

Do Inventories Matter in Dealership Markets? Evidence from the London Stock Exchange

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ABSTRACT

Using London Stock Exchange data, we test the central implication of the canonical model of Ho and Stoll (1983) that relative inventory differences determine dealer behavior. We find that relative inventories explain which dealers obtain large trades and show that movements between best ask, best bid, and straddle are highly correlated with both standardized and relative inventory changes. We show that the mean reversion in inventories is highly nonlinear and increasing in inventory levels. We show that a key determinant of variations in interdealer trading is inventories and that interdealer trading plays an important role in managing large inventory positions.

SUBSTANTIAL EMPIRICAL PROGRESS has been made in market microstructure literature in analyzing the components of the bid-ask spread and in analyzing information-based models of the bid-ask spread, but little progress has been made in the empirical analyses of inventory models of dealership markets. This is somewhat surprising given that the early theoretical work in the market microstructure area due to Garman (1976), Amihud and Mendelson (1980), and Ho and Stoll (1980, 1981, 1983) dealt primarily with the inventory hypothesis. In fact, Ho and Stoll's (1983) model makes strong predictions about the distribution of inventories and about the relationship between inventories and quote placement behavior.¹

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¹ The model of Biais (1993) is similar to the one-period model of Ho and Stoll (1983). Both models are closely related to the literature on open English auctions and second price auctions.

In this paper, we conduct direct tests of Ho and Stoll's (1983) inventory model of a competitive dealership market. Our paper makes two main contributions to the existing literature on inventories and dealer behavior. First, using a rich dataset from the London Stock Exchange, it tests for the first time the predictions of inventory models which pertain to the relative inventory position of dealers. Second, it presents the first set of empirical results on interdealer trading and the relationships between interdealer trading and dealer inventory levels.²

In the recent empirical literature, a number of papers have dealt with inventories and a few with dealership markets. Although each paper makes an important contribution to the market microstructure literature, none specifically tests the central implications of inventory models of competitive dealership markets. Ho and Macris (1984) present some interesting results on specialist behavior in the American Exchange (AMEX) options market. Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993) provide analyses of the time series behavior of specialist inventories on the New York Stock Exchange (NYSE) and show that the reversal of inventory positions takes place only over a number of days. However, the very nature of the NYSE market precludes any analysis of either the inventory models of dealership markets or the inventory model of a monopolistic dealership market (Garman (1976), Amihud and Mendelson (1980)) because the specialist on the NYSE is neither a competitive dealer nor a monopolist. Additionally, the slow inventory reversal over a number of days could be a consequence of the institutional requirement on the NYSE that specialists make an orderly market and accept trades on both sides of the spread (this point is also made by Chan, Christie, and Schultz (1994)) and may not be characteristic of dealership markets.

A second group of papers has attempted to test some of the implications of inventory models for dealership markets. Stoll (1976) and Neuberger (1992) use aggregate inventory data and are unable to investigate the behavior of individual dealers. Lyons (1995) studies the foreign exchange market using trade data from one competing dealer. Mann and Manaster (1996) look at the intraday behavior of scalpers in futures markets, a fundamentally different market structure from a dealership market. These papers lack the kind of detailed data available to us and hence do not explore the rich relationships between quote placement and individual dealer inventories that is central to the inventory model of dealership markets.

The other related group of papers due to Chan et al. (1994), Christie and Schultz (1994) and Christie, Harris, and Schultz (1994), analyzes the quote placement behavior of dealers on the Nasdaq market. Christie and Schultz (1994) conclude that there is little evidence that Nasdaq market makers post competitive quotes. Chan et al. (1995) document that quotes on the Nasdaq market system are one-sided and the inside spread declines near the close.

² Recent work on interdealer trading includes Reiss and Werner (1998) and Naik and Yadav (1996a).

However, they are unable to test directly the inventory model of dealership markets because the data source for Nasdaq (the Bridge Quotation System) does not allow them to identify trades to dealers or observe direct trades between market makers and retail customers. As a consequence, they are unable to identify the inventory positions of dealers.

Many of the implications of inventory models of dealership market pertain to the positioning of quotes by one market maker relative to that of other market makers as a function of their inventories. These implications cannot be tested with the data used in the above-mentioned studies because those studies do not have data on individual dealers' inventories. Our dataset, on the other hand, consists of all quotes and transactions on the London Stock Exchange.³ Our data clearly identify each transaction by whether it was a public trader buying or selling the stock, by which of the competing market makers executed the trade and, most importantly, by whether the market maker was trading on his own account or as an agent.⁴ The last feature enables us to construct market makers' inventory positions and, unlike the *indirect* tests of market maker behavior in the literature (Glosten and Harris (1988), Hasbrouck (1988), and Chan et al. (1994)), enables us to test *directly* the predictions of inventory models of competitive dealership markets.

Our paper is also distinguished from earlier work by its use of interdealer trades. Dealership markets like the London Stock Exchange and the Nasdaq in the United States are characterized by a large volume of interdealer trading. In particular, interdealer trading on the London Stock Exchange constitutes 53 percent of public trading. The prototypical asymmetric information models of Glosten and Milgrom (1985) and Kyle (1985) do not provide any role for interdealer trading. Ho and Stoll (1983), Naik, Neuberger and Viswanathan (1996), and Lyons (1996) provide models in which interdealer trading is driven by inventory differences and risk sharing considerations. However, there has been little empirical work on what motivates interdealer trading and whether interdealer trading is related in any systematic manner to inventories. Our paper highlights the differences in public and interdealer trades and investigates the relationship between interdealer trading and dealer inventories.

Our dataset consists of all quotes and transactions in a sample of thirty of the hundred most liquid (FTSE-100) stocks from June 1991 to July 1992. We use this to test the empirical validity of the predictions of the inventory model of dealership markets. We find that:

- Market makers posting competitive quotes execute a significantly larger proportion of the public trades.

³ Transactions level data on the NYSE is used by Harris (1986), Foster and Viswanathan (1993), Wood, McInish, and Ord (1985) and several others to explore many interesting issues. However, the focus of those studies is very different from ours.

⁴ In this paper we use the terms *dealers* and *market makers* interchangeably.

- The relative inventory position of market makers is significantly related to their ability to execute large trades.
- Changes in quotes and inventories are strongly correlated.
- Standardized and relative inventories (with respect to the median inventory) are mean reverting.
- The mean reversion coefficient is increasing in the inventory level.
- The mean half life from the mean reversion estimates is 2.5 trading days (in contrast to that obtained by Madhavan and Smidt (1993) of 7.3 trading days).
- The inventory level at which interdealer trades are executed is significantly higher than that of public trades.
- Higher levels of interdealer trading are associated with higher levels of inventories, the adjusted R^2 being 38 percent.

Our findings that the relative inventory position is significantly related to the ability to execute large trades is the first direct evidence supporting the inventory model of dealership markets and provides a rationalization for the observed one-sided quote setting behavior of dealers. Our exploration of the relationship between quote changes and relative and standardized inventories yields further results in support of this hypothesis: (a) market maker moves from best bid to best ask are associated with large significant increases in inventory (and vice versa), and (b) market maker moves from off the touch (neither highest bid nor lowest ask) to the best bid (ask) are associated with insignificant changes in standardized inventory but significant decreases (increases) in relative inventories.⁵ These results together provide direct evidence in support of several predictions of the inventory models of dealership markets.

Our results on the mean reversion in dealer inventories indicates that dealership markets like the London Stock Exchange differ considerably from markets with specialists like the New York Stock Exchange. First, the mean half-life of dealer inventories in our data is only 2.5 days. This contrasts sharply with the evidence of Hasbrouck and Sofianos (1993) and Madhavan and Smidt (1993) that the mean reversion in specialist inventories is small on the NYSE (Madhavan and Smidt estimate a half-life of 7.3 trading days after excluding certain inventory changes via intervention analysis). Second, our results strongly indicate that the mean reversion in standardized and relative inventories of dealers is highly nonlinear and the mean reversion coefficient is increasing in the inventory level.

Our finding that the mean reversion in relative inventories is highly nonlinear is consistent with the inventory model of dealership markets. Because inventory models of competitive dealership markets predict that a public buy (sell) will be executed by market makers with extreme inventory positions, one should find stronger mean reversion effects with extreme inven-

⁵ The word *touch* is used on the London Stock Exchange (and in this paper) to refer to the highest bid and lowest ask and is equivalent to the inside spread or the market spread.

tories as compared with inventories that are not at or near the extreme. Hence, the finding that the mean reversion is higher at higher inventory levels strongly supports inventory models of dealership markets. It also implies that any inference drawn from inventory half-lives under the assumption of a constant mean reversion coefficient for inventories is misleading.

Our exploration of interdealer trades shows that the average size of interdealer trades is much larger than those of public trades. However, public trades exhibit great variability and can be small or large, but interdealer trades show relatively small variation in size. In general, the average inventory level at which a dealer participates in interdealer trades is significantly higher than the average inventory level at which a dealer participates in a public trade. Importantly, we find that the extent of interdealer trading is increasing in the inventory level and that 38 percent of the variation in interdealer trading can be explained by differences in inventories. This shows that interdealer trading is intimately related to inventories, especially when the dealer has a large position.

The rest of the paper is organized as follows. Section I describes the testable restrictions implied by Ho and Stoll's (1983) inventory model of a competitive dealership market. Section II describes the data. Section III details the results of empirical investigation of the inventory model of dealership markets. Section IV discusses the relationship between interdealer trading and inventories. Section V concludes with suggestions for future research.

