentile)	Mean trade size (shares)	Upstairs			Downstairs		
		In-house (%)	Cross-broker (%)	Subtotal (%)	In-house (%)	Cross-broker (%)	Subtotal (%)
Panel A: Markka volume							
<50%	540	98.7	1.3	15.0	5.8	94.2	85.0
50–75%	1,555	98.6	1.4	14.5	4.3	95.7	85.4
75–90%	3,447	96.8	3.2	21.6	3.7	96.3	78.3
90–95%	6,463	94.0	6.0	41.7	4.3	95.7	58.3
≥95%	25,461	95.2	4.8	85.1	3.4	96.6	14.9
Panel B: Share volume							
<50%	540	98.8	1.2	16.8	6.0	94.0	83.2
50–75%	1,555	98.6	1.4	14.0	4.7	95.3	86.0
75–90%	3,447	96.9	3.1	19.4	3.8	96.2	80.6
90–95%	6,463	94.4	5.6	35.6	4.8	95.2	64.4
≥95%	25,461	94.7	5.3	83.4	4.8	95.2	16.6

An in-house trade is a trade where the brokerage firm is the same on both sides of the transaction. A cross-broker trade involves different brokerage firms. This table provides the average percentage of markka volume and share volume in trade size group. The trade size cutoffs in each group are determined based on each firm's trade size distribution; thus they vary in absolute trade size across firms. The numbers reported in the table are averaging across the 20 sample firms during the sample period 1993–1995. In-house and cross-broker percentages represent their respective portion of the subtotal.

<50th percentile, 50th–75th percentile, 75th–90th percentile, 90th–95th percentile, and ≥95th percentile of all trades of the firm.[6] For the smallest trade size group, only about 15% of markka volumes (17% of share volumes) are matched in the upstairs market, indicating that brokers are more likely to send small trades downstairs. It may not be economical to search for and locate counterparties for small orders in the upstairs market. In general, brokers process small orders upstairs if they can trade with their own inventories or they have orders at the other side of transactions available.

In contrast, for the largest trade size group, about 85% of markka volumes (83% of share volumes) are conducted in the upstairs market, suggesting that large orders are more likely to be processed upstairs.[7] These numbers are much higher than the corresponding numbers in the U.S. market. For example, Madhavan and Cheng (1997) show that, for the Dow Jones 30 stocks, only about 28% of large block trades with more than 50,000 shares are facilitated upstairs. Similarly Hasbrouck, Sofianos, and Sosebee (1993) report that only about 27% of the block volume in all NYSE listed stocks is conducted upstairs. Relative to the NYSE, the HSE is a thin market in which a trader may be afraid of a large price impact caused by a large trade. Therefore it is plausible that the upstairs market plays a more important role in providing liquidity for large trades when the downstairs market is relatively thinly traded.

Table 2 also reveals that the percentage of trades processed upstairs is lowest for the medium trade size (i.e., 50th–75th percentile) groups and is especially noticeable in the case of share volume. This finding is consistent with Barclay and Warner's (1993) stealth trading hypothesis, which predicts that informed traders are likely to concentrate on medium-size trades, along with Seppi's (1990) argument that informed traders are likely to trade downstairs.

Furthermore, Table 2 shows that upstairs trades are more likely to be internalized, that is, the same brokerage firm represents both sides of the transaction. The percentage of upstairs cross-broker trades, where different brokerage firms are employed to complete the transactions, is quite small, but increases with trade size. For the largest trade size group, cross-broker trades account for only 5% of the volume. Internalization is consistent with Grossman's (1992) notion that upstairs brokers are information repositories for their customers' unexpressed demands. Internalization may also occur because the brokers may not want to contact other brokers because doing so

[6] The trade size cutoffs in each group are determined based on each firm's trade size distribution; thus they vary in absolute trade size across firms. The reason for this classification is to define small, medium, and large trades for each firm relative to the order flow experience for the firm over the sample period.

[7] That brokers are more likely to process large trades upstairs suggests economies of scale in search-brokerage costs in the upstairs market, as noted by Keim and Madhavan (1996).

exposes them to front running or because they are acting as dealers who execute buys at the market offer and sells at the market bid, thereby pocketing the spread.[8]

Conversely, most of downstairs trades are cross-broker trades. This is to be expected because of the anonymous nature of downstairs trading. These results contrast the brokers' roles in the two markets. While the HETI system matches buys and sells and determines prices without the brokers' direct involvement in the downstairs market, brokers in the upstairs market need to search for customers and engage in price negotiation. Does the upstairs search-brokerage mechanism result in prices different from those produced by the downstairs anonymous exchange market in Finland? We provide an answer to this question in the section that follows.

3. Price Effects of Upstairs and Downstairs Trades

To assess whether there is differential pricing between the upstairs and downstairs markets, we compare the permanent, temporary, and total price effects of trades in the two markets. These effects are measured using conventional price impact analysis [see, e.g., Holthausen, Leftwich, and Mayers (1987, 1990) and Keim and Madhavan (1996)]. The permanent price effect of a trade presumably reflects a change in value resulting from new information conveyed by the trade. The temporary price effect measures the extent of price reversal following the trade. It is a transitory effect usually resulting from the existence of the bid-ask spread, which compensates liquidity providers. The total price effect of a trade reflects the extent of price concession, that is, the difference between the trade price and the previous price, needed to absorb the trade in the market.

Seppi (1990) argues that uninformed traders are more likely to go upstairs for direct negotiation, implying that upstairs trades should convey less information and hence have a smaller permanent price effect than downstairs trades. The upstairs search-brokerage mechanism suggests that the temporary price effect, which is needed to induce counterparties to trade, should be larger for upstairs trades than for downstairs trades. According to his model, uninformed traders are better off transacting upstairs than downstairs, implying that the total price effect should be smaller in the upstairs market. That is, the reduction in the adverse information cost should outweigh the added liquidity cost in the upstairs market. Similarly, Grossman (1992) argues that the function of information repositories allows brokers to give upstairs customers a better price than prevails downstairs. Therefore his model also implies a smaller total price effect for upstairs trades than for downstairs trades. A smaller total price effect, however, does not mean that the upstairs market

[8] We thank a referee and Lawrence Glosten, respectively, for pointing out these two alternative explanations for internalization of upstairs trades.

is better and more cost effective than the downstairs market for all investors. As Seppi (1990) points out, there are penalty costs for informed traders who, pretending to be uninformed, negotiate upstairs trades. For example, brokerage houses may refuse to trade with offenders. The total price effect that we measure is not able to capture such penalty costs.

