Do Correlated Exposures Influence Intermediary Decision-making? Evidence from Trading Behavior of Equity Dealers

by

Narayan Y. Naik and Pradeep K. Yadav[1]

This draft: October 12, 2001

JEL Classification: **G12, G20, G24**

Keywords: **Dealer firm, equivalent inventory, correlated risk exposure, unhedgeable risk, effective spreads**

[1] Narayan Y. Naik is from the London Business School, Sussex Place, Regent's Park, London NW1 4SA, U.K. (http://www.london.edu/faculty_research/, tel. +44 207 2625050, e-mail nnaik@london.edu). Pradeep K. Yadav is from the University of Strathclyde, 100 Cathedral Street, Glasgow, G4 OLN, U.K, and is currently visiting the Stern School at New York University (http://www.stern.nyu.edu/~pyadav, tel. 212-9980305, e-mail pyadav@stern.nyu.edu). We would like to thank Donald Campbell and Martin Kemmit for excellent research assistance, and thank Steven Wells and Graham Hart of the London Stock Exchange for providing us with the data. We are grateful, for many helpful comments and suggestions, to Robert Battalio, Hendrik Bessembinder, Bruno Biais, Richard Brealey, Mark Britten-Jones, Charles Cuny, Elroy Dimson, Roger Edelen, Thierry Foucoult, Julian Franks, Oliver Hansch, Francis Longstaff, Ananth Madhavan, Purnendu Nath, Anthony Neuberger, Stephen Schaefer, Eric Sirri, George Sofianos, Chester Spatt, S. Viswanathan, seminar participants at London Business School and Groupe HEC, and the session participants at the Western Finance Association Annual Meetings and the European Finance Association Annual Meetings. Part of this work was undertaken while Pradeep Yadav was visiting the Anderson School at UCLA. Both authors are grateful for research grant R000221596 from the UK Economic and Social Research Council. The authors are also grateful to the European Commission's TMR program grant (network reference ERBFMRXCT 960054), and the Scottish Institute for Research in Investment and Finance (SIRIF) for financial and infra-structural support.

Do Correlated Exposures Influence Intermediary Decision-making? Evidence from Trading Behavior of Equity Dealers

Abstract

This paper investigates whether dealers' trading and pricing decisions are governed by their equivalent inventories (based on total returns as in Ho and Stoll, 1983 or on unhedgeable returns as in Froot and Stein, 1998) or by their ordinary inventories, as would be the case in a decentralized market-making organisational structure. It finds that ordinary inventories, and not equivalent inventories best explain dealers' quote placement strategy, which dealer executes trades and the quality of execution offered to the trades. This finding is consistent with decentralized market making where, due to information sharing difficulties or the nature of compensation contracts, individual dealers care only about risk of stocks managed by them, and not the positions of other dealers within the firm.

Do Correlated Exposures Influence Intermediary Decision-Making?

Evidence from Trading Behavior of Equity Dealers

1. Introduction

If I am long one million dollars in General Motors, and I am short one million dollars in Ford, am I still long one million dollars in General Motors?

Dealers in competitive dealership markets take on inventory risk of the securities in which they make a market. There is an extensive literature that shows us that dealers actively manage this risk by controlling individual asset inventories[2]. However, typically, dealers make a market not just in one security, but in a large number of securities. For example, each of the 'wholesalers' on the NASDAQ, and about three-fourths of the dealers on the LSE make a market in over hundred stocks[3]. Hence, dealers' management of inventory risk, and their trading behavior, should arguably be based not on inventories at the individual security level but on overall inventories aggregated across their total portfolio of securities. In this paper we examine if this is indeed the case.

The importance of correlated exposures in the context of market-making was first emphasized by Ho and Stoll (1983) (hereafter H&S). They show that the dealer's trading behavior in a given stock should be guided (not by her *ordinary* inventory holdings in that stock but) by her *equivalent* inventory in that stock. This equivalent inventory is simply the dealer's ordinary inventory in that stock corrected for any reinforcing or offsetting effects arising from inventory positions in all other stocks with correlated returns.

---

[2]Hasbrouck and Sofianos (1993), Madhavan, and Smidt (1993) and Madhavan, and Sofianos (1998) analyse specialists' inventories on the NYSE; Lyons (1995) studies the inventory of one FX dealer; Mann, and Manaster (1996) examine behavior of scalpers in the Chicago futures market; Neuberger (1992), and Snell, and Tonks (1998) study the aggregate inventory of all London equity dealers while Hansch, Naik, and Viswanathan (1998) and Reiss and Werner (1998) examine individual dealer inventories. Chan, Christie, and Schultz (1995) document evidence consistent with active inventory control.
[3] See Ellis, Michaely, and O'Hara (1999) and Naik and Yadav (1999).

More recently, Froot and Stein (1998) (hereafter F&S) examine the decision-making problem of financial intermediaries when some but not all risks can be hedged. They show that the attitude of an intermediary towards an additional unit of risk in a stock depends on its *unhedgeable* component and the amount of correlated unhedgeable risk she carries in her portfolio. Hence, dealer decision-making in the F&S framework depends on ordinary inventory (a significant proportion of the risk of which is unhedgeable or stock-specific) and on an unhedgeable equivalent inventory measure based (not on correlation in total returns, as in H&S, but) on correlation in unhedgeable returns. This measure is relevant for an equity dealer who hedges completely the market risk of her portfolio with futures contracts such as S&P 500 futures in the US or FTSE100 futures in London.

Clearly, from a theoretical perspective, equivalent inventories (total or unhedgeable), rather than individual inventories, should govern dealers' trading behavior. However in practice, other factors also play an important role, factors not specifically incorporated in these theoretical models. For example, each market-making firm consists of a large number of individual dealers to whom trade related decision-making in different stocks is delegated. This decentralized structure provides incentives for the individual dealers (who take the actual trading and risk management decisions) to be concerned only about the ordinary inventory risk of the individual stocks managed by them, rather than the overall position of the dealer firm as a whole that also includes positions in correlated stocks of other individual dealers within the firm.

There are potentially two effects of the decentralized nature of market-making. First, there are difficulties in effectively sharing information in real time across the large number of dealers making a market in different but correlated stocks. And second, the performance of these individual dealers is evaluated, and their compensation is determined according to the trading profits they generate in stocks assigned to them. Imposing constraints on the position of an individual dealer in a particular stock based on the inventory of another dealer in a correlated stock contaminates the clean performance evaluation measure and hence increases the firm's agency costs. As a result, with decentralized market-making, the influence of correlated risk exposures predicted by theoretical models is unlikely to get fully reflected in the trading behavior of the firm. Thus, the net influence of correlated exposures on dealers' trading behavior can be determined only through empirical analyses.

In this paper, we use transactions audit-trail data from the London Stock Exchange (hereafter LSE) to investigate whether the trading behavior of dealers is governed by their total equivalent inventories as in the Ho and Stoll (1983) model, or by their unhedgeable equivalent inventories as in the Froot and Stein (1998) model, or by their ordinary inventories as in a decentralized market-making organizational framework (hereafter the decentralized market-making model). We examine four aspects of dealers' trading behavior: intensity of mean reversion in inventories, quote placement strategy, which dealer executes public and inter-dealer trades, and the quality of execution she offers to the trades.