I. Implications of the Inventory Model of a Competitive Dealership Market

We use as the basis for our empirical tests Ho and Stoll's (1983) model of a competitive dealership market. This model has competing risk averse market makers who differ in their inventories and in their risk preferences. Proposition 1 of Ho and Stoll (1983, p. 1057) states that the reservation fee of a market maker for buying or selling a fixed quantity of stock depends on the variance of the stock return, the risk aversion of the market maker, and the inventory level of the market maker. These reservation fees are such that market makers earn identical expected utility from trading and not trading. Generally, the market makers with the highest (lowest) reservation bid (ask) fees post the most competitive bid (ask) quotes. These quotes constitute the inside spread and equal the reservation bid and ask prices of market makers with the second highest and the second lowest reservation fees. Public sell and buy orders arrive exogenously and are executed by market makers offering the highest bid or lowest ask price. Sometimes the inventory differences among the market makers are large enough so that they engage in interdealer trading in order to reallocate their inventory risk.

For a given stock, the reservation fee of a market maker depends on both the risk aversion and the inventory level of the market maker. If one controls for differences in risk aversions by standardizing the inventories, then the reservation buying or selling fee of a market maker depends only on his

standardized inventory level. In such a case, market makers' quotes become a monotone function of their inventory levels, and the relative positioning of their quotes depends only on their relative inventory levels. This implies that market makers with relatively short (long) inventory positions post competitive bid (ask) prices. If we define the inside spread or the *touch* (denoted by subscript T) at time t as $A_{T,t}$ and $B_{T,t}$, where $A_{T,t}$ is the lowest ask price and $B_{T,t}$ is the highest bid price at time t , then the inventory models imply that the position of market maker i 's quotes relative to the touch is a monotone function of his inventory $I_{i,t}$ at time t relative to that of the market maker offering the most competitive price. For market maker i 's bid price we express this as

$$B_{i,t} - B_{T,t} = \mathcal{F}(I_{i,t} - I_{T,t}), \quad (1)$$

where $I_{T,t}$ is the inventory level of the market maker who is posting the highest bid price—that is, the market maker with the shortest inventory position. By symmetry, a similar relationship follows for the ask price. In inventory models of dealership markets the inventory level of each market maker determines his quotes, therefore the timing of quotes and inventories we use is that the quotes with subscript t ($B_{i,t}$ and $A_{i,t}$) follow immediately after the inventory with subscript t ($I_{i,t}$).

In inventory models of competitive dealership markets, the public sells (buys) are executed by market makers posting the highest bid (lowest ask). Therefore, in these models the change in a market maker's inventory depends on how competitive his quotes are vis-à-vis those of the other market makers. If we measure the degree of competitiveness of a market maker's quotes by the distance of his quotes from the touch, then the changes in a market maker's inventory depend on this distance. We express this as

$$\Delta I_{i,t+1} \equiv I_{i,t+1} - I_{i,t} = \mathcal{G}(B_{i,t} - B_{T,t}). \quad (2)$$

These two equations capture the essence of inventory models of competitive dealership markets and provide several testable restrictions that we examine in this paper. In particular, we examine

- whether large trades are executed by market makers with divergent inventories
- whether a larger fraction of the order flow is executed by market makers posting the best quotes
- whether the inventories of market makers exhibit mean reversion and whether the degree of mean reversion is increasing in the inventory level
- whether the changes in quotes are related to changes in inventories
- whether interdealer trading is related to the divergence of inventories.

II. Data Description

The dataset provides the details of all quotes and transactions on the London Stock Exchange (henceforth LSE) and identifies the following:

- the name of the stock traded
- the quotes (bid and ask prices) posted by each market maker registered in a stock as well as the quantities for which these quotes are firm
- the identities of the buyer and seller participating in the transaction
- the dealing capacity of the buyer and seller in a transaction, i.e., whether the dealer is acting as an agent representing an order from the public, or is acting as a principal or market maker
- the transaction price
- the quantity of the trade
- the date and time at which the transaction was actually executed.

Since large trades on the LSE are reported with a delay, some discussion of the time of transaction available to us is warranted. The rules of the LSE require that as soon as a trade is executed the market maker must report it to the exchange. Depending on the size of the trade, the exchange delays announcing the details of that trade to the public by as much as ninety minutes. Our data provide the time of execution of trade as reported by the market maker to the exchange. As a result, we know the exact time when a trade is executed.

Because every transaction appears in the LSE database, we can examine the actual trading behavior of individual market makers competing with each other in a given stock and construct the inventory position of individual market makers over time. Most important, for every transaction we know the dealing capacity of the parties, so we do not have to use an arbitrary rule to decide if the trade was a public buy or a public sell.⁶

Throughout this paper we use the following convention for calculating public and interdealer turnover. Suppose a public trader sells 100 shares to market maker A at £100. Market maker A then sells 50 shares to market

⁶ Transactions data on the LSE have been used by other researchers to explore interesting but different issues. See, for example, Reiss and Werner (1998) for a study of transacting costs; Abhyankar et. al. (1997) for intraday variation in the quoted spreads and volatility; Tonks and Snell (1995) for a study of the components of the bid-ask spread; Gemmill (1996), Board and Sutcliffe (1995), and Lai (1996) for studies of the impact of different transparency rules on trading costs; and Hansch and Neuberger (1996) for trading strategies of the market makers. Some recent research in progress that explores interdealer trading using the LSE data includes Reiss and Werner (1998) who study the costs of anonymous versus nonanonymous risk sharing mechanisms among dealers, and Naik and Yadav (1996a) who examine the effect of asymmetric information on interdealer trading among dealers. Other work includes Hansch, Naik, and Viswanathan (1998) who examine the effect of preferencing, internalization, and best execution on trading costs; Naik and Yadav (1996b) who look at differences in the quality of execution offered by different dealers and different brokers; and Board, Vila, and Sutcliffe (1996) who examine the commitment of different market makers as providers of liquidity and contributors to price discovery.

maker B at £51 and 50 shares to another public trader at £52. Further suppose that market maker B sells the 50 shares at £53 to yet another public trader. The total turnover in this case then amounts to 250 shares worth £256 out of which public turnover equals 200 shares worth £205 and the interdealer turnover equals 50 shares worth £51. Using this convention, on the LSE, in the calendar year 1992, the total turnover in the U.K. and Irish equities was worth £433 billion consisting of 8.5 million transactions. With 254 business days in 1992, these figures amount to an average daily turnover of £1.7 billion, average number of transactions of 33,500, and an average trade size of £51,000.⁷

Our data set consists of all transactions on the LSE from June 1991 to July 1992 (273 trading days). Because the most liquid or the FTSE-100 stocks account for over 60 percent of the turnover in U.K. and Irish equities on the LSE, we focus on market making in the FTSE-100 stocks. For computational tractability, we randomly select a representative sample of thirty of the FTSE-100 stocks. Table I reports the details of the thirty stocks in our sample, which are ranked in a descending order of total turnover. The average daily total turnover varies from £21.5 million in British Telecom to £2 million in Associated British Foods, the sample average being £6.9 million. A significant proportion of the total turnover is due to interdealer trading. As a fraction of total turnover, interdealer trading varies from 43 percent in Boots to 20 percent in Kwik Save Group with the sample average being 35 percent of total turnover. Generally, high turnover stocks have a higher proportion of interdealer trades.

The average daily number of public trades varies from 356 in British Telecom to 15 in Associated British Foods, the sample average being 93. The sample average size of public trades is £63,000. Interdealer trades tend to be larger, with a sample average size of £145,000, about 2.3 times the average public trade size. The variation in the interdealer trades, however, is considerably smaller, about two-thirds of that in public trades.

In our sample of thirty stocks, on average about thirteen market makers deal in each stock. Eight stocks have fifteen market makers or more, and five stocks have nine market makers or fewer with a minimum of seven. In general, stocks with a higher turnover have a higher number of market makers. When we rank the market makers in descending order of market share, we observe that on average the biggest market maker executes about 20 percent of the public trades, and the top three market makers execute 48 percent of public trades. These numbers suggest a concentration of market making business in the hands of a few market makers.

An interesting feature of our dataset is that the quoted bid-ask spread is constant, identical for all market makers, and, in general, wider than the inside quotes or touch. This means that at any point in time, a market maker's quotes are such that either he is on the bid side of the touch, or on the ask side of the touch, or is straddling the touch. On average, we observe that

⁷ Source: *Quality of Markets Quarterly*, London Stock Exchange Publication, Summer 1993.

about 70 percent of the market makers post quotes in such a way that they are either on the bid or ask side of the touch and 30 percent straddle the touch. This suggests that a majority of the market makers try to attract order flow primarily in one direction.⁸

In our dataset, we observe that both the inside and quoted spreads are lower for stocks with high turnover. In particular, the inside spread (the quoted spread) measured as a percent of the touch midprice varies from 0.47 percent (0.88 percent) in British Telecom to 2.10 percent (2.99 percent) in Guardian Royal Exchange with a sample average of 1.04 percent (1.61 percent). Our empirical findings are consistent with the inventory model of competitive dealership markets where the divergence of inventories across market makers causes the inside spread to be narrower than the quoted spread.

Our data record every transaction on the LSE in detail, but we do not have access to trading data for market makers at other trading locations. In particular, market makers have access to American Depository receipts (ADRs) on some of the stocks in our sample.⁹ Of our sample of thirty stocks, seven stocks have ADRs listed on the NYSE, one has an ADR listed on Nasdaq, and one has an ADR listed on the AMEX. These nine stocks are marked by an asterisk in Table I. All of the ADRs on the nine stocks were created before June 1, 1991 (our sample start date). In our empirical sections, we often divide our results into the two subsamples (ADRs and non-ADRs) in order to identify whether the nonavailability of foreign trading data on the nine stocks creates any bias in our results.