To measure the price impacts, we segment the trades into buyer initiated and seller initiated. The HSE database does not indicate whether a trade is initiated by the buyer or the seller, nor does it provide intradaily bid and ask quotes. Thus we use the tick rule to classify trades. If a trade occurs at a price lower than the previous trade price (downtick), the trade is classified as a seller-initiated trade. If a trade occurs at a price higher than the previous trade price (uptick), the trade is classified as a buyer-initiated trade. If a trade occurs at a price equal to the previous trade (zero-tick), the trade is excluded. Lee and Ready (1991) and Finucane (2000) suggest that the tick rule is a reasonably accurate method to classify trades as buyer initiated or seller initiated if zero-tick trades are ignored.

Denote p_t, p_{t-j}, and p_{t+s} as the logarithms of the transaction (uptick or downtick) price of the trade at time t, the price of the jth trade before the trade at time t, and the price of the sth trade after the trade at time t, respectively.[9] We assume that p_{t-j} serves as the equilibrium price before the trade at time t and p_{t+s} the equilibrium price after the trade at time t. The permanent price effect of the trade at time t then is $p_{t+s} - p_{t-j}$; the temporary price effect is $p_t - p_{t+s}$; and the total price effect is $p_t - p_{t-j}$. The choice of j and s depends on the extent of possible information leakage before a trade and a possible delay in the market's response to the trade. We choose $j = 5$ and $s = 3$ based on a trade-by-trade analysis. On average, we find no significant price movements five trades before and three trades after a trade.[10]

Trade-by-trade price movements around large upstairs and downstairs trades are shown in Figure 1 for downtick trades and in Figure 2 for uptick trades, large trades being those whose sizes are $\geq$95th percentile of all trades in a sample firm. Other trade size groups have similar trade-by-trade price movements. These figures reveal that there are substantial reactions to both downtick and uptick trades, but that these reactions display noticeable intermarket differences. For instance, for both uptick and downtick trades, the price change occurs in the downstairs market only at the time of the trade. Although these trade price changes are evident in the upstairs market, there are also noticeable price movements before and after the trade. For uptick (downtick) trades, the price decreases (increases) immediately prior to and

[9] We pool together upstairs and downstairs trades in sequence of their occurring time. Hence, for an upstairs trade at time t, the trade at $t-j$ or $t+s$ could be a downstairs trade, and vice versa.

[10] The mean (median) of the average time between any two consecutive intraday trades on a sample firm is 16 minutes (14 minutes). Hence the mean intraday time span for five trades is about 80 minutes, and is about 48 minutes for a three-trade interval.

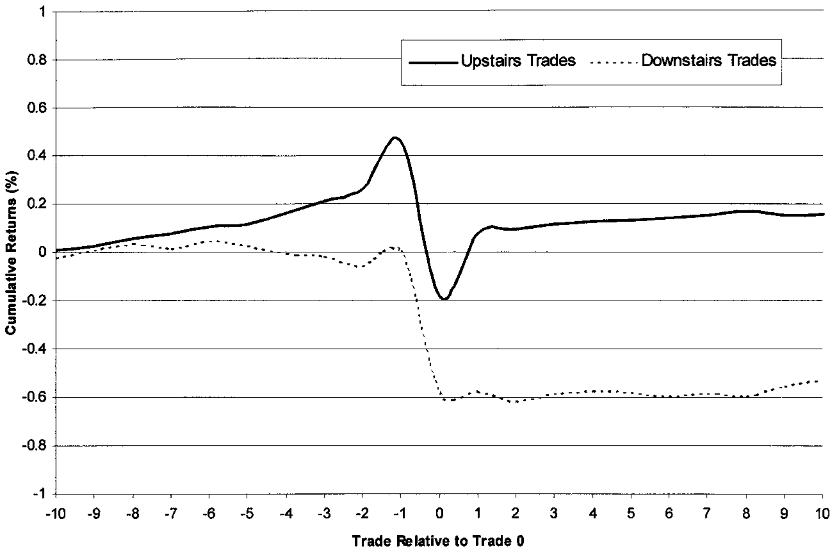

Figure 1
Cumulative average returns large downtick trades
This figure is constructed in the following manner. A large upstairs (or downstairs) trade (those in the highest five percentiles) with a downtick is designated as trade 0. The previous 10 trades (regardless of their trade locations, size, and tick) prior to trade 0 are trades −1, −2, and so forth. The trades after trade 0 are 1, 2, . . . , and so on. Trade-to-trade returns (i.e., the differences in log prices) are calculated from trades −10 to trade +10. These returns are then averaged and cumulated.

after the trade. The latter reaction is consistent with a liquidity or temporary price effect. The former may reflect the trade being anticipated.[11]

Table 3 compares the price effect measures of upstairs and downstairs trades by trade size.[12] Panel A reports the results for downtick trades and panel B for uptick trades. On average, the permanent price effects for downstairs and upstairs downtick trades are negative, indicating that seller-initiated

[11] An alternate but less satisfying explanation is that it may be the result of misclassifications by the tick rule. Although the rule appears accurate for downstairs markets, little is known concerning its accuracy in upstairs markets.

[12] Our estimates of the price effects of trades could be affected by the fact that a large trade may be split into several smaller trades and are counted as separate trades. The HSE data available to us do not indicate whether a trade is a part of another trade; however, the brokerage firm identifications are available for each trade on both sides. Hence, if a trade is a part of another trade, both trades must have the same broker on at least one side of the transactions. To see how sensitive our estimates of the price effects are to regrouping together trades that occur very close in time, we recreate two sample sets of trades from the original trades. The first one puts together trades that occur within five minutes and by the same buyer broker; the second set groups by the same seller broker. When putting together a number of trades into an assembled trade, we use a share-weighted average price for the assembled trade. There are about 6.9% of the assembled trades that involve both upstairs and downstairs markets. Since we are comparing the price effects of trades in these two markets, we discard those mixed trades from our analysis. The results based on regrouped data are essentially the same as those based on the original data. We also decreased the time interval between two consecutive trades from 5 minutes to 1 minute and increased it to 10 minutes. We obtained virtually the same results, indicating that our results are robust and not sensitive to how trades are regrouped.