We find that dealers' ordinary inventories exhibit stronger mean reversion than either of their equivalent inventories, that their quote changes are significantly related to changes in their ordinary inventories and not to either of their equivalent inventories, that dealers with divergent ordinary, rather than equivalent, inventories execute public trades and engage in inter-dealer trades, and dealers with divergent ordinary, rather than equivalent, inventories offer significantly better quality of execution[4]. These findings confirm that ordinary

[4] During our sample period, the LSE (like NASDAQ) is a competing dealer market in which dealers' bid and ask quotes are displayed on a screen. However, public trades are typically executed through bilateral negotiations over the telephone and may receive price improvement. The dependence of terms of trade offered on size and type of trader has been investigated in the literature (Reiss and Werner, 1994). This paper provides the first empirical evidence on the relation between inventories and quality of execution.

inventories govern dealer decision-making, and hence that the trading behavior of dealers is best explained by the decentralized market-making model.

The rest of the paper is organized as follows. Section 2 describes the testable implications of Ho and Stoll (1983), Froot and Stein (1998) and the decentralized market-making models. Section 3 describes the data and explains how ordinary and equivalent inventories are constructed. Section 4 describes the methodology used in investigating the issues and documents the empirical results. Section 5 describes the findings from numerous robustness checks. Finally, section 6 offers concluding remarks.

2. Key implications of theoretical models

In this section, we describe the key testable implications of Ho and Stoll (1983), Froot and Stein (1998) and the decentralized market-making model.

2.1. Key implications of Ho and Stoll's (1983) model

In H&S model, the reservation fee of a dealer for buying or selling a fixed quantity of a given stock depends on the variance of the stock return, the risk aversion of the dealer and the 'equivalent' inventory level of the dealer in that stock, where the equivalent inventory is the dealer's ordinary inventory of the stock corrected for any reinforcing or offsetting effects from her inventory positions in other correlated stocks. In their model, a dealer with the longest (shortest) equivalent inventory executes a buy (sell) trade, where the 'equivalent' inventory $EI_{i,t}^{j}$ of dealer *i* in stock *j* at time *t* is given by

$$EI_{i,t}^{j} = OI_{i,t}^{j} + \sum_{k \neq j} \beta_{j,k} OI_{i,t}^{j} \qquad \textbf{(1)}$$

where $OI_{m,t}^{j}$ is the ordinary inventory of dealer *i* in stock *j* at time *t*; $\beta_{j,k}$ is the regression coefficient capturing the dependence of the return of stock k on that of stock j, $\left(\frac{COV(R_j, R_k)}{VAR(R_j)}\right)$, and the summation extends over all other stocks $k \neq j$.

The H&S model implies that the trading behavior of dealers in a stock will be governed by equivalent inventories rather than ordinary inventories of that stock. The emphasis is on two aspects: first, on the correlated risks arising from inventory positions in all other securities at a firm-wide level; and second, on total risk rather than the unhedgeable risk emphasised by F&S discussed below.

2.1. Key implications of Froot and Stein's (1998) model

F&S argue that a financial intermediary cannot efficiently hedge all risks in capital markets, and show (see their Proposition 2, pp 64) that a financial intermediary will always wish to hedge fully its exposure to any tradeable risk. Their model implies that a dealer's attitude towards bidding for and pricing a block of shares will depend only on her attitude to the unhedgeable component of the risk. Hence, a dealer's trading behavior in a stock will depend on her inventory of that stock and the extent of correlated unhedgeable risk arising from her inventories in other stocks. That is, it would depend on an equivalent inventory defined on the basis of correlations in unhedgeable returns rather than correlations in total returns (as in H&S).

2.3. Key implications of the decentralized market-making model

As mentioned in the introduction, typically, market maker firms make a market not just in one security but in a large number of securities. These market-making firms delegate the task of posting quotes and negotiating trades in different securities to individual dealers. A large market maker firm may have dozens of such individuals. These individual dealers decide at a micro-level what quotes to post, whether to execute a particular trade, and if so, what price to charge for that trade.

With decentralized market-making, there exist two reasons why dealers may be more concerned with individual asset inventories rather than the (total or unhedgeable) equivalent inventories. First, as a practical matter, there exist difficulties in sharing relevant information across a large number of dealers who work for the same firm but make a market in different stocks. This is especially true when a large number of individual dealers are negotiating and executing trades across a large number of securities almost on a continuous basis. There could arguably be some information sharing at the trading desk level, but it is likely to be very weak at the firm-wide level.

Second, the performance of these individual dealers is evaluated, and their compensation is determined according to the trading profits they generate in the stocks assigned to them. Giving the freedom to an individual dealer to manage the inventory of her stocks gives a clean measure of her contribution to the profitability of the business. It also helps efficiently specify the individual dealer's compensation package. Imposing restrictions on the position an individual dealer can take in a given stock, based on the inventories of other dealers in correlated stocks, contaminates the performance evaluation measure and hence increases agency costs[5].

Thus in a decentralized market-making structure, due to information sharing costs or incentive contracts, an individual dealer cares only about the risk of the stocks managed by her. Hence, the dealer's trading behavior in a stock depends on her ordinary inventory of that stock.

[5] Essentially, the market making firm faces a trade off in which the benefits of cost reduction through offsetting of correlated exposures at individual stock level have to be weighed against the increase in overall agency costs due to the contamination of performance evaluation measure involved.

3. Data and construction of ‘ordinary’ and ‘equivalent’ inventory series

Our data spans the three months (65 trading days) from August 1, 1994 to October 31, 1994. Over the calendar year 1994, the average daily turnover of UK and Irish equities was £2.4 billion, the average number of transactions was 37,000 and the average trade size was £64,000 (Source: Quality of Markets Quarterly, Winter 1994). Trading in the large stocks (which are part of the FTSE-100 index) and in the medium stocks (which are part of the FTSE-250 index) accounts for over 85 percent of the turnover in U.K. and Irish equities on the LSE. Hence, we focus on market-making in the large and medium stocks. For computational tractability and for ease of presentation, we randomly select a total of twenty stocks: ten FTSE-100 stocks and ten FTSE-250 stocks.

Our data set provides time-stamped details of all quotes and all transactions for all stocks traded on the LSE. It identifies the dealer participating in each transaction, whether the dealer bought or sold, and their dealing capacity in the transaction, i.e. whether they acted as agent representing an order from the public, or as principal trading on their own account. Transactions data on the LSE has been used by several other researchers to explore interesting but different issues[6]. Most of these studies (eg Hansch, Naik, and Viswanathan, 1998; Reiss and Werner, 1998) use data sets in which the codes of different dealers and brokers change

[6] For example, Reiss and Werner (1994) study transaction costs; Snell and Tonks (1995) analyse components of the bid-ask spread; Gemmill (1996), and Board and Sutcliffe (1995) examine the impact of different transparency rules on trading costs; Hansch and Neuberger (1996) explore trading strategies of market makers; Board, Vila, and Sutcliffe (1996) examine the commitment of different market makers as providers of liquidity and contributors to price discovery; Reiss and Werner (1998) investigate inter dealer trading on the LSE; Hansch, Naik, and Viswanathan (1999) examine the effect of preferencing, internalization and best execution on trading costs; Naik and Yadav (1999) analyse the differences in the quality of execution offered by different dealers and different brokers; Naik and Yadav (2000) study changes in trading costs of public investors after the market reforms, and Hillier, Naik, and Yadav (1999a) and Hillier, Naik, and Yadav (1999b) examine dealers' inventory control around anticipated and unanticipated information events (earnings announcements and directors’ trades) respectively.

from security to security, thus making it impossible to generate portfolio related inferences that require aggregation across stocks. Importantly from the perspective of this paper, our data set assigns the same code to a dealer across different stocks. This enables the construction of inventory positions of individual dealers over time in individual stocks as well as cross-sectionally aggregated positions across all stocks.