III. Empirical Tests of the Inventory Model of Dealership Markets

A. Construction of Inventory Series

We now proceed with the construction of the inventory series of different market makers. Although our data allow us to construct the market makers' inventory positions at every instant, these positions cannot be compared directly because market makers differ in terms of their risk aversion or capitalization. We control for differences in risk aversion by standardizing their inventories in the following way.

Let $Q_{i,t}^j$ denote the level of inventory of market maker i in stock j at time t . In our sample, $j = 1, 2, \dots, 30$ and $i = 1, 2, \dots, M_j$, where M_j equals the number of market makers in stock j . Following this convention, we denote the inventory at the start of the sample period ($t = 0$) as $Q_{i,0}^j$. Although this starting inventory is not observed by us, as we show below in equation (4) the standardized inventories that we use in our empirical tests do not depend on the initial inventory level.

⁸ Other researchers have observed similar phenomenon on the Nasdaq. See, for example, Chan et al. (1994) and Wahal (1996).

⁹ We thank René Stulz for focusing our attention on this issue. A paper by Reiss and Werner (1998) also discusses this issue of trading in ADRs.

Table I
Turnover and Market Share Details of Sample Stocks

This table provides important descriptive statistics of the thirty sample stocks. Total Turnover equals the average daily turnover of both public and interdealer trades over the entire sample period. Intdlr Fraction is fraction of total turnover represented by trades among the dealers. Daily Public Trades are the average number of public trades (excluding interdealer trades) per day. Average Trade Value is the average value of public and interdealer trades in £'000s. No. of MMs is the number of market makers in each stock. Market Share of Top MM is the market share of the market maker who has the highest public turnover in that stock. Avg. Touch denotes the average inside spread, and Avg. Spread denotes the average individual quoted spread in each stock. Both are measured as a percentage of the touch midprice and are reported in basis points (bp). The full names of the stocks can be found in Table II.

Stock	Total Turnover (£'000s)	Intdlr Fraction	Daily Public Trades	Avg. Trade Value (£'000s)		No. of MMs	Market Share of Top MM	Avg. Touch (bp)	Avg. Spread (bp)
				Public	Intdlr				
Panel A: Individual Stocks									
BT*	21467	0.41	356	36	287	15	0.15	47	88
HAN*	19757	0.38	293	42	176	16	0.12	62	141
BAR*	15687	0.35	194	52	180	14	0.14	89	137
M&S	12997	0.36	312	27	163	14	0.15	62	99
GE	12825	0.29	160	57	174	15	0.17	66	147
RTZ*	11159	0.35	155	47	174	14	0.20	80	127
BA*	10696	0.41	153	41	140	15	0.19	94	167
BOO	10180	0.43	129	45	170	16	0.14	67	97
CAD*	8395	0.37	112	47	158	17	0.13	69	113
RIH	6394	0.26	83	57	103	13	0.27	190	281

T&L	6090	0.39	58	64	177	15	0.17	74	129
SUN	5665	0.28	46	88	120	13	0.26	98	137
LAN	5242	0.36	74	46	165	11	0.21	101	158
DIX	5241	0.35	36	94	131	12	0.18	128	181
STC	4599	0.33	31	101	141	13	0.25	114	162
L&G	4592	0.32	49	64	135	13	0.20	95	135
RBS*	4224	0.32	51	57	99	14	0.22	157	231
S&N	4081	0.31	57	50	109	16	0.13	79	140
CU	3898	0.38	41	60	122	13	0.21	97	137
GRE	3852	0.26	64	44	71	13	0.26	210	299
TOM	3701	0.33	51	49	131	9	0.22	76	113
SIE	3628	0.28	36	72	162	8	0.35	117	171
GKN	3547	0.35	42	55	133	13	0.34	104	153
KWI	3433	0.20	18	149	211	8	0.22	105	171
WIL*	2866	0.33	22	89	108	11	0.23	138	197
SED	2660	0.26	22	91	109	9	0.22	168	233
RMC	2588	0.29	24	77	139	13	0.17	110	175
NFC*	2471	0.26	60	31	99	7	0.30	132	209
DAL	2353	0.24	32	55	139	11	0.20	120	182
ABF	2024	0.28	15	99	143	11	0.17	72	113

Panel B: Averages

Sample	6877	0.35	93	63	145	12.7	0.20	104	161
ADR*	10747	0.37	155	69	157	13.7	0.19	96	157
Non-ADR	5219	0.33	66	49	140	12.3	0.21	107	163

*Denotes the presence of American Depository Receipts (ADRs) for that stock.

In every stock we consider all trades, public as well as interdealer, which market maker i executes in his capacity as a *principal*. We define $q_{i,t}^j$ to be positive (negative) when a public trader or other dealer sells (buys) q shares of stock j to (from) market maker i at time t . We further define $Q_{i,t}^j = Q_{i,0}^j + \sum_{s=1}^{s=t} q_{i,s}^j$ as the inventory level of market maker i in stock j at time t . In this way we construct a time series of each market maker i 's inventory level in each stock j from the start ($t = 0$) to the end ($t = T$) of our sample period. For each of the inventory series, we compute the sample mean

$$\begin{aligned}\bar{Q}_i^j &= \frac{\sum_{s=0}^{s=T} Q_{i,s}^j}{T+1} \\ &= \frac{\sum_{s=0}^{s=T} Q_{i,0}^j + \sum_{s=1}^{s=T} \left(\sum_{r=1}^{r=s} q_{i,r}^j \right)}{T+1} \\ &= Q_{i,0}^j + \frac{1}{T+1} \sum_{s=1}^{s=T} \left(\sum_{r=1}^{r=s} q_{i,r}^j \right),\end{aligned}\tag{3}$$

and sample standard deviation (S_i^j). We define $I_{i,t}^j$, the *standardized* inventory of market maker i in stock j at time t , as

$$\begin{aligned}I_{i,t}^j &= \frac{Q_{i,t}^j - \bar{Q}_i^j}{S_i^j} \\ &= \frac{Q_{i,0}^j + \sum_{s=1}^{s=t} q_{i,s}^j - Q_{i,0}^j - \frac{1}{T+1} \sum_{s=1}^{s=T} \left(\sum_{r=1}^{r=s} q_{i,r}^j \right)}{S_i^j} \\ &= \frac{\sum_{s=1}^{s=t} q_{i,s}^j - \frac{1}{T+1} \sum_{s=1}^{s=T} \left(\sum_{r=1}^{r=s} q_{i,r}^j \right)}{S_i^j},\end{aligned}\tag{4}$$

which is independent of the initial inventory $Q_{i,0}^j$.

Our dataset assigns a different code to each of the market makers across different stocks, so in total we create 382 standardized inventory series each of which has a zero mean and unit standard deviation by construction.¹⁰ The

¹⁰ The number of market makers in each of our sample stocks is given in Table I. The sum total of all the market makers in each of our thirty sample stocks equals 382.

empirical distribution of the end-of-day standardized inventories of market makers has a mean of zero, standard deviation of unity, skewness of 0.2, and kurtosis of 1.9.¹¹

This standardization procedure controls for the differences in the risk aversion of the dealers and makes their inventories comparable with each other. It also captures the notion that different market makers perceive the inventory risk in a similar way when their inventory is measured in terms of the distance (in standard deviations, also denoted by σ) of their standardized inventory from the respective sample mean. Finally, given that our empirical investigation shows an average inventory half-life of 2.5 trading days, and given that our sample runs over a period of one year, the estimation and use of sample moments to standardize the inventories seems like a reasonable way of controlling for differences in risk aversions. For notational convenience, hereafter we refer to the standardized inventories simply as inventories.

Having described our procedure for standardizing inventories, we now proceed with testing the implications of inventory models of competitive dealership markets. Before describing the tests and the results, it is important to point out two key assumptions made by the inventory models which, strictly speaking, do not hold in practice.

First, every dealer does not know the other dealers' inventories precisely. A dealer has some idea about the inventories of other dealers and learns from the quotes posted by the other dealers. This implies that *at each point in time* the market maker posting the highest bid price or the lowest ask price need not be the market maker with the shortest or longest inventory position. However, *in general*, market makers posting the best price are expected to have relatively extreme inventory positions. Second, the order flow on the LSE can be preferred to any dealer so far as he undertakes to match or better the best quoted price. As a result, market makers who do not post the most competitive prices can obtain a part of the public order flow. In our empirical investigation, we modify the testable restrictions suitably to take into account these two features of the real life dealership market that generates our data.

B. Test of Relative Inventory Position and Order Flow Execution

In this section, we examine whether the public orders are executed by market makers with divergent inventories and whether market makers with divergent inventories engage in interdealer trades that bring their inventories back to the desired level.

Although, in principle, the inventory effects should affect all trades, they are likely to be more pronounced for large trades. Therefore, we sort the public and interdealer trades by their size and focus on both the top 1 percent and top 5 percent of the public and interdealer trades. For each of these

¹¹ The Kolmogorov-Smirnov test of normality fails to reject the null of normality at a 10 percent level.