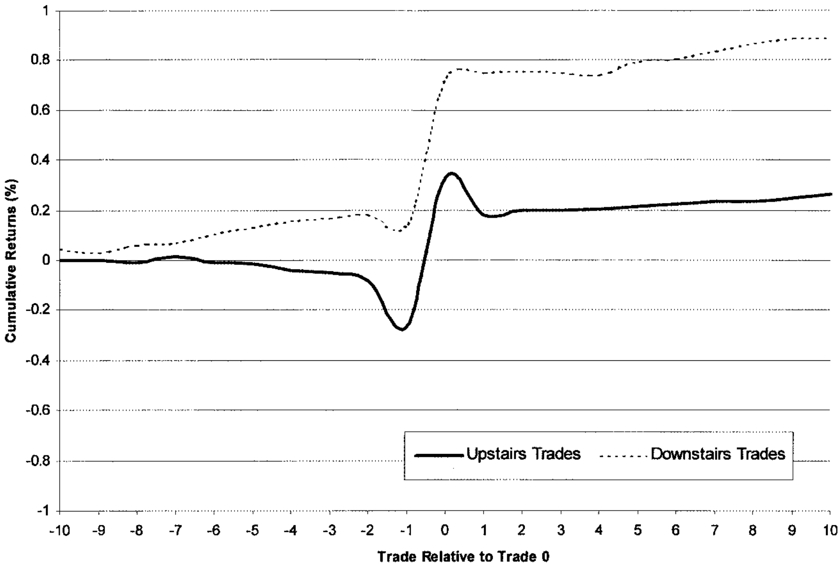

Figure 2
Cumulative average returns large uptick trades
This figure is constructed in the following manner. A large upstairs (or downstairs) trade (those in the highest five percentiles) with an uptick is designated as trade 0. The previous 10 trades (regardless of their trade locations, size, and tick) prior to trade 0 are trades -1, -2, and so forth. The trades after trade 0 are $1, 2, \ldots$, and so on. Trade-to-trade returns (i.e., the differences in log prices) are calculated from trades -10 to trade $+10$. These returns are then averaged and cumulated.

trades contain unfavorable information. The mean permanent price effect for downstairs downtick trades is about 64 basis points, and is about 11 basis points for upstairs downtick trades. The magnitude of the mean permanent price effect of downstairs trades is significantly larger than that of upstairs trades. This result applies to each of the five trade size groups.

For uptick trades, on average, the permanent price effects are positive, implying that buyer-initiated trades tend to contain favorable information. The mean permanent price effect for downstairs uptick trades is about 62 basis points and is about 15 basis points for upstairs uptick trades.[13] The difference is statistically significant for the whole sample as well as for each of the five trade size groups. Thus, for both downtick and uptick trades, the results imply that upstairs trades tend to be less information motivated than downstairs trades.

However, on average, the magnitude of the temporary price effect is significantly larger for upstairs trades than for downstairs trades. For downtick

[13] A permanent effect of approximately 60 basis points may seem large when compared to estimates obtained using U.S. data, but it is substantially smaller than the typical HEX stock bid-ask spread. Although data to calculate intraday spreads are not available, Booth et al. (2000) report that, for the same time period covered by this study, end-of-day spreads are typically 300–400 basis points for stocks with prices ranging from 10 to 1,000 markka.

Table 3
Temporary and permanent price effects of trades

	Temporary price effect			Permanent price effect			Total price effect		
Trade size in percentile	Upstairs (%)	Downstairs (%)	Up minus down	Upstairs (%)	Downstairs (%)	Up minus down	Upstairs (%)	Downstairs (%)	Up minus down
Panel A: Downtick trades									
<50%	−0.289	−0.098	−0.191†	−0.244	−0.656	0.412†	−0.534	−0.754	0.220†
50–75%	−0.275	−0.017	−0.258†	−0.108	−0.612	0.504†	−0.383	−0.628	0.245†
75–90%	−0.220	0.006	−0.214†	−0.098	−0.634	0.536†	−0.318	−0.628	0.310†
90–95%	−0.186	0.036	−0.150†	−0.085	−0.620	0.535†	−0.271	−0.585	0.314†
≥95%	−0.300	−0.002	−0.298†	0.000	−0.607	0.607†	−0.299	−0.609	0.310†
Overall	−0.265	−0.048	−0.217†	−0.109	−0.635	0.526†	−0.374	−0.683	0.309†
Panel B: Uptick trades									
<50%	0.293	0.153	0.140†	0.074	0.570	0.496†	0.367	0.723	0.356†
50–75%	0.243	0.021	0.222†	0.091	0.629	0.538†	0.334	0.650	0.316†
75–90%	0.162	−0.015	0.177†	0.211	0.706	0.495†	0.372	0.691	0.319†
90–95%	0.149	−0.035	0.184†	0.201	0.634	0.433†	0.350	0.598	0.248†
≥95%	0.132	−0.022	0.154†	0.213	0.624	0.411†	0.345	0.602	0.257†
Overall	0.201	0.072	0.129†	0.152	0.613	0.461†	0.353	0.685	0.332

The table presents mean temporary, permanent, and total price effects of upstairs and downstairs trades in the HSE during the period three trades after. The permanent price effect is defined as $p_{t+3} - p_{t-5}$, where p_{t-5} is the log transaction price five trades before the trade at time t. The temporary price effect is $p_t - p_{t+3}$, and the permanent price effect is $p - p_{t-5}$. Using the t-statistic derived from the cross-section of 20 firms, the null hypothesis that the mean price effects are the same for the two markets is rejected in every case at the 0.1% significance level as denoted by †. Up and down stand for the upstairs and downstairs markets, respectively. The trade size percentile cutoffs in each group are determined based on each firm's trade size distribution; thus they vary in absolute trade size across firms. The numbers reported in the table are averages across the 20 sample firms.

trades, the mean temporary price effect of upstairs trades is about 27 basis points, and is about 5 basis points for downstairs trades. Similarly, for uptick trades, the mean temporary price effect of upstairs trades is about 20 basis points, and is about 7 basis points for downstairs trades. On the face of it, these results indicate that there is a larger price reversal following upstairs trades than downstairs trades. The price reversal following large upstairs trades is evident in Figures 1 and 2, but is absent for large downstairs trades.[14] However, the results may reflect, in part, the fact that very often large trades are executed in the upstairs market when quotes are not deep and the limit orders are satisfied.

Nevertheless, on average, downstairs trades have a significantly larger price impact than upstairs trades. For the downtick sample, the mean total price effect is about 68 basis points for downstairs trades versus 37 basis points for upstairs trades. For the uptick sample, it is about 69 basis points for downstairs trades versus 35 basis points for upstairs trades. Therefore, on average, upstairs traders appear to be able to obtain roughly 30 basis points better execution than downstairs traders.

The pricing differences between the upstairs and downstairs markets in Finland is larger than those in the United States, as documented by Madhavan and Cheng (1997). According to their analysis, the difference in the mean total price effect between upstairs and downstairs trades in the United States is no more than two basis points. This small pricing difference may be partially due to an NYSE regulation which requires that an upstairs trade has to be exposed to the public in the downstairs market, as opposed to Finland's "best price" rule. That is, brokers who arrange an upstairs trade must offer other investors an opportunity to trade in accordance with price and time priority auction principles, and permit either side of the upstairs trade to obtain possible price improvement. Thus when negotiating a price for the upstairs trade, brokers take possible participation of downstairs traders into consideration. This enforced downstairs participation may narrow the price difference between the two U.S. markets.