3.1. Construction of 'ordinary' and 'equivalent' inventory series

As dealers differ in terms of capitalization and/or risk aversion, their inventories cannot be directly compared with each other. Therefore, we follow Hansch et. al.'s (1998) procedure (described in the Appendix) and construct the standardized ordinary inventory (OI) series, for each stock and for each dealer separately. Similarly, using information on the identity of each dealer across different stocks, we construct H&S's 'equivalent' inventory series defined in eq. (1) for each dealer for each of our twenty sample stocks. Towards that end, we collect, from the London Share Price Database, monthly stock returns of each of the 1854 stocks in our data set over the five year period prior to the start of our sample period. We use these sixty monthly returns series to calculate $\beta_{j,k}$ - the slope of the regression line capturing the dependence of the return of stock *k* on the return of stock *j*, for all relevant pairs of stocks *(j, k)*. In our case, *j* varies from one to twenty – the twenty sample stocks, and *k* varies from one to remaining 1853 stocks. Using these $\beta_{j,k}$, we calculate the pound sterling value of equivalent inventories for each dealer in our 20 sample stocks. Finally, to make the equivalent inventories comparable across dealers, we standardize them by subtracting the sample mean and dividing by the sample standard deviation.

We compute our equivalent inventory measures in four different ways. These measures differ from each other in the way $\beta_{j,k}$ is computed (i.e., using total returns as in

H&S and using unhedgeable returns as in F&S) and in the number of stocks over which the second term in eq. (1) is summed. First, we construct the *Total Firm-wide Equivalent Inventory (TEI_FW)* based on correlations in *total* returns and aggregating positions across 1854 stocks. Second, in the context of the decentralised market-making, we consider one common form of organisation in which the market-making function is organised, i.e. by trading desks based on industry sectors. In such a case, the relevant correlated exposures will be at the industry-desk level. We capture this by calculating *TEI_ID*, the *Total Industry-desk Equivalent Inventory*, by summing the second term in eq. (1) only over the stocks belonging to the same industry group.

Analogous to the two measures of equivalent inventory above, we also construct two measures of equivalent inventory in the spirit of F&S by assuming that dealers hedge away all market-risk at each point in time. We call these measures *Unhedgeable Firm-wide Equivalent Inventory (UEI_FW)* and *Unhedgeable Industry-desk Equivalent Inventory (UEI_ID)* respectively. To incorporate hedging of market-risk, we modify the calculation of regression coefficients in eq. (1). Instead of regressing total returns of stock *k* on total return of stock *j*, we now regress the "abnormal" or market-filtered returns (using the market model) earned by stock *k* on those earned by stock *j* during the five-year period to the start of our sample period. As before, for *UEI_FW*, we sum the second term in eq. (1) over all stocks *k*, where *k* varies from one to 1853. For *UEI_ID*, we sum the second term in eq. (1) only over the stocks belonging to the same industry group.

3.2. Sample statistics

Table 1 reports descriptive statistics relating to the twenty sample stocks listed in decreasing order of their turnover. The average daily total turnover of our sample stocks varies from £30.1 million in NatWest Bank to £0.4 million in WPP Group, the sample average being about £6 million. A significant proportion of the total turnover is due to public trading. The average daily public turnover varies from £16.3 million in NatWest Bank to £0.3 million in WPP Group, the sample average being £3.7 million. The average daily number of public trades of our sample stocks varies from 172 in NatWest Bank to 4 in First Leisure Corporation, the sample average being 42. The sample average size of public and inter-dealer trades (not reported) is respectively £112,000 and £210,000. Within our sample of twenty stocks, an average of about ten dealers deal in each stock. Four stocks have fourteen dealers or more while twelve stocks have ten dealers or fewer.

For firm-wide equivalent inventories based on correlations in total returns as in H&S (TEI_FW), the average $\beta_{j,k}$ across the twenty sample stocks equals 0.37, varying from a minimum of 0.15 to a maximum of 0.86. For firm-wide equivalent inventories based on unhedgeable returns as in F&S (UEI_FW), the average $\beta_{j,k}$ equals 0.41, varying from 0.14 to 0.89. These firm-wide $\beta_{j,k}$ are based on summing the second term in eq. (1) over 1854 stocks. When we consider market-making organised around industry desks, the number of stocks included in the equivalent inventory construction varies from a minimum of 6 to a maximum of 39, average being 14. The average $\beta_{j,k}$ equals 0.21 (0.16) for total (unhedgeable) industry-desk based equivalent inventory, varying from about 0.05 to 0.44 for the total risk measure and from 0.03 to 0.43 for the unhedgeable risk measure.

Table 1 also reports the R^2 of the regression from the market model, as reported by the June 1994 issue of the London Business School Risk Measurement Service. This R^2 averages 37%, varying from a maximum of 63% to a minimum of 4%. 16 out of the 20 sample stocks have an R^2 greater than 30%. This R^2 captures only the dependence on market returns, and not the additional systematic dependence that exists with respect to industry and other risk factors such as size and book-to-market. Clearly, for the vast majority of our sample stocks, the level of dependence on systematic factors that generate correlations between stock returns is large in magnitude, and would ordinarily be expected to influence dealers' trading behavior, unless dealers care only about positions in the stocks they trade, either because they do not know the positions of other dealers or because of the nature of their performance evaluation measure.

Having described the salient features of the data, we now proceed with our empirical investigation.

4. Empirical investigation

In this section, we examine which measure of inventory (total equivalent, unhedgeable equivalent and ordinary) explains best four different aspects of dealers' trading behavior. First, we analyze the mean reversion in dealers' inventories and examine which inventory measure tends to revert to the mean most rapidly. Second, we analyze dealers' quote placement behavior and investigate which inventory measure is most associated with it. Third, we examine the extent to which a dealer's buy and sell trades are related to the divergence of her different inventory measures. Finally, we investigate the extent to which the quality of execution offered to trades by a dealer is related to the divergence of the different measures of her inventories.

4.1. Mean reversion in inventory

If dealers are risk averse or face inventory carrying costs, their inventories would display mean reversion. If the inventory of a dealer goes above (below) her target inventory level, she will potentially change her quotes and/or, during negotiation, offer better prices to attract order flow in a direction that brings her inventory towards the target. In a competitive dealership market, when a dealer has an extreme inventory position she can post competitive quotes on one side and has a better chance of executing order flow in that direction, resulting in relatively rapid reduction in the inventory imbalance. However, when a dealer's inventory is close to the median inventory, at that time she cannot post competitive quotes and therefore has a poor chance of executing the public order flow, resulting in a relatively slow reduction in the inventory imbalance. This argument implies mean reversion in relative inventories, i.e., relative to the inventory of the median dealer.

In competitive dealership markets, the strength of mean reversion should increase with the magnitude of the inventory level. Up to a certain level of deviation of inventory from the target level, dealers may not worry too much. But once the deviation reaches a threshold level, dealers may actively start managing their inventory risk exposure. This suggests that instead of a linear model, it may be more appropriate to use a threshold autoregressive piecewise linear model in inventory levels. Therefore, following Hansch et. al. (1998), we estimate a piecewise linear model for mean reversion in inventories with the thresholds pre-specified as corresponding to a distance of one standard deviation and two standard deviations from the mean on either side.