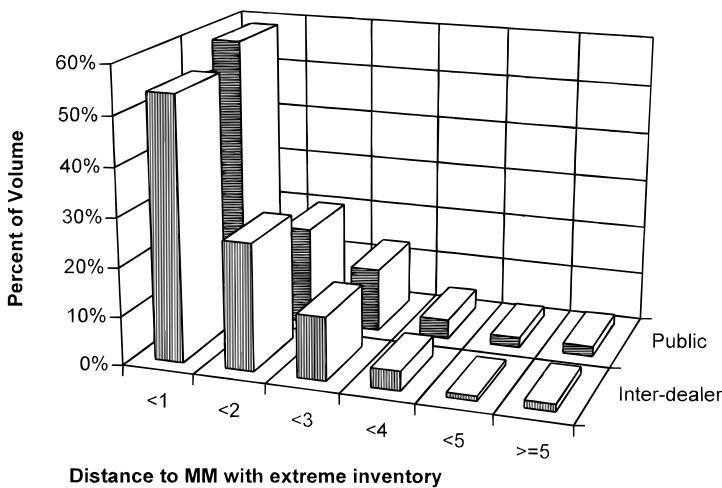


Figure 1. Volume of 1 percent of largest trades. This figure shows the fraction of trading volume executed by the market makers as a function of the distance between the inventory of the market maker who executed the trade and that of the market maker who was most favorably placed to execute the trade for the top 1 percent of trades in the thirty stocks.

trades, we measure the distance of the inventory of the market maker executing the trade from the inventory of the market maker who at that time is most favorably placed to execute that trade. If we take the model of Ho and Stoll (1983) literally, then the market maker with the most divergent inventory should execute all the trades. As we have discussed, this extreme version of the inventory hypothesis is unlikely to hold in practice because market makers often do not know the inventories of other dealers and because order flow is preferenced in dealership markets.

Figures 1 and 2 summarize our findings. The vertical axis represents the fraction of the public and interdealer turnover executed by the market makers, the horizontal axis shows the distance between the inventory of the market maker who executes a trade and that of the market maker most favorably placed to execute that trade. In the top 1 percent of the trades, we find that market makers who are either most favorably placed or within one standard deviation distance from the most favorably placed execute 59 percent of public turnover and 54 percent of interdealer turnover. Market makers whose inventory is within one and two standard deviations of the most favorably placed execute about 20 percent of the public turnover and 26 percent of interdealer turnover. Only 1 percent of the public or interdealer turnover goes to the market makers whose inventory is more than five standard deviations away from the most favorably positioned market maker. The corresponding figures for the 5 percent largest public and interdealer transactions are very similar. Overall, these results suggest that a significant proportion of large trades are executed by market makers with divergent inventories.

The finding that 1 percent of large trades are executed by market makers who are more than five standard deviations away from the market maker

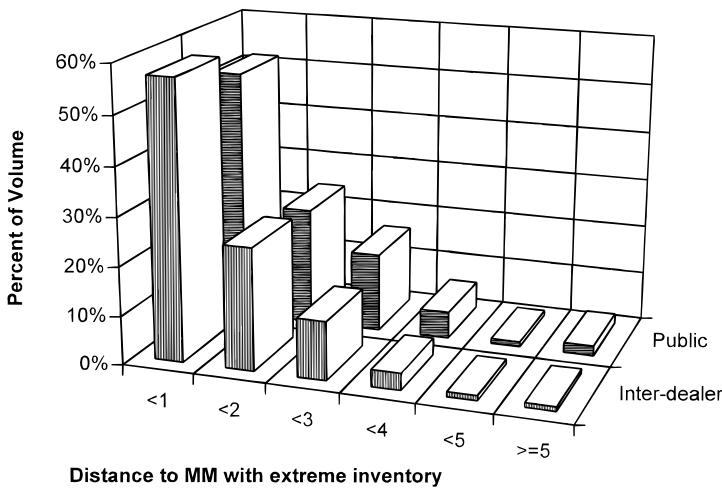


Figure 2. Volume of 5 percent of largest trades. This figure shows the fraction of trading volume executed by the market makers as a function of the distance between the inventory of the market maker who executed the trade and that of the market maker who was most favorably placed to execute the trade for the top 5 percent of trades in the thirty stocks.

with the divergent inventory appears at first sight to be surprising. Two explanations seem plausible. First, the market maker may have a long-term trading relationship with the customer and therefore may choose to undertake these trades in order not to lose the regular business to a competitor. Second, our measure of the inventory position may contain some noise, due to the presence of trading in ADRs on the stock. To shed light on the ADR effect, we examine the two subsamples of ADR and non-ADR stocks. We find that in both samples, similar proportions of the public and interdealer trades are executed by market makers situated a similar distance away from the extreme inventory. For example, in the case of ADR stocks 0.6 percent (0.9 percent) of the public trades (interdealer trades) are executed by market makers who are more than five standard deviations away from the most favorably placed market maker. The corresponding figures for non-ADR stocks equal 1.1 percent and 1.5 percent, respectively. These numbers suggest that considerations like long-term trading relationships rather than inventory mis-measurements due to ADR trading may be the reason for observing these inventory exacerbating trades.

In Ho and Stoll's model, all trades are executed by market makers with extreme inventories, thus any deviation from this leads to a rejection of this extreme version of the inventory model. For reasons described earlier, in practice, trades are executed by market makers at some distance away from the extreme inventory. Even if we are able to measure this distance, it seems difficult to ascertain its statistical significance because there does not exist any theory that tells us what the distribution of this distance should be. We are, however, able to test the importance of inventories in dealership markets in a slightly different way.

This test involves measuring the distance of the inventory of the market maker executing a trade from that of the inventory of a randomly selected market maker. If inventories were not an important factor in competitive dealership markets, then all market makers would stand an equal chance of executing a public trade. If this were the case, then the average distance of the inventory of the market maker executing a trade from that of the inventory of a randomly selected market maker would not be significantly different from zero. If, on the other hand, the average distance turns out to be significantly different from zero and in the direction predicted by the inventory models, this would lend support to the notion that inventories play an important role in competitive dealership markets.

We implement the test as follows. We measure the inventory level of each market maker in stock j just before the execution of a large trade and compute the average inventory \bar{I}_t^j . This average inventory represents the expected inventory of a randomly selected market maker. For large public buy orders, we calculate the distance $\bar{I}_t^j - I_{*,t}^j$, where $I_{*,t}^j$ denotes the inventory of the market maker who executes the public order, and find the mean distance over all the large public orders. Similarly, for large public sell orders, we calculate the distance $I_{*,t}^j - \bar{I}_t^j$ and find the mean distance over all the large public sell orders. We repeat the test with the large interdealer trades as well.

The assumption of no inventory effects means that distance measured is normally distributed with zero mean. However, for the purpose of reliable statistical inference, it is necessary to ensure that the market makers' inventories are independent across observations. For instance, if we decide to test the statistical significance of inventory effects for the top 5 percent of the trades, then in British Telecom there would be about 18 large trades per day or more than two large trades per hour. If one were to assume that the LSE rule of 90-minute publication delay is a measure of the time required to reallocate the inventory risk of a large trade, then more than two large trades per hour would not provide sufficient time for the reallocation of inventory risk, thereby leading to potentially correlated inventories across observations.

To overcome this potential problem of correlated inventories, we focus only on a subset of large trades that are at least 90 minutes apart and sort these trades by size and choose the 300 largest public trades and the 300 largest interdealer trades in each stock. We ascertain whether inventories in this subsample are uncorrelated by computing the average Spearman rank correlation coefficient between the ordering of inventories at time t and $t - 1$. We find the average Spearman rank correlation to be 0.02371 and cannot reject the null hypothesis of zero rank correlation for any stock. This suggests that the rule of selecting large trades that are at least 90 minutes apart provides us with independent inventory observations and enables us to interpret the statistical significance of the findings correctly.¹²

¹² We also run our tests for all of the top 1 percent and the top 5 percent of the trades and find similar results.

Table II
Test of Inventory Control Hypothesis

This table shows the mean difference of standardized inventories between the market maker executing the trade and a randomly chosen market maker, together with the corresponding *t*-statistics. These results are for the top 300 public and top 300 interdealer trades that are at least 90 minutes apart.

Company	Public Trades		Interdealer Trades	
	Mean	<i>t</i> -statistic	Mean	<i>t</i> -statistic
British Telecom	-0.32	-4.55	-0.24	-2.72
Hanson	-0.12	-3.05	-0.09	-1.83
Barclays	-0.40	-5.18	-0.35	-5.89
Marks & Spencer	-0.53	-6.04	-0.41	-6.81
General Electric	-0.76	-3.47	-0.61	-9.68
RTZ	-0.74	-7.41	-0.50	-6.98
British Airways	-0.19	-5.15	-0.16	-3.61
Boots	-0.46	-5.49	-0.26	-4.23
Cadbury Schweppes	-0.26	-3.38	-0.35	-6.03
Royal Insurance Holdings	-1.26	-4.27	-0.47	-6.26
Tate & Lyle	-0.48	-5.23	-0.25	-4.05
Sun Alliance Group	-0.85	-5.25	-0.43	-4.34
Land Securities	-0.21	-2.94	-0.58	-8.42
Dixons Group	-0.69	-8.16	-0.46	-6.64
Standard Chartered	-1.42	-10.14	-0.76	-8.30
Legal & General GP	-0.77	-9.87	-0.67	-6.79
Royal Bank of Scotland	-1.08	-7.71	-0.36	-3.61
Smith & Nephew	-0.57	-6.22	-0.68	-9.66
Commercial Union	-0.48	-5.83	-0.69	-8.73
Guardian Royal Exchange	-0.82	-4.42	-0.76	-10.00
Tomkins	-0.53	-7.32	-0.59	-9.40
Siebe	-0.73	-10.41	-0.45	-8.38
GKN	-1.06	-8.95	-0.61	-6.57
Kwik Save Group	-0.98	-10.28	-0.29	-4.25
Willis Corroon	-0.54	-7.01	-0.39	-7.18
Sedgwick Group	-1.27	-7.29	-0.58	-5.32
RMC Group	-0.75	-6.81	-0.70	-9.42
NFC	-0.77	-10.86	-0.50	-7.82
Dalgety	-1.25	-9.45	-0.92	-10.75
Associated British Foods	-0.69	-6.95	-0.51	-8.05

The findings in Table II show that for large public trades the mean distances are all negative and significantly different from zero in all 30 out of 30 stocks; for large interdealer trades the mean distances are negative and significantly different from zero in 29 out of 30 stocks. These results provide strong support to the implication of inventory models of dealership markets that large trades are executed by market makers with divergent inventories.