Differential pricing between the upstairs and downstairs markets may also depend on market thinness. The sample HSE stocks are much more thinly traded than the Dow Jones 30 stocks in Madhavan and Cheng's (1997) sample. Actively traded stocks tend to have many buyers and sellers standing ready to trade, which creates great market depth, even for large trades in the downstairs market. Consequently, differential pricing between the upstairs and downstairs markets may be trivial for very actively traded stocks.[15]

[14] It is surprising that there is no reversal in the data for the downstairs market of HSE, which is an open limit order book system. These results are inconsistent with theories of an open limit order book, which predict some reversal from transaction prices [see Glosten (1994)].

[15] We also conduct the price effect analyses, as done in Table 3, by each individual broker and find that there are no material differences in the mean price effects across brokers. Keim and Madhavan (1996) similarly suggest that the broker type has little effect on liquidity.

4. Price Discovery in Upstairs and Downstairs Markets

The price impact analysis for individual trades conducted in the previous section allows us to estimate the extent of differential pricing between the upstairs and downstairs markets. However, the method cannot be used to analyze how the pricing for the same security in the two markets may interact. We need a model to further enhance our understanding of what functions the two markets may provide and how they interact. In particular, we would like to know whether the benefit to uninformed traders of the upstairs market, documented in Table 3, depends in part on price discovery in the downstairs market. The downstairs market matches public demands for and supplies of shares and determines a clearing price at a given point in time. Brokers in the upstairs market may use the price information provided from the downstairs market to set the price schedule. Conversely the trading activity in the upstairs market may affect the clearing price in the downstairs market. In this section we use a simple pricing model to show where price discovery occurs and how the two markets interact.

The econometric framework underpinning our price discovery measures is a vector error correction model (VECM). These models are often used to study the interactions between the prices of two or more assets because they are able to capture the phenomenon that the prices of similar assets generally do not drift away from each other for extended periods. The list of VECM applications is extensive and is growing. For a survey of early work, see Brenner and Kroner (1995). More recent examples are found throughout the current literature and are too numerous to mention here.

Because price discovery is an economic concept and not a statistical one, our analysis also requires a market microstructure model that spells out how the upstairs and downstairs markets react to news. A caveat is necessary at this point. As Hasbrouck (1996) cogently points out, a VECM is a very flexible specification and is capable of representing various microstructure schemes. This means that, Friedman's logical positivism aside, the acceptability of VECM-based price discovery findings rests on the plausibility of the underlying microstructure model.

4.1 A simple pricing model

Our microstructure model rests on the work of many others, with the primary building blocks being Amihud and Mendelson (1987), Glosten (1987), and Hasbrouck (1996: 684). As a result, we posit the following pricing relationships:

$$m_t = m_{t-1} + u_{1,t} + u_{2,t} + w_t \quad (1)$$

$$p_{1,t} = b_1(p_{1,t-1} - m_{t-1}) + m_{t-1} + u_{1,t} + (1 - b_1)u_{2,t} + w_t \quad (2)$$

$$p_{2,t} = b_2(p_{2,t-1} - m_{t-1}) + m_{t-1} + u_{2,t} + (1 - b_2)u_{1,t} + w_t. \quad (3)$$

Equations (1)–(3) are pricing specifications for the efficient price (m_t), the upstairs market price ($p_{1,t}$), and the downstairs market price ($p_{2,t}$) for a single stock in period t. As in Section 3, the $p_{i,t}$ are transaction prices. The remaining terms represent innovations that are associated with information arrival. Innovation w_t depicts updates to the public information set. In contrast, innovation $u_{1,t}(u_{2,t})$ portrays the private information revealed through trading in the upstairs (downstairs) market. It is convenient to think of trade innovations as being comprised of two parts ($u_{i,t} = g_{i,t}x_{i,t}$). One part ($g_{i,t}$) is a trade impact parameter that reflects what is being learned from the trade.[16] The other part ($x_{i,t}$) is a signed trade indicator with a value of -1 ($+1$) if the trade is seller (buyer) initiated.[17] All innovations are serially uncorrelated with covariances of zero.[18]

The model is interpreted in the following manner. Innovations $u_{1,t}$ and $u_{2,t}$ occur only in their respective market, but w_t occurs in both the upstairs and downstairs markets. The three innovations are immediately priced in the efficient market so that the efficient price is a martingale. Innovation w_t is immediately priced by the upstairs and downstairs markets. However, although $u_{1,t}(u_{2,t})$ is immediately priced by the upstairs (downstairs) market, only a portion, $1-b_2$ $(1-b_1)$, of it is immediately priced by the downstairs (upstairs) market. Moreover, we permit the portion of $u_{i,t}$ not being immediately priced to be the same in each of the subsequent periods. Thus an alternative interpretation of b_i is that it measures the speed at which the upstairs and downstairs prices approach the efficient price.[19]

Since we are using transactions data, we define price discovery to be the process by which the upstairs and downstairs prices approach (or in the extreme become equal to) the efficient price.[20] In the context of the above

[16] In the downstairs market case, it may be helpful to consider the size of the impact parameter to be positively related to the bid-ask spread because this spread contains, among other things, an asymmetric information component. Viewing $g_{1,t}$ in the same way is problematic. This is because the upstairs market broker/dealers do not provide quotes, although the menu of downstairs market limit orders is viewable in the upstairs trading rooms.

[17] Alternatively $x_{i,t}$ could be defined to be signed volume. Hasbrouck (1991), however, reports that the indicator specification provides more consistent empirical estimates.

[18] Although the individual innovations do not covary with each other, collectively the innovations in the upstairs and downstairs market will almost surely be correlated with each other because of the shared innovations. For instance, if we assume that the variances of w_t, $u_{1,t}$, and $u_{2,t}$ are equal and b_1 and b_2 are 1.0 and 0.0, the correlation between the collective innovations is 0.5 and 1.0. If one b_i is 1.0 and the other is 0.0, the correlation is 0.817.

[19] Several different information-based explanations as to why the adjustment is not instantaneous have been given. For instance, Hong and Stein (1999) rely on the notion of bounded rationality and suggest that it is because heterogeneous investors have different information sets that evolve over time. Barberis, Shliefer, and Vishney (1998) hypothesize that investors have a conservative bias and do not quickly update their priors in response to new information. Finally, Daniel, Hirshleifer, and Subrahmanyan (1998) suggest that partial adjustments are a result of investors assessing and reacting to private and public information differently.