We examine which of the inventory measures tends to revert to the mean most rapidly by estimating the following regression[7]

$$\Delta I_t = \alpha + \phi_1 D^1 I_{t-1} + \phi_2 D^2 I_{t-1} + \phi_3 D^3 I_{t-1} + \phi_4 D^4 I_{t-1} + \phi_5 D^5 I_{t-1} + \psi_t \qquad \textbf{(2)}$$

where: D^l *(l= 1, 2, …, 5)* are dummy variables that take a value of one depending on the distance of the inventory in multiples of standard deviations (σ), D^1 = *1* if $I_{t-1} \geq 2\sigma$, otherwise zero; D^2 = 1 if $2\sigma > I_{t-1} \geq \sigma$, otherwise zero; D^3 = *1* if $\sigma > I_{t-1} > -\sigma$, otherwise zero; $D^4 = 1$ if $-\sigma \geq I_{t-1} > -2\sigma$, otherwise zero, and $D^5 = 1$ if $-2\sigma > I_{t-1}$, otherwise zero. ϕ_l, $l = 1, 2, \ldots, 5$ represents the intensity of mean reversion which depends on the relative inventory level, and ψ_t is a white noise error term.

Table 2 summarizes our findings. Consistent with the nature of trading in competitive dealership markets, we find strong non-linearities in the intensities of mean reversions. When inventories diverge a great deal, the intensity of mean reversion is much greater (about three times that when inventories are around their mean). For ordinary inventory the intensity of mean reversion ϕ_l varies from -0.561 when inventory is more than two standard deviations away from the mean to -0.151 when inventory within one standard deviation from the mean[8]. The mean reversion coefficients for each of the four measures of equivalent inventories show a similar pattern. The average ϕ_l across the four equivalent inventory measures for all stocks varies from -0.365 in regime one to -0.124 in regime three.

Irrespective of the applicability of the different competing models of dealer behavior, if individual inventories are stationary, equivalent inventories should be stationary as well since equivalent inventories are linear combinations of ordinary inventories. Hence, in general, equivalent inventories will also display mean reversion if ordinary inventories are mean reverting. For the purpose of our investigation, the question that is important is the following: which of the three inventory measures reverts to the mean *most rapidly*. Is it total equivalent as predicted by Ho and Stoll (1983) or is it unhedgeable equivalent as argued by Froot and Stein (1998) or is it ordinary inventory as predicted by decentralized market-

[7] To compare and contrast our findings with those of Hansch, Naik, and Viswanathan (1998), we use a specification similar to theirs. Unlike us, their data does not allow construction of equivalent inventories.

making model?

In the context of the above, the difference in the mean reversion of ordinary and equivalent inventories is reported in the last four columns of Table 2.We find that across all stocks the intensity of mean reversion in ordinary inventory is greater than that in equivalent inventories in all 20 (four inventory measures times five regimes) cases, and this difference is statistically significant in 18 out of these 20 cases. The results for high liquidity (FTSE-100) stocks separately and medium liquidity (FTSE-250) stocks separately are qualitatively similar as well. We also test the apparent dominance of ordinary inventories using an alternative approach. We compute, for each dealer i dealing in stock j, the pairwise difference $({}_{o}\phi_{l}^{j,i} - {}_{e}\phi_{l}^{j,i})$, where $\phi_{l}^{j,i}$, $l = 1, 2, \ldots, 5$ represent the mean reversion estimates for the five regimes in eq. (2); and the pre-scripts '*o*' and '*e*' represent ordinary and equivalent (either total or unhedgeable, firm-wide or industry-desk based) inventories respectively. We then conduct a cross-sectional t-test to determine whether the average of these differences is significantly different from zero. Once again, we find that mean reversion in ordinary inventories is significantly greater than that in equivalent inventories (not reported).

The strong results above indicate that dealers care most about their ordinary inventory rather than either measure of their equivalent inventories, a finding that supports the implications of the decentralized market-making model relative to either the Ho and Stoll (1983) model or the Froot and Stein (1998) model.

4.2. Quote changes and inventory changes

In the inventory models of dealership markets, like Ho and Stoll (1983) and Biais

[8] Our results with ordinary inventories are similar to those of Hansch, Naik, and Viswanathan (1998) who conduct similar regression during 91-92 period.

(1993), a dealer's quote position is a monotone function of her inventory position. This implies that the changes in a dealer's quote position over time must be a function of the changes in her inventory position over time. In this sub-section, we measure the change in a dealer's ordinary and equivalent inventories corresponding to a change in her quote position.

In theoretical models, the dealer with longest (shortest) inventory position posts lowest ask (highest bid) price. The testable empirical implications have to be formulated in the context of the institutional practice of dealers on the LSE. We know from Hansch et. al. (1998) that LSE dealers follow the practice of having a constant quoted bid-ask spread in a stock, and this quoted bid-ask spread is identical for all dealers, and wider than the *market spread*, i.e. the difference between the best bid and best ask prices. As a result, at any point in time, a dealer's quote position is such that either her bid quote equals the best bid, or her ask quote equals the best ask, or both her quotes straddle the market spread. Moreover, starting from any one of these three positions, when a dealer decides to change the relative position of her quotes, she 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 3.

The inventory changes associated with quote position changes should arguably be as follows. First consider a dealer who starts by being at the best bid or the best ask. When the dealer moves her quotes from posting the highest bid quote to posting the lowest ask quote, it represents a change from being an aggressive buyer to being an aggressive seller. This is consistent with the notion that during the time the dealer was posting the highest bid quote, she was able to buy a large quantity of stock, resulting in a significant increase in her inventory, which she is trying to reduce by posting the lowest ask quote. Therefore, the change in inventory of a dealer moving from posting the highest bid quote to posting the lowest ask quote must be positive and significant. By the same argument, the change in inventory of a dealer moving from posting the lowest ask quote to posting the highest bid quote must be negative and significant. Similarly, when a dealer moves her quotes from the highest bid (lowest ask) to straddling the market spread, the change in her inventory must be positive (negative) but not as large in magnitude when she moves her quotes to the opposite side of the market spread.

Next consider a dealer who starts from straddling the market spread but at some later point in time either posts the lowest ask quote or the highest bid quote. A move from straddling the market spread to posting the lowest ask quote suggests a keenness to sell and therefore implies a positive change in dealer's inventory. Similarly, a move from straddling the market spread to posting the highest bid suggests a keenness to buy and therefore implies a negative change in inventory. As before, the magnitude of the change in inventory when the dealer moves from straddling the market spread to either side of the market spread will be smaller than when she moves her quotes from one side of the market spread to the other side.

To test these implications of inventory models, we compute the change in a dealer's ordinary and equivalent inventories, whenever her quote position relative to the market spread undergoes a change (i.e., either when she gets on to the market spread or when she gets off the market spread). We average these changes across all dealers and across all stocks. Table 4 summarizes our findings. For notational convenience, in Table 4 we use the term 'Bid to Ask' to denote the quote transition scenario in which a dealer's quotes are at the bid side of the market spread at the start and then change to being at the ask side of the market spread. The terms Bid to Straddle, Ask to Bid, Ask to Straddle, Straddle to Bid and Straddle to Ask indicate corresponding quote transition scenarios.

We find that dealers' quote changes are strongly related to the changes in their ordinary inventory. The mean change in a dealer's ordinary inventory from Bid to Ask (Ask to Bid) equals 0.138 (-0.129) standard deviations; the same mean change from Bid to Straddle (Ask to Straddle) equals 0.067 (-0.058) standard deviations – both changes being significant. These changes are in the direction predicted by the inventory models. It is important to note that the mean change in inventory when the quotes are moved from Bid to Ask (Ask to Bid) is larger in magnitude compared to when the quotes are moved from Bid to Straddle (Ask to Straddle). This magnitude difference is also consistent with inventory models that predict a monotone relation between quote positions and inventories. Finally, the mean change in a dealer's ordinary inventory from Straddle to Bid and from Straddle to Ask respectively equals 0.027 and -0.018. These mean changes are also consistent with inventory models.