Our results seem to be robust to prior leakage of information about large trades. Since prices for large trades are often sought from several market makers before finalizing the deal with one of them, it is possible that the

market maker who executes a large trade is aware of it before actually being asked to execute it. If a market maker is aware of the trade, then in anticipation, he may enter into transactions to build up an inventory position. However, prior leakage of information about large trades is more likely for trades that are executed later in the day than those executed earlier in the day because dealers are concerned about carrying large inventory risks overnight. We therefore divide our sample of 300 large public and interdealer trades into trades executed in the morning and trades executed in the afternoon. Table III shows the mean distance for the public trades executed in the morning and in the afternoon. For trades executed in the morning, we find that in 29 of the 30 sample stocks the average distance is negative and significantly different from zero. For trades executed in the afternoon, the corresponding number turns out to be 27 of the 30 stocks. In the case of the interdealer trades (not reported), the corresponding numbers are 28 of 30 for the morning and 26 of 30 for the afternoon.

C. Test of Quote Competitiveness and Order Flow Execution

Because of the practice of order flow preferencing, it is argued that posting competitive quotes may have little value in dealership markets. In this section, we examine the marginal value of posting best quotes by measuring how much excess market share relative to the long run market share a dealer obtains during a period in which he posts the most competitive quotes. In particular, we divide each day into trading intervals of thirty minutes. At the beginning of each interval we identify the market makers who are on the bid side of the touch. Over the next thirty minutes, we examine the trades involving the public selling stock to the market makers. For these trades, we measure the fraction executed by market makers who are on the bid side of the touch and test if this fraction is significantly greater than their collective market share over the whole sample period. We repeat the exercise on the ask side of the touch.

The findings in Table IV show that market makers offering competitive prices on one side of the touch execute a greater proportion of the order flow. Market makers on the bid side of the touch execute 6.6 percent more public sell trades than their normal market share. This difference is statistically significant in 29 of the 30 stocks. The corresponding number on the ask side is 5.3 percent, which is statistically significant in 28 of the 30 stocks. Hence, the evidence suggests that market makers on the LSE have an incentive to post competitive prices. This contrasts with the results of Christie and Schultz (1994) who argue that market makers on the Nasdaq have no incentive to post competitive quotes due to order flow preferencing.

D. Tests of Mean Reversion in Inventories

In inventory models of dealership markets, the likelihood of executing public orders depends on the degree of competitiveness of a market maker's quotes, which in turn depends on his relative inventory position. When

Table III

**Test of Inventory Control Hypothesis—Public Trades in the Morning
and in the Afternoon**

This table shows the mean difference of standardized inventories between the market maker actually executing the public trade and a randomly chosen market maker, together with the corresponding *t*-statistics, for morning and afternoon trading separately. No. indicates the break up of the 300 trades into trades executed in the morning and in the afternoon.

Company	Morning			Afternoon		
	No.	Mean	<i>t</i> -statistic	No.	Mean	<i>t</i> -statistic
British Telecom	145	-0.38	-3.85	155	-0.26	-2.62
Hanson	147	-0.14	-1.82	153	-0.11	-1.69
Barclays	148	-0.43	-4.15	152	-0.37	-3.24
Marks & Spencer	149	-0.55	-5.78	151	-0.51	-3.55
General Electric	143	-0.61	-1.72	157	-0.98	-3.09
RTZ	140	-0.78	-6.04	160	-0.71	-4.72
British Airways	157	-0.28	-5.43	143	-0.15	-1.73
Boots	124	-0.60	-4.46	176	-0.37	-3.41
Cadbury Schweppes	155	-0.28	-3.10	145	-0.23	-2.46
Royal Insurance Holdings	128	-1.43	-2.29	172	-1.14	-5.01
Tate & Lyle	153	-0.52	-3.66	147	-0.43	-3.83
Sun Alliance Group	142	-0.65	-4.16	158	-1.04	-3.79
Land Securities	148	-0.27	-2.36	152	-0.18	-1.65
Dixons Group	135	-0.80	-5.83	165	-0.61	-5.72
Standard Chartered	147	-1.41	-7.85	153	-1.43	-6.68
Legal & General GP	124	-0.78	-6.31	176	-0.74	-7.56
Royal Bank of Scotland	138	-1.06	-4.73	162	-1.09	-6.21
Smith & Nephew	132	-0.62	-4.05	168	-0.53	-4.77
Commercial Union	131	-0.54	-3.86	169	-0.44	-4.40
Guardian Royal Exchange	152	-0.67	-2.57	148	-0.97	-3.70
Tomkins	140	-0.46	-4.35	160	-0.59	-5.95
Siebe	135	-0.76	-7.13	165	-0.70	-7.56
GKN	119	-1.09	-5.97	181	-1.05	-6.69
Kwik Save Group	141	-1.16	-8.62	159	-0.82	-6.14
Willis Corroon	149	-0.56	-5.85	151	-0.52	-4.30
Sedgwick Group	152	-1.33	-5.18	148	-1.21	-5.14
RMC Group	141	-0.69	-6.43	159	-0.81	-4.35
NFC	119	-0.85	-7.91	181	-0.72	-7.65
Dalgety	146	-1.19	-7.61	154	-1.32	-6.20
Associated British Foods	139	-0.88	-4.83	161	-0.52	-5.49

a market maker has an extreme inventory position, he is able to post competitive quotes on one side and stands a better chance of executing the public order flow in the desired direction. This results in a relatively quick reduction of his inventory imbalance. On the other hand, when a market maker's inventory is closer to the median, he is not able to post competitive prices and therefore stands a poor chance of executing the public order flow. As a result, his inventory takes a longer time to revert to the desired

Table IV
Marginal Value of Posting Best Quotes

Bid (ask) fraction in the percentage of business executed by the market makers posting the most competitive prices on the bid (ask) side in excess of their overall market share. The corresponding *t*-statistics indicate if this fraction is significantly different from zero.

Company	Bid		Ask	
	Fraction	<i>t</i> -statistic	Fraction	<i>t</i> -statistic
British Telecom	4.4	3.96	2.9	3.85
Hanson	10.1	7.92	7.5	5.97
Barclays	6.2	9.22	9.2	9.61
Marks & Spencer	3.2	2.14	5.1	3.80
General Electric	7.9	3.16	1.3	1.05
RTZ	5.7	7.32	5.7	5.80
British Airways	8.2	5.60	9.6	3.52
Boots	3.7	4.26	1.9	2.04
Cadbury Schweppes	3.7	5.48	0.4	1.23
Royal Insurance Holdings	10.4	3.97	7.9	3.64
Tate & Lyle	10.4	7.55	7.4	4.04
Sun Alliance Group	7.6	7.75	5.1	4.34
Land Securities	7.1	7.27	6.1	5.26
Dixons Group	5.0	4.34	4.9	3.72
Standard Chartered	8.7	6.31	6.7	7.16
Legal & General GP	3.7	2.04	4.0	2.58
Royal Bank of Scotland	3.2	2.86	2.7	2.46
Smith & Nephew	8.0	7.02	4.3	3.85
Commercial Union	6.7	4.46	5.8	2.98
Guardian Royal Exchange	7.2	6.40	3.6	2.06
Tomkins	6.8	4.12	3.5	2.05
Siebe	6.4	1.82	7.5	3.05
GKN	4.2	4.50	3.4	3.55
Kwik Save Group	6.5	4.24	7.0	6.01
Willis Corroon	7.7	5.97	4.1	2.12
Sedgwick Group	7.1	4.38	6.2	2.07
RMC Group	9.9	4.90	7.7	3.30
NFC	3.8	3.68	4.6	2.66
Dalgety	10.1	13.69	8.8	11.65
Associated British Foods	4.6	5.64	4.0	4.81
Grand sample average	6.6	9.11	5.3	7.14

level. This implies that in competitive dealership markets, the relative inventories of the market makers should be mean reverting and the strength of mean reversion should be increasing in the relative inventory level.

Let $I_{M,t}$ denote the *median* inventory level at time t , and let $RI_{i,t} = I_{i,t} - I_{M,t}$ denote market maker i 's inventory position relative to the median inventory at time t . Then, the inventory model of a competitive dealership market implies that the force of mean reversion in a market maker's relative inventory position should be increasing in the relative inventory level, i.e.,

$$\Delta RI_{i,t} \equiv (RI_{i,t} - RI_{i,t-1}) = \mathcal{H}(RI_{i,t-1}). \quad (5)$$

In this subsection we test equation (5) by allowing for five different mean reversion coefficients for five different *bands* of relative inventory positions and examine if the intensity of mean reversion is increasing in the level of relative inventory. In particular, we run the following *piecewise linear* regression,

$$\begin{aligned}\Delta RI_{m,t} = & \alpha + \beta_1 D^1 RI_{m,t-1} + \beta_2 D^2 RI_{m,t-1} + \beta_3 D^3 RI_{m,t-1} \\ & + \beta_4 D^4 RI_{m,t-1} + \beta_5 D^5 RI_{m,t-1} + \epsilon_{m,t-1},\end{aligned}\quad (6)$$

where

$$D^i = \begin{cases} 1 & \text{if } (i-1) \leq |RI_{m,t-1}| < i \text{ and } i \leq 4, \\ 1 & \text{if } (i-1) \leq |RI_{m,t-1}| \text{ and } i = 5, \\ 0 & \text{otherwise,} \end{cases} \quad (7)$$

where i is a positive integer, m denotes the market maker, and $RI_{m,t}$ represents the relative inventory of market maker m at the end of day t . The D^i are indicator variables that allow for differences in the degree of mean reversion as a function of different bands of relative inventory levels. For example, β_1 captures the intensity of mean reversion when the relative inventory level lies between zero and one standard deviation, β_2 captures the intensity of mean reversion when the relative inventory level is greater than or equal to one but less than two standard deviations, and so on. We compute the inventory level dependent mean reversion coefficients (β_i 's) from this piecewise linear regression for all market makers in all stocks.