[20] Other measures of price discovery involving bid and ask quotes are offered in the literature. For example, it may be argued that the frequency of quote revisions is positively related to the notion of price discovery. Investigating this and other quote-related metrics is not possible in Finland because, as indicated previously (see note 16), quotes are not provided in the upstairs market. Limit order prices, however, are available

microstructure model, there are two factors that determine the nature of this process. The first is the magnitude of b_i. Ceteris paribus, the smaller the portion of the innovations not immediately priced (b_i), the quicker the transaction prices converge to the efficient price.[21] If, for example, b_2 in Equation (3) is zero, the downstairs price converges instantaneously to the efficient price. In other words, the downstairs price is the efficient price. The second factor is the relative magnitude of the innovations. If one market's unique innovations are typically larger in absolute terms than those of the other market, the first market's price evolves more like the efficient price than the second market's price. Again, at the extreme, if trades in the upstairs market never reveal any information, that is, $u_{1,t}$ is always zero, the downstairs price evolves via only public information and information from downstairs trades, while the upstairs price converges to the downstairs price. Moreover, the larger w_t is relative to $u_{i,t}$, the more that the time-series behaviors of the upstairs and downstairs prices resemble that of the efficient price.

4.2 A VECM representation

To evaluate empirically the price discovery functions of the upstairs and downstairs markets, it is necessary to measure b_i, $u_{i,t}$, and w_t. Unfortunately neither they nor the efficient price are directly observable, making it necessary to recast our microstructure model to contain only the observable upstairs and downstairs prices. Relying on the model's implication that the upstairs and downstairs prices are cointegrated and employing some tedious algebra, Equations (1)–(3) may be recast into the following VECM with k lags:

$$\Delta P_t = A + Bz_{t-1} + \sum_{j=1}^{k} C_j \Delta P_{t-j} + E_t, \tag{4}$$

where $P = (p_{1,t}, p_{2,t})'$ is the vector of upstairs and downstairs prices in logarithms, $A = (a_1, a_2)'$ is a drift vector, $B = (-b_1, b_2)'$ is the error correction coefficient vector with b_1 and b_2 being positive numbers, $z_{t-1} = (p_{1,t-1} - p_{2,t-1})$ is the error correction term, C_j is a 2×2 matrix of parameters, and $E_t = (e_{1,t}, e_{2,t})'$ is a zero mean vector of serially uncorrelated errors with covariance matrix:

$$\Omega = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}. \tag{5}$$

throughout the continuous trading session, but only the closing bid and ask prices are retrieved and kept by the HSE (see note 2).

[21] If $0 \leq b_i < 1$, the convergence to the efficient price will be monotonic. If $b_i = 1$, the price will be a martingale but will not be the efficient price. If $b_i > 1$, the price will diverge from the efficient price. The magnitude of b_i depends on data frequency, with higher-frequency data being associated with larger b_i values than lower frequency data, ceteris paribus.

The term $\sigma_1^2(\sigma_2^2)$ is the variance of $e_{1,t}(e_{2,t})$ and ρ is the correlation between $e_{1,t}$ and $e_{2,t}$.

In addition to the drift term, the VECM has three parts. The first, $(-b_1, b_2)' \times z_{t-1}$, represents the long-run equilibrium dynamics between the upstairs and downstairs prices. Although the VECM b_i are the same as those in the microstructure model, their interpretation is slightly different. In the VECM, the upstairs and downstairs prices are modeled so that they converge to each other rather than individually approach the efficient price. Thus the speed of price adjustment is relative to each other, with the larger- and not the smaller-magnitude b_i being associated with the faster convergence speed. To clarify this assertion, let us return to the example where $b_2 = 0$. In this case the downstairs price does not adjust (that is, its speed of adjustment is zero) to the upstairs price because it is the efficient price. If b_1 is not zero, the upstairs price adjusts to the downstairs price. The second part, $\Sigma C_j \Delta P_{t-j}$, depicts the short-run dynamics between the upstairs and downstairs prices. These effects work in conjunction with the error-correction coefficients to permit both prices to approach the efficient price. Without them the upstairs and downstairs prices would converge, with no guarantee that their equilibrium value is the efficient price. The final part, $(e_{1,t}, e_{2,t})$, shows the innovations resulting from information being made public and from information being revealed through trading. The $e_{i,t}$ are complicated moving averages involving b_i, $u_{i,t}$, and w_t. It is not possible to disentangle $e_{i,t}$ to determine the values for the microstructure model's innovations because taken together $e_{i,t}$ in this regard is underidentified.

4.3 Price discovery measures

Using the estimation results from the VECM, the Gonzalo and Granger (1995) common factor and Hasbrouck (1995) information share methods to explore the price discovery implications of our microstructure model. The crux of both methods is that they decompose the impact of an innovation into permanent and temporary components in a framework analogous to Stock and Watson (1988) and allocate the permanent component to, in our case, the upstairs and downstairs markets. The permanent effects are associated with information, while the transitory effects are related to market phenomena such as the bid-ask bounce, price discreteness, inventory adjustments, etc. Gonzalo and Granger (1995) base their decomposition solely on the error correction coefficients. Hasbrouck (1995), however, recasts his VECM into a vector moving average representation and concentrates on the parameters of the innovations. Although seemingly different, Baillie et al. (2001) show that both price discovery metrics are derived from the orthogonal of the error correction coefficient vector and may provide qualitatively similar results.

In our context, the Gonzalo and Granger (1995) method defines the common factor to be a linear combination of $p_{1,t}$ and $p_{2,t}$ such that it equals the sum of $\gamma_1 p_{1,t}$ and $\gamma_2 p_{2,t}$, where γ_i measure the contribution of the $p_{i,t}$ to the efficient price. This definition is equivalent to considering the common factor to be the price of a portfolio containing one stock with some of the shares purchased in the upstairs market and some in the downstairs markets, with γ_i serving as portfolio weights. Gonzalo and Granger (1995) show that γ_i is orthogonal to b_i, the error correction coefficients. Thus standardizing these weights so that they sum to one permits the contribution of the *i*th market's permanent components of its innovations to the common factor to be specified as

$$\gamma_1 = \frac{b_2}{b_1 + b_2} \tag{6.1}$$

$$\gamma_2 = \frac{b_1}{b_1 + b_2}. \tag{6.2}$$

New information from both markets could be incorporated into the common factor, that is, $0 \leq \gamma_i \leq 1$. Nevertheless, we are particularly interested in the following two polar null hypotheses:

Hypothesis 1. $\gamma_1 = 1.0$ and $\gamma_2 = 0.0$.

Hypothesis 2. $\gamma_1 = 0.0$ and $\gamma_2 = 1.0$.

Hypothesis 1 posits that the common factor is derived solely from the upstairs price, while Hypothesis 2 asserts that the common factor is derived solely from the downstairs price. In other words, Hypothesis 2 implies that brokers use the downstairs price as the basis for pricing upstairs trades and Hypothesis 1 implies the opposite. Gonzalo and Granger (1995), building on the work of Johansen (1991), develop a log-likelihood statistic to test Hypothesis 1 and Hypothesis 2 separately.