In contrast, we do not observe any consistent and significant relation between changes in dealers' quotes and the changes in either measure of their equivalent inventories (see Table 4 columns three to seven). In fact, none of the quote changes are distinguishable from zero suggesting an absence of any relation between quote changes and either measure of equivalent inventory changes. The disaggregated results for high liquidity stocks and medium liquidity stocks separately (not reported) are also qualitatively very similar: there is a strong relation between quote changes and ordinary inventory changes but not equivalent inventory changes. These findings indicate that dealers care most about their ordinary inventories and position their quotes in a way that reduce the imbalance in their ordinary inventory, rather than total or unhedgeable equivalent inventory. This result is against the predictions of Ho and Stoll (1983) and Froot and Stein (1998) models, but is consistent with the trading behavior of dealers predicted by the decentralized market-making model.

4.3. *Inventories, public order flow execution, and inter-dealer trading*

In theoretical models of competitive dealership markets, dealers with divergent inventories execute buy and sell orders. In this sub-section, we examine the level of ordinary and equivalent inventories of dealers executing public and inter-dealer trades to understand whether dealers with divergent ordinary inventories or dealers with divergent equivalent inventories execute public trades and engage in inter-dealer trades[9]. Since inventory effects are likely to be more pronounced for large-size trades as compared to medium-size or small-size trades, we conduct our analysis separately for different trade-size (small, medium and large) categories. As average trade size differs considerably across stocks (see Table 1), we define small, medium and large trade-size in multiples of the NMS or the normal market size of that stock (defined at 2.5% of the average daily trading volume over the previous year). Consistent with prior research conducted with LSE data, we define trades less than or equal to one NMS to be 'small', trades greater than one NMS but less than three NMS to be 'medium', and trades greater than or equal to three NMS to be 'large'[10].

We examine whether dealers with the most divergent ordinary or equivalent inventory levels execute public orders and engage in inter-dealer trades. In particular, we measure the difference between the (ordinary or equivalent) inventory I_τ^j of the dealer executing the trade τ in stock j and the median $\overline{I_\tau^j}$, at the time of the trade, of the inventory across all dealers making a market in that stock. If (ordinary or equivalent) inventories were relevant for the

[9] In inventory models of dealership markets like Ho and Stoll (1983), inter-dealer trading occurs when dealers choose the certainty of inter-dealer trading in preference to the uncertain probability of a public trade arrival. Recent models like Lyons (1996) and Naik, Neuberger, and Viswanthan (1999) also have similar implications except that, in these models, dealers trade with each other also for informational reasons.

[10] The NMS for each stock is defined by the Exchange, and the dealers are required to post quotes with a quote-depth of one NMS. Three times NMS is an important cutoff from regulation and post-trade disclosure on the LSE (see Gemmill (1996)).

decision making of dealers, the average difference across all trades will not be zero. Our test metric, duly signed to enable aggregation of buy and sell trades, is the distance difference DD_τ^j defined in eq. (3) below. The average of DD_τ^j should be significantly positive if inventories are related to order flow execution.

$$\begin{aligned} DD_\tau^j &= (I_\tau^j - \overline{I}_\tau^j) \ \textit{for a dealer sell trade} \\ DD_\tau^j &= -(I_\tau^j - \overline{I}_\tau^j) \ \textit{for a dealer buy trade} \end{aligned} \qquad \textbf{(3)}$$

Table 5 reports, for public trades and inter-dealer trades separately, the average of the distance difference DD_τ^j for ordinary inventory and for various measures of equivalent inventory. Since relative importance of inventory effects may be a function of liquidity of the stocks, we report our findings separately for high-liquidity (FTSE-100) stocks and medium-liquidity (FTSE-250) stocks. The parentheses contain t-statistics for hypotheses that these average inventory distance differences equal zero.

We find that the ordinary inventory distance differences explain extremely well which dealer executes large-size trades. In particular, across all stocks (see Table 5 top panel) the ordinary inventory of the dealer executing the trade is 0.61 standard deviations (or 0.61σ) away from the median, and this is highly significant statistically (t-statistic of 12.32). The distance is somewhat larger for high liquidity stocks as compared to medium liquidity stocks (0.74σ as opposed to 0.56σ), however the difference is not statistically significant. The results with inter-dealer trades are similar. Dealers with ordinary inventories that deviate from the median by about 0.42σ trade with each other and this is highly significant statistically (t-statistic 7.79). For high liquidity stocks the distance equals 0.39σ while for medium liquidity stocks it equals 0.45σ. The results for medium-size trades are also qualitatively similar to those for large-size trades with the magnitude of the inventory distance being somewhat smaller, 0.24σ for public trades (t-statistic of 14.03) and 0.37σ for inter-dealer trades (t-statistic of 15.59). These findings indicate that dealers with divergent ordinary inventory execute large and medium public trades and inter-dealer trades.

The results for small inter-dealer trades are also qualitatively similar, dealers with ordinary inventories that deviate from the median by about 0.23σ trade with each other (t-statistic 22.92). The average ordinary inventory distance of the dealer executing small public trades is considerably smaller compared to that for small inter-dealer trades (0.03σ vis-à-vis 0.23σ), yet it also continues to be positive and statistically significant. The average distance difference for small trades is small in magnitude potentially because dealers have to often execute retail public trades irrespective of the level of their inventory due to the institutional practice of order flow preferencing and for the sake of maintaining customer relationships. Many market-makers are linked with specific retail service providers and brokers, and (for trades up to one NMS in size) are obliged to execute the trades sent by them at the best system prices, irrespective of their own quotes and their inventories underlying these quotes. These obligations and practices do not extend to inter-dealer trades. Even though the magnitude of average ordinary inventory distance is small for small public trades, the findings for small-size trades are consistent with the findings with medium and large trades, and indicate very strongly that dealers with divergent ordinary inventory execute public trades and engage in inter-dealer trades.

In sharp contrast to the results for ordinary inventory, the average of the inventory distances are not significantly greater than zero at the five percent level either for public trades or for inter-dealer trades using either the total or unhedgeable, firm-wide or industry-desk based equivalent inventory measures. Similarly, the results are not significantly different from zero either for high liquidity stocks or for medium liquidity stocks and for large, medium and small trades. Occasionally, the distance difference turns out to be statistically significant at the ten percent level but it is of a sign opposite to that predicted by theoretical models. These results suggest the absence of any relationship between trade execution and either measure of the dealer's equivalent inventory.

Overall, the findings in Table 5 provide clear evidence that public trades and inter-dealer trades, irrespective of the size of the trade and the liquidity of the stocks, are executed by dealers with divergent ordinary inventories, and not by dealers with divergent total or unhedgeable, firm-wide or industry-desk based equivalent inventories. These findings strongly reject the predictions of Ho and Stoll (1983) and Froot and Stein (1998) models, but are consistent with the predictions of the decentralized market-making model where what dealers care most about is the ordinary inventory of the individual stock.