The findings in Panel A of Table V show that the variation in the degree of mean reversion is strongly related to the level of inventory. In particular, the greater the divergence of inventory, the greater is the force of mean reversion, evidence consistent with the predictions of the inventory models of dealership markets.

Our finding that the force of mean reversion depends on the inventory imbalance has two main implications. First, specifying a single mean reversion coefficient irrespective of the level of inventory fails to capture important nonlinear effects in the time series of inventories in dealership markets. Second, inventory half-lives calculated on the basis of single mean reversion coefficients are misleading because the speed of mean reversion reduces as the inventory divergence decreases.

As a basis for comparison with the existing literature, we run a regression constraining all β 's to be equal and find a value of -0.28 . Clearly, a mean reversion coefficient of -0.28 fails to capture the inventory-level dependent variation from -0.66 to -0.19 in the mean reversion coefficients. Furthermore, a mean reversion coefficient of -0.28 implies an inventory half-life $\{-\ln 2/\ln(1-\beta)\}$ of 2.11 days, which differs considerably from the inventory-level dependent half-lives ranging from 1.02 days starting from five σ to 3.3 days starting from one σ (see Table V, Panel A).

Table V
Mean Reversion Coefficients

The table shows the average mean reversion coefficients of the following piecewise linear regression:

$$\Delta RI_{m,t} = \alpha + \beta_1 D^1 RI_{m,t-1} + \beta_2 D^2 RI_{m,t-1} + \beta_3 D^3 RI_{m,t-1} + \beta_4 D^4 RI_{m,t-1} + \beta_5 D^5 RI_{m,t-1} + \epsilon_{m,t}$$

where

$$D^i = \begin{cases} 1 & \text{if } (i-1) \leq |RI_{m,t-1}| < i \text{ and } i < 4, \\ 1 & \text{if } (i-1) \leq |RI_{m,t-1}| \text{ and } i = 5, \\ 0 & \text{otherwise,} \end{cases}$$

where i is a positive integer, m denotes the market maker ($m = 1, 2, \dots, 382$), and $RI_{m,t}$ is the relative (to the median market maker) inventory of market maker m at the end of day t . The D^i are indicator variables that allow for differences in the degree of mean reversion as a function of different bands of relative inventory levels. We run this regression for the 382 market makers. We also calculate implied half-lives of inventories. The regression is repeated for the standardized inventories.

β	Relative Inventory		Standardized Inventory	
	Mean Reversion	Implied Half-life	Mean Reversion	Implied Half-life
Panel A: All Stocks				
β_1	-0.19	3.30	-0.14	4.59
β_2	-0.27	2.20	-0.22	2.79
β_3	-0.37	1.94	-0.30	2.48
β_4	-0.49	1.45	-0.42	1.85
β_5	-0.64	1.02	-0.61	1.27
Panel B: ADR Stocks				
β_1	-0.14	4.59	-0.12	5.42
β_2	-0.19	3.29	-0.16	3.98
β_3	-0.31	2.46	-0.29	2.83
β_4	-0.44	1.59	-0.41	1.73
β_5	-0.58	1.24	-0.54	1.36
Panel C: Non-ADR Stocks				
β_1	-0.22	2.79	-0.18	3.49
β_2	-0.31	1.87	-0.26	2.30
β_3	-0.40	1.57	-0.31	2.05
β_4	-0.52	1.19	-0.44	1.59
β_5	-0.70	0.93	-0.64	1.21

For the sake of completeness, we run the above regression with standardized inventories as defined in equation (5) and find that they also exhibit considerable level dependent variation, although the degree of mean reversion is somewhat smaller in magnitude compared to the relative inventories.

The inventory half-lives range from 1.27 days starting from five σ to 4.59 days starting from one σ . When we impose the same beta coefficient across all levels of inventories, we obtain a value of -0.24 which implies an inventory half-life of 2.53 days.

In order to isolate the effect of the presence of ADRs on nine of our sample stocks, we also run the regression only for the nine stocks. Table V, Panels B and C, reports our findings. The overall pattern of the results is very similar to that for all stocks, but the mean reversion appears to be lower for ADR stocks than for non-ADR stocks. One reason for this difference could be that the ADR stocks are more liquid, that is, they have a greater number of public trades per day than non-ADR stocks (see Table I). The more frequent arrival of public trades may induce a market maker with divergent inventory to wait for the next public trade instead of reducing his inventory risk by immediately trading with another market maker.

Our results differ from those of Madhavan and Smidt (1993) and Hasbrouck and Sofianos (1993) for the NYSE specialists. Madhavan and Smidt specify a constant mean reversion coefficient and estimate this coefficient using specialists' inventories in 16 stocks.¹³ They find, after intervention correction, an average inventory half-life of 7.3 trading days, the minimum being just over 5 days and the maximum being 334 days. Their average half-life is much higher than our observation of 1.27 days to 4.59 days for standardized inventories. One reason for this difference may be that the specialist on the NYSE needs to maintain an orderly market and in the process has to accept trades on both sides of the spread. Although the dealers on the LSE also accept orders on both sides of the spread due to order flow preferencing, we have previously shown in Table IV that on average they attract order flow in one direction when they are on one side of the touch. Another reason may be that individual market makers on the LSE observe a smaller proportion of the total order flow as compared to the NYSE specialist. If order flow carries information, then market makers on the LSE may exercise tighter inventory control than the NYSE specialist who gets to see a larger part of the order flow.

E. Tests of Changes in Quotes and Inventories

In inventory models of competitive dealership markets, a market maker's relative quote position is a monotone function of his relative inventory position. This implies that the *changes* in a market maker's quote position over time must be a function of the *changes* in his relative inventory position over time. In this section, we examine how much relative inventory change, on average, a market maker experiences before he changes his relative quote position and whether the inventory changes associated with different quote changes are consistent with the predictions of the inventory models of competitive dealership market.

¹³ Table III in Madhavan and Smidt (1993) reports values of $\hat{\beta}$ ranging from -0.03 to -0.31 , the average being -0.134 .

An example will help illustrate the investigation. Consider a market maker who is posting the highest bid price at time t (i.e., $B_{i,t} - B_{T,t} = 0$). During the time he is on the bid side of the touch, he buys stock from the public (see Table IV). This increases his inventory and reduces his ability to continue to post the highest bid price. At some later point in time, t_1 ($t_1 > t$), he accumulates so much inventory that he can no longer afford to post the highest bid price and decides to revise his quote position downward relative to the touch (i.e., $B_{i,t_1} - B_{T,t_1} < 0$).¹⁴ While revising his bid quote downward, the market maker faces two choices: he can either lower his quotes by a small amount so that his quotes straddle the touch, or he can lower his quotes by a large amount so that his ask price forms the ask side of the touch. Which of these choices he makes depends on the extent of increase in his inventory.

The monotone relationship between inventories and quotes specified by the inventory models implies that

$$(B_{i,t_1} - B_{T,t_1}) - (B_{i,t} - B_{T,t}) = \mathcal{K}\{(I_{i,t_1} - I_{T,t_1}) - (I_{i,t} - I_{T,t})\}, \quad (8)$$

where $I_{T,t}$ is the inventory of the market maker with the shortest inventory position at time t . By symmetry, a similar relationship holds for the ask quotes as well.

Recall that on the LSE the quoted bid-ask spread in a stock is constant, identical for all market makers, and wider than the touch. As a result, at any point in time, a market maker's relative quote position is such that either his bid quote forms the bid side of the touch, or his ask quote forms the ask side of the touch, or both his quotes straddle the touch. Moreover, starting from any one of these three positions, when a market maker decides to change the relative position of his quotes, he faces the choice of moving to either of the other two positions. This implies a total of six possible quote position changes that could be observed in the data. We summarize these six quote position changes in Table VI along with the associated relative inventory changes.

The inventory model of competitive dealership markets predicts that the inventory change when a market maker moves from the bid (ask) side of the touch to the ask (bid) side of touch must be large and positive relative to the inventory of the market maker with the shortest (longest) inventory position. Similarly, the change in inventory of a market maker when he moves from the bid (ask) side of the touch to straddling the touch must be small and positive relative to the inventory of the market maker with the shortest (longest) inventory position.¹⁵

¹⁴ Recall from Section I that quotes at time t follow immediately the inventory at time t .

¹⁵ In Table VI, we use the notation $++$ ($--$) to denote large positive (large negative) inventory change, $+(-)$ to denote small positive (small negative) inventory change, and S (L) to denote that the change in inventory is measured relative to the inventory of the market maker having contemporaneously the shortest (longest) inventory position.

Table VI
Quote Changes and Associated Inventory Changes

This table summarizes the six quote change possibilities and the associated relative inventory changes. *Ask* denotes a quote equal to the ask side of the touch, *Bid* denotes a quote equal to the bid side of the touch, *Straddle* denotes a straddling position (i.e., neither quote is competitive). In the table, ++ stands for large positive, +(-) stands for small positive (small negative), and S and L denote the change relative to the “shortest” and “longest” inventory positions respectively. NA (not applicable) indicates that these cells do not pertain to any *change* in relative quote position.