Following a somewhat different tack than Gonzalo and Granger (1995), Hasbrouck (1995) decomposes the common factor innovations and defines a market's information share to be the proportional contribution of its innovations to the variance of the innovations in all markets. In the absence of contemporaneous correlation of the market innovations, Martens (1998) and Baillie et al. (2001) show that for the two market case, Hasbrouck's (1995) information share measures are

$$S_1 = \frac{\gamma_1^2 \sigma_1^2}{\gamma_1^2 \sigma_1^2 + \gamma_2^2 \sigma_2^2} \tag{7.1}$$

$$S_2 = \frac{\gamma_2^2 \sigma_2^2}{\gamma_1^2 \sigma_1^2 + \gamma_2^2 \sigma_2^2} \tag{7.2}$$

and S_1 and S_2 sum to unity. If the variance of the upstairs market's innovations, σ_1^2, and downstairs market's innovations, σ_2^2, are equal, the Gonzalo and Granger (1995) and Hasbrouck (1995) metrics provide qualitatively similar results, as S_1/S_2 equals γ_1^2/γ_2^2.

According to our microstructure model, the intermarket innovations display some level of contemporaneous correlation. Following Hamilton (1994), Hasbrouck (1995) suggests Cholesky factorization of $\Omega = FF'$ to eliminate this correlation, which results in a triangular matrix version of Equation (5):

$$F = \begin{bmatrix} \sigma_1 & 0 \\ \rho\sigma_1 & \sigma_2(1-\rho^2)^{1/2} \end{bmatrix}. \tag{8}$$

Baillie et al. (2001) point out that Equations (7.1) and (7.2) can be expanded to reflect this elimination of contemporaneous correlation through factorization. The upstairs and downstairs information shares, if the upstairs price is the first price in the factorization, become

$$S_1 = \frac{(\gamma_1\sigma_1 + \gamma_2\sigma_2\rho)^2}{(\gamma_1\sigma_1 + \gamma_2\sigma_2\rho)^2 + \gamma_2^2\sigma_2^2(1-\rho^2)}. \tag{9.1}$$

$$S_2 = \frac{\gamma_2^2\sigma_2^2(1-\rho^2)}{(\gamma_1\sigma_1 + \gamma_2\sigma_2\rho)^2 + \gamma_2^2\sigma_2^2(1-\rho^2)}. \tag{9.2}$$

Equations (9.1) and (9.2) show that the Hasbrouck (1995) information shares not only depend on γ_i, the orthogonals of the error correction coefficients, but also on σ_i and ρ. They also show that the factorization imposes a greater information share on the first price.

Hasbrouck (1995) considers the upper (lower) bound of the ith market's information share to occur when market i is the first (second) variable in the factorization. These equations also show that the higher the correlation, the greater the spread between the upper and lower bounds. Intuitively, the upper bound incorporates the first series own contribution σ_1^2 and its correlation with the second series $(\sigma_2^2\rho^2)$. The lower bound incorporates only the second market's "pure" contribution that is uncorrelated with the first market $(\sigma_2^2(1-\rho^2))$. This ordering-caused discrepancy can be substantial if the innovations are highly contemporaneously correlated, an empirical phenomenon not experienced by Hasbrouck (1995), who uses extremely high-frequency (one-second) data.[22] To provide a complete picture, therefore, it is necessary to consider sequentially the upstairs and downstairs prices as the first and second markets in the factorization. Unfortunately Hasbrouck (1995) and others who have used his technique have not been able to construct a statistical significance test for these bounds. Our efforts in this regard have also been unsuccessful. Thus we follow Hasbrouck's (1995) suggestion and provide the cross-sectional standard error of these bounds for our 20 stocks as a measure of variation.

[22] By way of illustration, if the innovations are perfectly and positively correlated and p_1 is the first price in the factorization, the information share for the upstairs market is 1.0 and for the downstairs market is 0.0, regardless of the value of γ_1 and γ_2. Reversing the order of factorization gives the upstairs (downstairs) market an information share of 0.0 (1.0).

In sum, we use the models of Granger and Gonzalo (1995) and Hasbrouck (1995) to assess the relative importance of the upstairs and downstairs markets' contributions to price discovery. If the nonanonymous upstairs market is better for uninformed traders and the anonymous downstairs market is at least as good for informed traders, we expect that price discovery should occur primarily but not necessarily solely in the downstairs market and that the results of our empirical tests should be closer to Hypothesis 2 than Hypothesis 1. Such a finding would be consistent with the results in Section 3 that indicate that upstairs trades are less informative than downstairs trades.

4.4 Construction of price pairs

To properly test the hypotheses outlined above, it is necessary to pair a downstairs price with an upstairs price. We use the MINSPAN pairing procedure proposed by Harris et al. (1995). Specifically, to form the first pair with the first trade from the second market, we consider two trades from the first market, one before and the other after the trade from the second market, and select the trade from the first market that occurs closer in time to the trade from the second market. The second pair and the pairs that follow are formed in the same manner. The MINSPAN procedure minimizes the observation time span within the pair by looking forward in trading time as well as backward.[23]

The average number of MINSPAN matched pairs is 2,876, with Nokia having the largest number (5,859) and OKO the smallest (230). On average the matched pairs contain 75.7% of the upstairs trades and 21.0% of the downstairs trades. Within each pair, the mean time between the two trades is 14.4 minutes. The mean time between each matched pair, however, is 49.9 minutes. In 58.7% of the matched pairs, the upstairs trade precedes the downstairs trade.[24]

4.5 Empirical results

In Table 4 we report the VECM estimation results for the error correction coefficients (b_i), the variance of the innovations (σ_i^2), and the contemporaneous correlation of the innovations (ρ).[25] The mean error correction coefficient

[23] We also consider Harris et al.'s (1995) REPLACE ALL approach. One drawback of the REPLACE ALL procedure is that for most pairs we find that the upstairs trades tend to be matched with the most recent downstairs trades. Thus the upstairs price may potentially contain more recent information than the downstairs price, creating a possible discovery bias for the upstairs market. The REPLACE ALL price discovery results are qualitatively the same as the MINSPAN findings, however.

[24] This pattern does not necessarily imply that an upstairs trade "causes" a downstairs trade. We believe that the pattern results from there being about four downstairs trades for every upstairs trade. Thus the MINSPAN matching procedure tends to select an upstairs price as the first price in the matched pair. In any case, a dummy variable capturing this order is incorporated in the VECM, but in every case its coefficient is not statistically significant.