4.4. Inventories and quality of execution

In inventory models of dealership market like Amihud and Mendelson (1980), Ho and Stoll (1983), and Biais (1993), a dealer's reservation prices to buy or sell are a monotone function of her inventory. If inventory considerations are important, one would expect these to be reflected in the quality of execution offered to a trade i.e., effective spread charged by the dealer executing the trade. We define the Effective Spread ES_τ charged for trade τ in relation to the prevailing mid-price defined as the average of the best bid and the best ask price. Hence, for a public buy (i.e. dealer sell) trade:

$$ES_\tau = \frac{(Transaction\ Price_\tau - MidPrice_\tau)}{MidPrice_\tau} \qquad \textbf{(4a)}$$

And for a public sell (ie dealer buy) trade:

$$ES_\tau = -\frac{(Transaction\ Price_\tau - MidPrice_\tau)}{MidPrice_\tau} \qquad \textbf{(4b)}$$

The results of Hansch et. al. (1999) indicate that the effective spread charged is a function of stock specific factors, the inside spread, and on whether the particular trade was preferenced, and whether it was internalised[11]. There is also documented evidence that the temporary price impact of large public buys is significantly different from that of large public sells (e.g. Keim and Madhavan, 1996), and this can arguably cause dealers to behave differently when they sell compared to when they buy. Hence, we run the following regression separately for public-buys and for public-sells using all measures of equivalent inventory:

$$ES_\tau = \sum_{i=1}^{20} \gamma_j D_{j,\tau} + \delta_1 OI_\tau + \delta_2 EI_\tau + \delta_3 Inside\,Spread_\tau + \delta_4 PI_\tau + \delta_5 PNI_\tau + \delta_6 NPI_\tau + \xi_\tau \qquad \textbf{(5)}$$

where D_j *(j=1, 2, ...20)* are stock specific dummy variables which take value of one for that stock and zero otherwise, γ_j *(j=1, 2, ... 20)* are stock specific intercept terms; OI_τ and EI_τ are respectively the ordinary inventory level and the equivalent inventory level of the dealer executing that trade a second before the trade; $InsideSpread_\tau$ is the inside spread at the time of the trade (defined as best ask minus best bid divided by the mid-price); PI_τ is a dummy variable for Preferenced & Internalized trades, PNI_τ is a dummy variable for Preferenced & Non-Internalized trades, NPI_τ is a dummy variable for Non-Preferenced & Internalized trades, and ξ_τ is a white noise error term[12].

According to inventory models of dealership markets, the greater the inventory of a dealer, the keener she is to sell, and the lower will be the effective spread she will charge to a public-buy (i.e. dealer-sell) trade and the larger would be the effective spread she will charge

[11] A public-buy (public-sell) trade is preferenced when it is executed by a dealer not posting the lowest ask (highest bid) price. A public trades is internalized if the broker firm is the same as the dealer firm.

[12] In the context of the quality of execution, the mid-nineties have seen a major controversy over quote-clustering and collusion by dealers on the NASDAQ (Christie and Schultz, 1994, Christie, Harris, and Schultz, 1995, and Barclay, 1997), a problem that was alleviated after the 1997 market reforms (described in Barclay, Christie, Harris, Kandel, and Schultz, 1999). Quote clustering does not appear to have been a problem on the

to a public-sell (i.e. dealer-buy) trade. This should translate into a negative (positive) slope coefficient on inventory in the regression in eq. (5) for public-buy (public-sell) trades.

Table 6 reports the results of running the regressions of eq. (5) for public trades, with ordinary inventory and either total or unhedgeable, firm-wide or industry-desk based equivalent inventory, one at a time. The results are reported separately for large, medium and small public trades. In all cases, ordinary inventories have significant explanatory power for public-sell trades. Consistent with expectation, dealers charge, based on their ordinary inventories, a significantly higher (p-value << 0.01) effective spread. For large and medium trades, they charge about twenty basis points more for a divergence of one standard deviation of ordinary inventory, and for small trades, they charge about four basis points more on average. In contrast, most of the equivalent inventory measures do not have significant explanatory power. The regression coefficients on the equivalent inventory measures are not significantly different from zero (p-values >> 0.1) except for industry-desk based total and unhedgeable equivalent inventory in the set of medium size trades.

For public-buy trades, the effective spread charged depends significantly on ordinary inventories in a direction consistent with the inventory models only for large trades, and even for these trades the dependence is significant only at marginal significance levels (p-value about 0.1). For large public buy trades, dealers charge (based on their ordinary inventories) a marginally significantly lower effective spread of about ten basis points for a divergence of one standard deviation of ordinary inventory. In contrast, the effective spread charged to large public-buy trades does not depend significantly on any of the equivalent inventory measures.

For medium and small public buy trades, the effective spread charged does not depend significantly on any inventory measure, neither ordinary inventory nor any of the equivalent

---

LSE, at least during the sample period (see Naik and Yadav, 2000).

inventories.

The strong and significant dependence of the quality of execution of public sell trades on ordinary inventory is being documented for the first time in the empirical market microstructure literature. However, what is more important from the perspective of this paper is that the equivalent inventory measures do not have significant explanatory power in these regressions. This suggests that the relative keenness of the dealers to execute (at least) public (sell) trades is consistent with their desire to reduce the divergence of their ordinary inventories rather than that of either measure of their equivalent inventory. These results, once again, reject the predictions of Ho and Stoll (1983) and Froot and Stein (1998) models but are consistent with the predictions of decentralized market-making model where individual dealers care the most about their own ordinary inventory risk exposure.

The above analysis focuses on public trades. Ordinarily, a similar relation should hold with inter-dealer trades as well. However, there are well-established pricing norms followed on the LSE for inter-dealer trades, and these norms are likely to result in effective spreads charged in inter-dealer trades not being dependent at all on inventory. On the LSE, there are two types of inter-dealer trades. First, trades are executed anonymously through an order-matching system called the *Inter-Dealer Broker* (IDB) system. And second, trades are executed non-anonymously through telephone negotiations. The anonymous inter-dealer trades are executed at or very close to mid-quote prices (plus a commission cost) while the non-anonymous inter-dealer trades are executed either at the best bid or at the best ask price (see Reiss and Werner, 1997 for details). Hence, the effective spread charged to anonymous inter-dealer trades is generally zero while that charged for non-anonymous trades is generally half of the prevailing inside spread. These pricing norms do not allow dealers much flexibility in setting effective spreads, and therefore, effective spreads charged to inter-dealer trades on the LSE need not depend significantly on inventory and may not help in shedding light on the dealer behavior predicted by different models. Consistent with this expectation, when we run the regression in eq. (5) with inter-dealer trades, we fail to find a relation (not reported) between effective spreads charged in inter-dealer trades and any inventory measure.

5. Robustness checks

In section 4, we document strong results that the risk exposures arising from positions in correlated stocks is not an important determinant of trading behavior of dealers in individual stocks. In this section, we examine the robustness of our results to potential measurement errors in several ways.

First, we investigate whether the perceived absence of portfolio effects is driven by poor measurement. The most common manifestation of poor measurement is inadequate statistical resolution. However, in our case, the results are statistically very strong. The coefficients on ordinary inventory are consistently large in magnitude, of the same sign and statistically highly significant, while those on equivalent inventory measures are consistently very small in magnitude, often of varying sign, and statistically totally insignificant. It is true that the fact that a parameter estimate is not significantly different from zero for equivalent inventories is not a proof that the underlying parameter is in fact zero. However, the t-statistics are consistently so close to zero that is difficult to dispute the inference that the parameter is virtually zero, at least from an economic standpoint.

Second, we repeat our empirical analyses using inventory levels instead of relative inventories. Hence, we test whether public and inter-dealer trades are executed by dealers with negative (positive) inventory levels. Similarly, we test whether ordinary and equivalent inventory levels influence the quality of execution. We find that only ordinary inventory levels continue to explain dealers' trading behavior.

Third, we re-calculate the equivalent inventory measures by summing the second term in eq. (1) over just those stocks for which the $\beta_{j,k}$ are significantly different from zero. Once again, we find that the results are virtually identical. In the same vein, we test the robustness of the conclusion to the way we estimate $\beta_{j,k}$ in eq. (1). Our earlier analysis estimated the $\beta_{j,k}$ *ex-ante* using historical returns. So, we re-run the analyses using equivalent inventories calculated on the basis of a perfect foresight $\beta_{j,k}$ estimated using in-sample returns. Once again, we find that only ordinary inventories are important determinants of dealers' trading behavior.