Associated Inventory Change			
From	To Bid	To Ask	To Straddle
Bid	NA	+ +(S)	+ (S)
Ask	++(L)	NA	+ (L)
Straddle	-(S)	-(L)	NA

The preceding discussion pertains to the change in the inventory of a market maker who starts from being on one side of the touch. We next consider the case of a market maker who starts from being on neither side of the touch (i.e., from straddling the touch) at time t but gets back on the touch at some later point in time. During the time a market maker is straddling the touch, the *expected change* in his inventory equals zero.¹⁶ However, during the same time other market makers posting the highest bid price (lowest ask price) attract public sell (buy) orders and experience a systematic increase (decrease) in their inventories. As a result, the inventory position of a straddling market maker relative to the shortest or the longest inventory position changes over time. And this change brings the straddling market maker back on to the touch. Hence a market maker who moves from straddling the touch to the best bid (ask) must experience a negative change in inventory relative to the shortest (longest) inventory position.

To test these implications of inventory models, we compute the change in a market maker's relative inventory position, $(I_{i,t} - I_{T,t})$, whenever his quote position relative to the touch undergoes a change (i.e., either when market maker i gets off the touch or when he gets on to the touch). We average these changes across all stocks and across all market makers. For the sake of completeness, we also measure the changes in their standardized inventory levels associated with the changes in quotes. For notational convenience, in Table VII we use the term “Bid to ask” to denote the time from when a market maker's quotes start forming the bid side of the touch to the time when his quotes start forming the ask side of the touch. The terms “Bid to straddle,” “Ask to bid,” “Ask to straddle,” “Straddle to bid,” and “Straddle to ask” indicate corresponding quote transition scenarios.

¹⁶ This is because although a market maker straddling the touch executes some preferred order flow, it consists of public buys as well as public sells. Because these are random and equally likely, *on average*, they lead to no change in the inventory level.

Table VII
Quote Changes and Changes in Relative
and Standardized Inventories

This table shows quote changes and the associated changes in the standardized inventory and in the standardized inventory relative to the market maker with the shortest or longest position. Ask denotes a quote equal to the ask side of the touch, Bid denotes a quote equal to the bid side of the touch, Straddle denotes a straddling position, i.e., neither quote is competitive. Figures are in units of standard deviations of market makers' standardized inventories.

Transition Scenario	Relative to Longest Position		Relative to Shortest Position		Standardized Inventory	
	Change	t-statistic	Change	t-statistic	Change	t-statistic
Bid to straddle	-0.05459	-5.08	0.05442	6.44	0.05441	9.23
Bid to ask	-0.07499	-6.06	0.08906	5.31	0.11962	10.89
Ask to straddle	0.07886	5.31	-0.06933	-7.19	-0.04461	-7.35
Ask to bid	0.08204	6.73	-0.08147	-5.88	-0.11550	-9.53
Straddle to bid	0.02722	1.97	-0.01856	-1.63	0.01299	1.76
Straddle to ask	-0.03133	-2.03	0.03381	2.08	0.00320	0.72

Table VII summarizes our findings, which strongly support the relationship between quote changes and inventory changes predicted by the inventory model of competitive dealership markets. The mean change in a market maker's inventory relative to the shortest (longest) inventory position from bid to ask (ask to bid) equals 0.089 (0.082); the same mean change from bid to straddle (ask to straddle) equals 0.054 (0.079)—both changes being significant. The mean changes are in the direction predicted by the inventory hypothesis. Additionally, the fact that larger changes are observed when the quotes are moved from bid to ask (ask to bid) is consistent with inventories being an important reason why dealership markets are characterized by one-sided quote placements by dealers.

Further support of the inventory hypothesis is provided by changes in the market makers' standardized inventory levels. We find that the mean changes in market makers' inventory from bid to straddle equals 0.054, from bid to ask equals 0.12, from ask to straddle equals -0.045, and from ask to bid equals -0.116, with all changes being significant. These results are similar in magnitude to those just discussed for relative inventories. Consistent with the inventory hypothesis, market makers who quote the best quotes get a greater proportion of the one-sided order flow, changing their inventories and eventually their quotes.

Finally, we consider market makers who are straddling the touch and move to best bid or best ask. We find that the mean change in inventories from straddle to ask and straddle to bid is small and insignificantly different from zero. However, the mean change in relative inventory of a market maker from straddle to bid equals -0.019 relative to the shortest inventory and from straddle to ask equals -0.03 relative to the longest inventory. Although market makers who straddle the quotes get balanced

order flow through preferencing, their relative inventory position changes because market makers who are posting the best quotes are receiving one-sided order flow. Hence, the inventory position of these market makers does not change but their relative inventory position does, leading to their providing the best quotes. This is strong evidence that quote placement behavior is driven by relative inventories.

IV. Interdealer Trading and Inventories

In this section, we examine the extent to which market makers use interdealer trading in the management of their inventories. In the canonical inventory model of Ho and Stoll (1983) interdealer trading occurs when the inventories of the market makers diverge a lot and when the dealers chose between the uncertain probability of a public trade arrival and the certainty of interdealer trading. Thus, in Ho and Stoll's model the dealers have greater willingness to trade in the interdealer market when they have divergent inventories.¹⁷

From Section III.B, we know that interdealer trading is similar to public trading in the sense that dealers with divergent inventories are more likely to participate in interdealer trades that reduce the divergence of their inventories. In this section, we investigate whether there exist any significant differences in the sizes of trades and the inventory levels at which market makers engage in interdealer trades compared to public trades.

First, we note the size of every trade, public as well as interdealer, and the inventory level at which each dealer executes that trade. For each stock, we compute a size-weighted average inventory level for the public trades and the interdealer trades. We aggregate these across stocks and find that the average inventory level at which a market maker sells to the public equals 0.18σ and that at which he sells to the other dealers equals 0.51σ , a difference of 0.33σ . Similarly, the average inventory level at which a market maker buys from the public equals -0.23σ and that at which he buys from the other dealers equals -0.42σ , a difference of -0.19σ . Moreover, the average inventory levels as well as the differences are all significantly different from zero. Thus, the data suggest that the inventory level at which the dealers engage in trading among themselves is about twice that when they engage in trading with the public.

Second, we examine if market makers actively manage their inventories by increasing trading among themselves as their inventories diverge. For this purpose we segregate the change in the inventory of a market maker into two components, one arising out of his trading with other dealers and the other arising out of his trading with public investors. Suppose from the end of day $t - 1$ to the end of day t , market maker m executes N_t^{id} trades with other dealers (i.e.,

¹⁷ Recent models by Naik et al. (1996) and Lyons (1996) also provide similar implications except that market makers in these models engage in interdealer trading for inventory as well as informational reasons.

interdealer trades) and N_t^P trades with public investors. In order to be consistent with equation (4), we measure these public and interdealer trades in units of standard deviation S_m of market maker m 's inventory in that stock.¹⁸ We define $\Delta I_{m,t}^{id}$ ($\Delta I_{m,t}^P$) as the net change in the inventory of market maker m as a result of engaging in N_t^{id} (N_t^P) number of interdealer (public) trades from the end of day $t - 1$ to the end of day t :

$$\Delta I_{m,t}^{id} = \sum_{k=1}^{k=N_t^{id}} \hat{q}_{m,k}^{id} \quad \text{and} \quad \Delta I_{m,t}^P = \sum_{k=1}^{k=N_t^P} \hat{q}_{m,k}^P, \quad (9)$$

where $\hat{q}_{m,k}$ is the size of the k th trade measured in units of standard deviations of market maker m 's inventory in that stock ($\hat{q}_{m,k} = q_{m,k}/S_m$).

We express the change in the inventory of market maker m from the end of day $t - 1$ to the end of day t , $\Delta I_{m,t}$, as the sum of the change due to his trading with the public and the change due to his trading with other dealers; that is, $\Delta I_{m,t} = \Delta I_{m,t}^P + \Delta I_{m,t}^{id}$. In order to investigate whether the relative proportion of public and interdealer trading depends on the level of inventory, we run the following two regressions:

$$\begin{aligned} \Delta I_{m,t}^{id} = & \alpha^{id} + \gamma_1^{id} D^1 I_{m,t-1} + \gamma_2^{id} D^2 I_{m,t-1} + \gamma_3^{id} D^3 I_{m,t-1} + \gamma_4^{id} D^4 I_{m,t-1} \\ & + \gamma_5^{id} D^5 I_{m,t-1} + \epsilon_{m,t}^{id} \end{aligned} \quad (10)$$

and

$$\begin{aligned} \Delta I_{m,t}^P = & \alpha^P + \gamma_1^P D^1 I_{m,t-1} + \gamma_2^P D^2 I_{m,t-1} + \gamma_3^P D^3 I_{m,t-1} + \gamma_4^P D^4 I_{m,t-1} \\ & + \gamma_5^P D^5 I_{m,t-1} + \epsilon_{m,t}^P, \end{aligned} \quad (11)$$

where

$$D^i = \begin{cases} 1 & \text{if } (i-1) \leq |I_{m,t-1}| < i \text{ and } i \leq 4, \\ 1 & \text{if } (i-1) \leq |I_{m,t-1}| \text{ and } i = 5, \\ 0 & \text{otherwise,} \end{cases} \quad (12)$$

and where i is a positive integer, m denotes the market maker, and $I_{m,t}$ represents the standardized inventory of market maker m at the end of day t .

Equations (10) and (11) divide the mean reversion coefficient for inventories obtained in Section III.D, β_i , into two parts. The first part, γ_i^{id} , captures the mean reversion in inventories due to interdealer trading; the second

¹⁸ To reduce the notational burden, the superscript j to indicate a given stock has been suppressed in this section.

part, γ_i^p , captures the mean reversion in inventories due to public trading. Thus, $\gamma_i^{id} + \gamma_i^p$ equals β_i where β_i is given in Table V, third column. This decomposition enables us to evaluate the extent to which interdealer trading contributes to mean reversion in inventories across different inventory levels.