[25] The unit root tests of ADF [Dickey and Fuller (1979, 1981)] and Phillips-Perron [Phillips (1987) and Phillips and Perron (1988)] indicate that the price series contain a unit root, a common finding in studies analyzing asset prices. These results are available upon request. Both Johansen's (1991) trace and $\lambda_{\max}$ statistics show

Table 4
Selected VECM results for upstairs and downstairs markets

		Error correction coefficients		Innovations		
				Variance		Cross-market correlations
Company	Sample size	Upstairs (b_1)	Downstairs (b_2)	Upstairs (σ_1^2)	Downstairs (σ_1^2)	(ρ)
Amer	2,729	$0.840^{\dagger}$	0.060	0.118	0.106	0.900
Cultor	1,009	$0.933^{\dagger}$	0.001	0.201	0.215	0.899
Enso	4,224	$0.624^{\dagger}$	$0.327^{\#}$	0.054	0.061	0.908
Huhtamaki	2,285	$0.630^{\dagger}$	0.273^{*}	0.099	0.108	0.917
Instru	1,195	$0.742^{\dagger}$	0.161	0.318	0.323	0.950
Kesko	2,224	$0.693^{\dagger}$	0.214	0.079	0.084	0.883
Kone	1,273	$0.997^{\dagger}$	−0.187	0.139	0.141	0.941
KOP	6,192	$0.768^{\dagger}$	0.125	0.135	0.154	0.905
Kymmene	5,583	$0.717^{\dagger}$	$0.195^{\#}$	0.057	0.063	0.841
Metra	2,188	$0.798^{\dagger}$	0.121	0.096	0.112	0.907
Metsa-Serla	2,660	$0.896^{\dagger}$	0.076	0.127	0.139	0.895
Nokia	5,859	$1.023^{\dagger}$	−0.099	0.157	0.184	0.922
OKO	230	1.600	0.113	0.072	0.080	0.951
Outokumpu	3,169	$0.800^{\dagger}$	0.153	1.673	1.670	0.913
Partek	1,128	0.521^{*}	0.534^{*}	0.092	0.098	0.912
Pohjola	1,810	$0.854^{\dagger}$	0.140	0.420	0.432	0.920
Rautaruukki	2,014	$0.835^{\dagger}$	0.177	0.234	0.259	0.931
Repola	6,820	$0.827^{\dagger}$	0.071	0.036	0.043	0.847
Stockmann	830	$0.684^{\dagger}$	0.370	0.208	0.214	0.935
Unitas	4,801	$0.817^{\dagger}$	0.134	0.340	0.372	0.908
Mean	2,911	0.830	0.148	0.233	0.243	0.909
(std. error)	(443)	(0.049)	(0.035)	(0.079)	(0.079)	(0.006)

This table reports the upstairs and downstairs market error correction coefficient from Equation (4). The VECM contains five autoregressive lags. We use White's (1990) heteroscedasticity-consistent t-statistics to test the statistical significance of the coefficients, with the null hypothesis being that the coefficient equals zero. Superscripts †, $^{\#}$, and * denote significance at the 0.1%, 1.0%, and 5.0% levels, respectively. The table also includes the variances of the innovations from Equation (5) as well as the cross-market correlations of these innovations.

for the upstairs market is 0.830 and for the downstairs market is 0.148. This means that, on average, 17.0% of the innovations revealed in the downstairs market are immediately priced in the upstairs market. In contrast, 85.2% of the upstairs market's unique innovations are immediately incorporated in the downstairs' price. On an individual stock basis, all but one of the b_1's are significantly different from zero. The exception is OKO, which has 224 observations. In contrast, all but four b_2's (Enso, Huhtamaki, Kymmene, and Partek) are *not* statistically significant. In no instance is b_1 or b_2 significantly greater than one, indicating a smooth convergence to equilibrium after an innovation.[26] The upstairs and downstairs innovations are highly correlated and their variances are typically of similar size. The high average correlation, 0.909, is largely because of the downstairs market's ability to immediately price the upstairs market's innovations.

that the upstairs and downstairs price series are cointegrated with a common stochastic trend. The cointegrating vector is (−1.0, 1.0). This indicates that the upstairs and downstairs prices do not diverge without bound from each other.

[26] Two b_1's (Nokia and OKO) are numerically greater than one. The t-statistic for the null hypothesis that b_1 is greater than one is 0.256 for Nokia and 0.649 for OKO.

Table 5
Gonzalo and Granger (1995) common factor weights for the upstairs and downstairs markets

	Common factor weight			Common factor weight	
Company	Upstairs (γ_1)	Downstairs (γ_2)	Company	Upstairs (γ_1)	Downstairs (γ_2)
Amer	0.066	0.934†	Metsa-Serla	0.092	0.908†
Cultor	0.003	0.997†	Nokia	0.000	1.000†
Enso	0.349†	0.651†	OKO	0.122	0.878*
Huhtamaki	0.302*	0.698†	Outokumpu	0.164	0.836†
Instru	0.242	0.758†	Partek	0.507$^{\#}$	0.493$^{\#}$
Kesko	0.171	0.829†	Pohjola	0.153	0.847†
Kone	0.000	1.000†	Rautaruukki	0.182	0.818†
KOP	0.139	0.861†	Repola	0.076	0.924†
Kymmene	0.221†	0.779†	Stockmann	0.490*	0.510*
Metra	0.114	0.886†	Unitas	0.132	0.868†
Mean				0.176	0.824
(Std. error)				(0.032)	(0.032)

This table reports the Gonzalo and Granger (1995) common factor weights for the upstairs and downstairs markets. These weights sum to one. We test the null hypothesis that either the upstairs market H1: $\gamma_1 = 1.0$ and $\gamma_2 = 0.0$ and in the downstairs market H2: $\gamma_1 = 0.0$ and $\gamma_2 = 1.0$ is the sole source of the common factor using the Gonzalo and Granger (1995) log-likelihood test $Q_{GG} = Tln\{(1-\lambda_n)/(1-\lambda_n^*)\}$, where T is the number of observations, and λ_n and λ_n^* are the largest eigenvalues from the estimated model [in our case Equation (4)] and the model under the null, respectively. Q_{GG} is χ^2 (1) distributed. Superscripts †, $^{\#}$, and * denote statistical significance at the 0.1%, 1.0%, and 5.0% levels, respectively.

The Gonzalo and Granger (1995) common factor statistics given in Table 5 are derived from the VECM results in Table 4. Turning first to the common factor statistics, the null hypothesis that the upstairs price is the only component of the common factor (Hypothesis 1: $\gamma_1 = 1.0$ and $\gamma_2 = 0.0$) is rejected for all 20 stocks. However, the null hypothesis that the downstairs price is the only component (Hypothesis 2: $\gamma_1 = 0.0$ and $\gamma_2 = 1.0$) is not rejected for all but five stocks. For these stocks (Enso, Huhtamaki, Kymmene, Partek, and Stockmann), both the upstairs and the downstairs prices contribute to the common factor. The similarity between the error correction coefficient conclusions and those of the common factor analysis is because the latter is essentially a joint test of the values of the error correction coefficients.