Fourth, in addition to our parametric test examining inventory distance of dealers executing public and inter-dealers trades (Table 5), we also conduct a non-parametric test based on ranks where in we compare the rank of the dealer executing the trade with that of the median rank. We find that dealers with divergent ordinary inventory ranks, and not divergent equivalent inventory ranks, execute public and inter-dealer trades.

Fifth, six stocks in our sample (Asda Group, Land Securities, NatWest Bank, Enterprise Oil, Wellcome and WPP Group) either have ADR's listed on them on the NYSE and the NASDAQ, or have options listed on them on the London Traded Options Market, or both. This can potentially contaminate inventory measurement. Therefore, we repeat our analyses excluding these stocks and find qualitatively similar results.

Finally, we examine whether our results are being driven by stocks with relatively low levels of dependence on the systematic factors that arguably generate correlations between pairs of individual stocks. We expect the importance of portfolio effects to depend on the R^2 of the regression of the return of each of our sample stocks on systematic risk factors. We proxy this by the R^2 of the regression on the main factor, i.e. market returns. Table 1 shows that, within our sample, the highest explanatory power of market returns is for NatWest Bank (63%), Spirax-Sarco Engineering (56%), and Land Securities (51%). We accordingly re-run our analyses for each of the twenty sample stocks separately. The results for NatWest Bank, Spirax-Sarco Engineering, and Land Securities are each qualitatively identical to the results for the whole sample. In particular, ordinary inventories, and not equivalent inventories (whether total or unhedgeable and whether firm-wide or industry-desk based) best explain the trading behavior of dealers.

6. Concluding remarks

In this paper, we investigate, for the first time, the importance of correlated exposures in the trading and pricing decisions of financial intermediaries. We compute the ordinary inventory positions of London equity dealers across all stocks using a particularly rich transactions dataset from the LSE. Following Ho and Stoll (1983), and Froot and Stein (1998) respectively, we also construct dealers' total equivalent inventories and unhedgeable equivalent inventories in each individual stock, based on dependence between total returns and market-filtered returns. We examine whether the trading and pricing decisions of these dealers in individual stocks are more closely related to their ordinary inventory of that stock, or to either measure of their equivalent inventory. We construct equivalent inventory in two ways: one based on centralized market-making structure that aggregates correlated risk exposures across all stocks and the other based on an industry-desk based organisational structure that aggregates correlated risk exposures across stocks belonging to the same industry.

We find strong evidence that the decision-making of dealers is governed by their ordinary inventories, and not by either of their equivalent inventories. In particular, we find that dealers' ordinary inventories revert significantly more rapidly to the mean compared to either measure of their equivalent inventories. We observe that a dealer's quote changes are significantly related to her ordinary inventory changes and not to either measure of her equivalent inventory changes. We find that the dealers with divergent ordinary inventories, rather than divergent equivalent inventories, execute public trades and engage in inter-dealer trades. Finally, we find that dealers offer significantly better quality of execution to trades that reduce the divergence of ordinary inventories rather than trades that reduce the divergence of either measure of their equivalent inventories. Furthermore, these findings are robust to several alternative specifications.

Our findings strongly reject the predictions of the Ho and Stoll (1983) model and the Froot and Stein (1998) model. However, they are consistent with the decentralised organisation of dealer firms, where the market-making function is delegated to a large number of individual dealers. In such a decentralized framework, due to difficulties in sharing information across individual dealers, and/or the nature of their incentive contracts, individual dealers care only about the inventory risk exposures of the stocks they manage rather than worrying about the risk exposures in correlated stocks of other individual dealers within the firm. In particular, their trading behavior is driven by the risk contributed by individual stock inventories and not by any measure of their equivalent inventories.

It is important to note that our finding of the lack of active ex ante risk management (based on reinforcing or off-setting effects from correlated stocks) does not preclude ex post risk management at the centralized firm level. The firm can certainly hedge (at periodic intervals) the market risk of its portfolio with suitable futures contracts. Our results show that, such centralized risk management, to the extent it exists, does not affect the trading behavior of the dealer firm in individual stocks.

So we come back to the question we asked at the beginning of this article: "*If I am long one million dollars in GM, and I am short one million dollars in Ford, am I still long one million dollars in GM?*". The answer seems to be, "*Yes, I behave as if I am still long one million dollars in GM, (and short one million dollars in Ford)*".

REFERENCES

Amihud, Y., Mendelson, H., 1980, Dealership markets: Market making with inventory, Journal of Financial Economics 8, 31-53.

Barclay, M. J., 1997, Bid-Ask Spreads and the avoidance of odd-eighth quotes on NASDAQ: An examination of exchange listings, Journal of Financial Economics 45, 35-60.

Barclay, M. J., Christie, W. G., Harris, J. H., Kandel, E., Schultz, P. H., 1999, The Effects of Market Reform on the Trading Costs and Depths of NASDAQ stocks, Journal of Finance 54, 1-34.

Barclay, M. J., Warner, J. B., 1993, Stealth trading and volatility: Which trades move prices? Journal of Financial Economics 34, 281-306.

Biais, B., 1993, Price Formation and Equilibrium Liquidity in Fragmented and Centralized Markets,' Journal of Finance 48, 157-186.

Board, J., Sutcliffe, C., 1995, The effects of trade transparency in the London Stock Exchange: A summary, Unpublished working paper, London School of Economics.

Board, J., Fremault Vila, A., Sutcliffe, C., 1996, Market maker heterogeneity and order preferencing: Evidence from the London Stock Exchange, Unpublished working paper, London School of Economics.

Chan, K., Christie, W., Schultz, P., 1995, Market structure and the intra day pattern of bid ask spreads for NASDAQ securities, Journal of Business 68, 35-60.

Christie, W., Schultz, P., 1994, Why do NASDAQ market makers avoid odd-eighth quotes? Journal of Finance 49, 1813-1840.

Christie, W., Harris, J., Schultz, P., 1994, Why did NASDAQ market makers stop avoiding odd-eighth quotes? Journal of Finance 49, 1841-1860.

Ellis, K., Michaely, R., O'Hara, M., 1999, The making of a dealer market: From entry to equilibrium in the trading of NASDAQ stocks, Unpublished working paper, Cornell University.

Froot K., Stein, J., 1998, Risk Management, Capital Budgeting and Capital Structure Policy for Financial Institutions: an integrated approach, Journal of Financial Economics 47, 55-82.

Gemmill, G., 1996, Transparency and liquidity: A study of block trading on the London Stock Exchange under different trading rules, Journal of Finance 51, 1765-1790.

Hansch, O., Naik, N. Y., Viswanathan, S., 1998, Do Inventories Matter in Dealership Markets? Evidence from the London Stock Exchange, Journal of Finance 53, 1623-55.

Hansch, O., Naik, N. Y., Viswanathan, S., 1999, Preferencing, internalization, best execution and dealer profits, Journal of Finance 54, 1799-1828.

Hansch, O., Neuberger, A., 1996, Strategic trading by market makers on the London Stock Exchange, Unpublished working paper No 224-1996, London Business School.

Hasbrouck, J., Sofianos, G., 1993, The trades of market-makers: An analysis of NYSE specialists, Journal of Finance 48, 1565-1594.

Hillier, D. J., Naik, N. Y., Yadav, P. K., 1999a, Inventory control of dealers around known information events: An empirical analysis of earnings announcements, Unpublished working paper, London Business School and University of Strathclyde.