Table VIII summarizes our findings. We observe that a large proportion of the mean reversion in inventories occurs due to trading with the public when inventories are near the mean. However, as the inventory level starts to diverge, interdealer trading starts to play an increasingly important role. We also observe that most of the difference in mean reversion between intermediate levels of inventories (2σ to 3σ) and high levels of inventories (4σ and above) arises primarily from differences in the extent of interdealer trading.

Table VIII indicates that interdealer trading is more important when inventories are high. To examine further how the proportion of interdealer trading varies with inventory levels, we regress the fraction of change in inventory due to interdealer trading during the day on the inventory band level at the start of the day. In particular, we run the following regression.

$$\frac{\Delta I_{m,t}^{id}}{\Delta I_{m,t}^{id} + \Delta I_{m,t}^p} = \eta_1 D^1 + \eta_2 D^2 + \eta_3 D^3 + \eta_4 D^4 + \eta_5 D^5 + \nu_{m,t}, \quad (13)$$

where the dependent variable is the net inventory change due to interdealer trading as a fraction of net total inventory change over a day, and the dummies D_i represent different bands of inventory levels as defined in equation (12).

We find that $\eta_1 = 0.28$, $\eta_2 = 0.35$, $\eta_3 = 0.39$, $\eta_4 = 0.40$, and $\eta_5 = 0.39$. The adjusted R^2 for the regression is 38 percent, indicating that a substantial variation in the proportion of interdealer trading can be explained by the variation in inventory levels. In general, the fraction of interdealer trading increases with inventories, which is consistent with the results obtained in the decomposition of the mean reversion coefficients earlier in this section.

In order to shed light on the differences in the relative importance of mean reversion of inventories for ADR and non-ADR stocks, we repeat the regressions in equations (10) and (11) for the two subsamples. Panels B and C of Table VIII summarize our findings. We find that although market makers' inventories of the highly liquid ADR stocks mean revert marginally less quickly compared to those of the less liquid non-ADR stocks, the relative importance of interdealer trading increases as the inventories start to diverge in both the ADR and the non-ADR stocks.

On the whole, the evidence suggests that interdealer trading is an important mechanism for managing inventory risks in dealership markets, especially when inventories diverge a lot. These results are consistent with the models of Ho and Stoll (1983), Naik et al. (1996), and Lyons (1996) in which the interdealer market facilitates the management of inventory risks and

Table VIII
Decomposing the Mean Reversion Coefficients

The table shows the average coefficients of the following piecewise linear regressions:

$$\Delta I_{m,t}^{id} = \alpha^{id} + \gamma_1^{id} D^1 I_{m,t-1} + \gamma_2^{id} D^2 I_{m,t-1} + \gamma_3^{id} D^3 I_{m,t-1} + \gamma_4^{id} D^4 I_{m,t-1} + \gamma_5^{id} D^5 I_{m,t-1} + \epsilon_{m,t}^{id}$$

and

$$\Delta I_{m,t}^p = \alpha^p + \gamma_1^p D^1 I_{m,t-1} + \gamma_2^p D^2 I_{m,t-1} + \gamma_3^p D^3 I_{m,t-1} + \gamma_4^p D^4 I_{m,t-1} + \gamma_5^p D^5 I_{m,t-1} + \epsilon_{m,t}^p$$

where

$$D^i = \begin{cases} 1 & \text{if } (i-1) \leq |I_{m,t-1}| < i \text{ and } i < 4, \\ 1 & \text{if } (i-1) \leq |I_{m,t-1}| \text{ and } i = 5, \\ 0 & \text{otherwise,} \end{cases}$$

where i is a positive integer, m denotes the market maker ($m = 1, 2, \dots, 382$), and $I_{m,t}$ is the standardized inventory of market maker m at the end of day t , the superscript id refers to interdealer trading, and the superscript p refers to public trading. The D^i are indicator variables that allow for differences in the degree of mean reversion as a function of different bands of inventory levels. We run this regression for the 382 market makers. The sum of the public and interdealer coefficients is shown in the Total column. As discussed, this coefficient is exactly equal to β_i where β_i is the corresponding mean reversion coefficient of standardized inventories in Table V.

γ	Interdealer	Public	Total	Fraction Interdealer
Panel A: All Stocks				
γ_1	-0.027	-0.113	-0.14	19%
γ_2	-0.03	-0.19	-0.22	22%
γ_3	-0.08	-0.22	-0.30	27%
γ_4	-0.14	-0.28	-0.42	33%
γ_5	-0.30	-0.31	-0.61	49%
Panel B: ADR Stocks				
γ_1	-0.021	-0.099	-0.12	17%
γ_2	-0.033	-0.127	-0.16	21%
γ_3	-0.08	-0.21	-0.29	28%
γ_4	-0.15	-0.26	-0.41	37%
γ_5	-0.28	-0.26	-0.54	52%
Panel C: Non-ADR Stocks				
γ_1	-0.04	-0.14	-0.18	22%
γ_2	-0.06	-0.20	-0.26	23%
γ_3	-0.08	-0.23	-0.31	26%
γ_4	-0.13	-0.31	-0.44	30%
γ_5	-0.28	-0.36	-0.64	44%

allows dealers to take large inventory positions that they would be unwilling to take in an auction-type market where they can only unwind their inventory positions against the public order flow.

V. Concluding Remarks

In this paper we test the sharp empirical predictions of Ho and Stoll's (1983) model pertaining to relative inventories, relative quote positions, and order flow execution. We use a rich database from the London Stock Exchange, which allows us to observe market maker inventories directly, something previous studies have not been able to do. Our results provide strong support for the inventory models of competitive dealership markets. As predicted by the inventory models, we find that the dealers with extreme inventory positions execute large orders which move their inventories toward desired levels. We observe that a significantly larger proportion of the public order flow goes to the market makers posting the most competitive quotes, which suggests that market makers, by strategic positioning of quotes, can attract the public order flow primarily in one direction. We also find a significant relationship between quote changes and inventory changes as predicted by the model.

Compared with NYSE specialists' inventories, we find much stronger evidence of mean reversion in dealers' inventories. More strikingly, we find that the intensity of mean reversion increases with the distance of inventory from the desired level. This is consistent with the prediction of the inventory model. It points out that there exist significant nonlinearities in mean reversion coefficients and that any inference about inventory half-lives obtained under the assumption of constant mean reversion may be misleading.

Finally, our paper explores the relationship between interdealer trading and inventories. We find that interdealer trades have a higher average size than public trades. However, public trades can be small or large and show much volatility, while interdealer trades seem to be more standardized in size. Importantly, the average inventory level at which a dealer participates in an interdealer trade is significantly higher than the average inventory level at which a dealer participates in a public trade. We also find that the extent to which a dealer engages in interdealer trades is directly related to his inventory level, an implication consistent with inventory models of dealership markets.

Taken together, our results provide an extensive body of evidence that inventories play an important role in competitive dealership markets. Also, our empirical work provides the first exploration of interdealer trading, a topic that needs more attention in the theoretical and empirical market microstructure literature.

Appendix A

History and Structure of the London Stock Exchange

The capital markets in London have an interesting history dating back to 1553 when the first joint stock company, called "Muscovy," was formed by 240 investors by subscribing to one share each worth £25 for the specific purpose of provisioning three ships to search for a northeast passage to the

then mysterious Far East (modern day China). The capital markets in London have come a long way—witnessing the South Sea bubble, the industrial revolution, and more recently the computerization and globalization of the financial services industry. The most recent (and sweeping) changes in the London Stock Exchange occurred in October 1986 (the Big Bang). The age-old trading floor was discarded in favor of electronic screens displaying information and the floor-based face-to-face trading was replaced by negotiations over the phone. Fixed commissions were eliminated and negotiated rates became common practice. Rules restricting firms to participate either as a broker (agent) or as a jobber (principal/dealer) were abolished and dual capacity trading was introduced. Restrictions on LSE membership were lifted, and many foreign firms were allowed to become market makers. These sweeping changes transformed the London Stock Exchange into a highly competitive dealership market.

Currently, the London Stock Exchange is the third largest stock exchange in the world.¹⁹ Although similar in structure to the Nasdaq, the LSE differs from the Nasdaq in several important ways.²⁰ On the LSE, information is disseminated through the Stock Exchange Automatic Quotation (SEAQ) system. The SEAQ screen displays the competing quotes (in large sizes) of all the market makers registered in that stock. However, the market makers generally deal within their quotes, particularly when they are not on the touch, and they also deal at the quoted prices for much larger sizes. On the LSE, all trades including the large ones are brought directly to the market makers and filled immediately. Typically, the entire block is taken up by one market maker who then searches for counterparties and works off the trade as subsequent order flow and market conditions allow.

Market makers on the LSE can deal with each other via the interdealer broker (IDB) system, which is similar to the Computer Assisted Trading System on the Toronto Stock Exchange where market makers can either post limit orders or trade anonymously against the IDB quotes of other market makers. The IDB system helps a market making firm, which may have just taken on a large trade, to lay off an imbalance in its inventory position.²¹ The IDB system also conveys some information about the order flow and helps to partly offset the fragmentation inherent in a geographically dispersed screen-based multi-market maker system.

¹⁹ The largest stock exchange is the NYSE (a daily turnover of about £4.0 billion), and the second largest is the Nasdaq (a daily turnover of £2.0 billion). The LSE is a close third (a daily turnover of £1.7 billion).

²⁰ See Neuberger and Schwartz (1990) for a comprehensive discussion of the London Stock Exchange and Schwartz (1991) for an excellent comparison of the LSE with the NYSE, Nasdaq, and other exchanges.

²¹ Interdealer trades constitute about 53 percent of public trading. See Naik, Neuberger and Viswanathan (1996) for a model where market makers optimally use the interdealer market to lay off a public trade.

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