The information share results are less definitive. As reported in Table 6, if the downstairs price is the first variable in the Cholesky factorization, the mean maximum downstairs information share for the 20 stocks is 0.992. If the factorization order is reversed, the mean minimum information share is 0.131. The corresponding figures for the upstairs market are 0.869 and 0.008, with the latter (the mean minimum information share) being economically very small. This reversal of dominance is typical for each of the 20 stocks because of the high contemporaneous correlation between the upstairs and downstairs innovations.[27]

However, as shown in Equations (9.1) and (9.2), if one common factor weight value is one and the other is zero, the Gonzalo and Granger (1995) and

[27] Martens (1998), Tse (1999), Huang (2000), and Baillie et al. (2001) also report a substantial difference in their Hasbrouck (1995) maximum and minimum information share results.

Table 6
Hasbrouck (1995) information shares for the upstairs and downstairs markets

	Information shares (S)					
	Upstairs			Downstairs		
Company	Maximum	Minimum	Midpoint	Maximum	Minimum	Midpoint
Amer	0.832	0.001	0.417	0.999	0.168	0.584
Cultor	0.813	0.000	0.406	1.000	0.187	0.594
Enso	0.918	0.020	0.469	0.980	0.082	0.531
Huhtamaki	0.918	0.014	0.466	0.986	0.082	0.534
Instru	0.933	0.003	0.468	0.997	0.067	0.532
Kesko	0.865	0.012	0.439	0.988	0.135	0.562
Kone	0.834	0.006	0.420	0.994	0.166	0.580
KOP	0.861	0.003	0.432	0.997	0.139	0.568
Kymmene	0.804	0.013	0.409	0.987	0.196	0.591
Metra	0.862	0.003	0.432	0.997	0.138	0.568
Metsa-Serla	0.827	0.001	0.414	0.999	0.173	0.586
Nokia	0.822	0.001	0.412	0.999	0.178	0.588
OKO	0.916	0.000	0.458	1.000	0.084	0.542
Outokumpu	0.879	0.004	0.442	0.996	0.121	0.558
Partek	0.957	0.044	0.500	0.956	0.043	0.500
Pohjola	0.883	0.003	0.443	0.997	0.117	0.557
Rautaruukki	0.907	0.004	0.456	0.996	0.093	0.545
Repola	0.752	0.001	0.377	0.999	0.248	0.623
Stockmann	0.944	0.015	0.480	0.985	0.056	0.521
Unitas	0.866	0.003	0.435	0.997	0.134	0.566
20-stock mean	0.869	0.008	0.439	0.992	0.131	0.561
(std. error)	(0.012)	(0.002)	(0.007)	(0.002)	(0.012)	(0.007)
5-stock mean	0.908	0.021	0.465	0.979	0.092	0.535
15-stock mean	0.856	0.004	0.430	0.996	0.144	0.570

This table provides the Hasbrouck (1995) information shares for the upstairs and downstairs markets. The names of the five stocks for which the Gonzalo and Granger (1995) null hypothesis that the downstairs market is the sole source of the common factor (Hypothesis 2: $\gamma_1 = 0.0$ and $\gamma_2 = 1.0$) is rejected are in boldface. The maximum (minimum) upstairs market contribution to the common factor's innovation is when the upstairs price is the first (second) variable in the Cholesky factorization. The downstairs market's contributions are similarly defined the maximum (minimum) contribution of the upstairs market and the minimum (maximum) of the downstairs market sum to one.

the Hasbrouck (1995) conclusions are the same. According to the Gonzalo and Granger (1995) test results, this is not the case for five stocks. Table 6 also provides the summary measures for these five stocks (names in boldface). A comparison of the five-stock means and the means for the other 15 stocks reveals that, although the values are somewhat similar, the dominance of the downstairs market is not as strong. For instance, the upstairs mean minimum information share is 0.021 for the five stocks and 0.004 for the 15 stocks. The corresponding downstairs metrics are 0.144 and 0.092.

Another sensible approach to interpret the Hasbrouck (1995) information share values (at least in the two market case) is to consider the maximum and minimum values as endpoints of a distribution, thereby making it possible to use their midpoint as a measure of location. Doing so results in the upstairs (downstairs) market having a mean information share of 0.439 (0.535) for the 20 stocks. Although the Hasbrouck (1995) model also shows that the downstairs market contributes more to price discovery than the upstairs market, the downstairs market's dominance is not as dramatic as the common factor conclusions, a result of the Hasbrouck (1995) model incorporating the correlation between the series innovations, while the Gonzalo and Granger (1995) model does not.

Overall our price discovery results are consistent with Seppi's (1990) model, which predicts that uninformed traders prefer the upstairs market, while informed traders randomize (in equilibrium) their trades between the upstairs and downstairs markets. Hence in some markets, the information content of upstairs trades would be trivial, but in other markets it may not be. In any case, there should be more information revealed from trades in the downstairs market.

5. Concluding Remarks

This article provides new empirical evidence on the trading and pricing behavior of a security that is traded in upstairs and downstairs markets. Using data from the Helsinki Stock Exchange, we find that the permanent price effect of upstairs trades is significantly smaller, implying that information-motivated trades occur less in the upstairs market than in the downstairs market. Conversely, the temporary price effect is significantly larger in the upstairs market, suggesting that liquidity providers require a higher compensation in the upstairs market. The total price effect is significantly smaller for upstairs trades than for downstairs trades. The results are consistent with Seppi's (1990) hypothesis that the upstairs market is better in pricing (institutional) uninformed liquidity trades. The results also are consistent with Grossman's (1992) hypothesis that upstairs brokers can give better prices to their customers when they know the unexpressed demands of their customers.

Our common factor analysis supports the conclusions drawn from the price impact findings. For most sample firms, the downstairs price reveals the common factor by impounding trade and other information. Consequently brokers largely use the downstairs price plus a transitory component as the basis for pricing upstairs trades. This price discovery function of the downstairs market reflects the permanent (temporary) effect in the upstairs market being smaller (larger) than the permanent (temporary) effect of the downstairs market.

Our empirical evidence of differential pricing between the upstairs and downstairs markets has an important practical implication for international investors. Because of the globalization of investing, international fund managers need to know the pricing practices and the liquidity of international upstairs and downstairs markets when making investment decisions. We find that, taken as a whole, the upstairs market is more beneficial for uninformed traders and the downstairs anonymous market is more advantageous for informed traders to camouflage their trades. As a result, most of price discovery occurs in the downstairs market, upon which the upstairs market relies. It is likely that this phenomenon characterizes other relatively thin markets as well.

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