Hillier, D. J., Naik, N. Y., Yadav, P. K., 1999b, Dealer Inventory control when insiders trade, Unpublished working paper, London Business School and University of Strathclyde.

Ho, T., Stoll, H., 1983, The dynamics of dealer markets under competition, Journal of Finance 38, 1053-1074.

Keim, D., Madhavan, A., 1996, The Upstairs Market for Large-Block Transactions: Analysis and Measurement of Price Effects, Review of Financial Studies 9, 1-36.

Lyons, R., 1995, Tests of microstructure hypotheses in the foreign exchange market, Journal of Financial Economics 39, 1-31.

Lyons, R., 1996, Optimal transparency in a dealership market with an application to foreign exchange, Journal of Financial Intermediation 5, 225-256.

Madhavan, A., Smidt, S., 1993, An analysis of daily changes in specialist inventories and quotations, Journal of Finance 48, 1595-1628.

Madhavan, A., Sofianos, G., 1998, An empirical analysis of NYSE specialist trading, Journal of Financial Economics 48, 189-210.

Mann, S., Manaster, S., 1996, Life in the pits: Competitive market making and inventory control, Review of Financial Studies 9, 953-975.

Naik, N. Y., Neuberger, A., Viswanathan, S., 1999, Trade disclosure regulation in markets, Review of Financial Studies 12, 873-900.

Naik, N. Y., Yadav, P. K., 1999, Execution costs and order flow characteristics in dealership markets: Evidence from the London Stock Exchange, Unpublished working paper, London Business School and University of Strathclyde.

Naik, N. Y., Yadav, P. K., 2000, Trading costs of public investors in auction and dealership markets: Evidence from London Stock Exchange reforms, Unpublished working paper, London Business School and University of Strathclyde.

Neuberger, A., 1992, An empirical examination of market maker profits on the London Stock Exchange, Journal of Financial Services Research 6, 343-372.

Reiss, P., Werner, I., 1994, Transaction costs in dealer markets: Evidence from the London Stock Exchange, in Andrew Lo Ed, The Industrial Organization and Regulation of the Securities Industry, University of Chicago Press, 125-176.

Reiss, P., Werner, I., 1997, Friend or foe? The pricing of London inter-dealer trades, Unpublished working paper, Stanford Business School.

Reiss, P., Werner, I., 1998, Does risk sharing motivate inter-dealer trading? Journal of Finance 53, 1657-1704.

Snell, A., Tonks, I., 1995, Determinants of price quote revisions on the London Stock Exchange, Economic Journal 105, 77-94.

Snell, A., Tonks, I., 1998, Testing for asymmetric information and inventory control effects in market maker behaviour on the London Stock Exchange, Journal of Empirical Finance 5, 1-25.

Appendix Construction of ordinary and equivalent inventory series

We construct the inventory series of different dealers along the lines of Hansch, Naik and Viswanathan (1998) reproduced here for ready reference. Let $Q_{i,t}^{j}$ denote the level of ordinary inventory of dealer i in stock j at time t. Following this convention, we denote the inventory at the start of the sample period as (t = 0) as $Q_{i,0}^{j}$. Although this starting inventory is not observable by us, we show below that the standardized inventories we use in our empirical tests do not depend on the initial inventory level.

In every stock, we consider all trades, public as well as inter-dealer, which dealer i executes in her capacity as a principal. We define $q_{i,t}^{j}$ as positive (negative) when dealer i buys (sells) a quantity q of stock j. We further define $Q_{i,t}^{j} = Q_{i,0}^{j} + \Sigma_{s=1}^{s=t} q_{i,s}^{j}$ 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

$$
\begin{aligned}
\overline{Q_i^j} &= \frac{\sum_{s-0}^{s=T} Q_{i,s}^{j}}{T+1} \\
&= \frac{\sum_{s=0}^{s=t} Q_{i,0}^{j} + \sum_{s=1}^{s=t}\left(\sum_{r=1}^{r=s} q_{i,r}^{j}\right)}{T+1} \\
&= \sum_{s=0}^{s=t} Q_{i,0}^{j} + \frac{1}{T+1}\sum_{s=1}^{s=T}\left(\sum_{r=1}^{r=s} q_{i,r}^{j}\right)
\end{aligned}
$$

and sample standard deviation (S_i^j).

Because market makers differ in terms of their risk aversion or capitalization, their inventories cannot be compared with each other directly. We control for differences in risk aversion by standardizing their inventories (i.e. subtracting the sample mean and dividing it by the sample standard deviation of the inventory series. We define $I_{i,t}^{j}$ the *standardized* ordinary inventory of dealer *i* in stock *j* at time *t* as

$$
\begin{aligned}
I_{i,t}^{j} &= \frac{Q_{i,t}^{j} - \overline{Q}_{i}^{j}}{S_{i}^{j}} \\
&= \frac{Q_{i,0}^{j} + \sum_{s=1}^{s=t} q_{i,s}^{j} - Q_{i,0}^{j} - \frac{1}{T+1}\sum_{s=1}^{s=T}\left(\sum_{r=1}^{r=s} q_{i,r}^{j}\right)}{S_{i}^{j}} \\
&= \frac{\sum_{s=1}^{s=t} q_{i,s}^{j} - \frac{1}{T+1}\sum_{s=1}^{s=T}\left(\sum_{r=1}^{r=s} q_{i,r}^{j}\right)}{S_{i}^{j}}
\end{aligned}
$$

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

Since our dataset identifies each of the dealers across different stocks, we use this information to create the equivalent inventory series for each dealer in each of our twenty sample stocks. Due to differences in the price per share of different stocks, we convert the ordinary inventory values in Pound Sterling using the contemporaneous inside spread mid-price P_{t}^{j} in stock *j* at time *t* before constructing an equivalent inventory series. For each of our sample stocks, we compute the equivalent inventory level of dealer *i* in stock *j* at time *t* as

$$EQ_{i,t}^{j} = Q_{i,t}^{j} P_{t}^{j} + \sum_{k=1,k\neq j}^{k=1853} \beta_{j,k} Q_{k,t}^{j} P_{t}^{k}$$

where $\beta_{j,k}$ is the regression coefficient capturing the dependence of the return of stock *k* on that of stock *j*, $\beta_{j,k} = \frac{COV(R_j, R_k)}{VAR(R_j)}$. Similar to ordinary inventory construction, we define the standardized equivalent inventory of dealer *i* in stock *j* at time *t* as

$$EI_{i,t}^{j} = \frac{EQ_{i,t}^{j} - \overline{EQ_{i}^{j}}}{SE_{i}^{j}}$$

where $\overline{EQ_{i}^{j}}$ and SE_{i}^{j} are the mean and standard deviation of the equivalent inventory series of dealer i in stock *j*.

Table 1 Descriptive statistics of sample stocks

This table provides important descriptive statistics of the twenty sample stocks. Total Turnover equals the average daily Pound Sterling value of public and inter-dealer trades over the sample period. Public Turnover equals the average daily Pound Sterling value of public trades over the sample period. Daily public trades are the average number of public trades (excluding inter-dealer trades) per day. # of dealers is the number of market makers in each stock. Avg. inside spread is measured as a percentage of inside spread mid-point and are reported in basis points (bp). Avg. $\beta_{j,k}$ reports the average of the regression coefficients used in the construction of the respective equivalent inventory. # of stocks indicate the number of stocks in the industry the sample stock belongs to. Market model R-square reports the R-square when return of the sample stock is regressed on the FTSE All Share index.

Name of the Stock	Total Turnovr £000's	Public Turnovr £000's	Daily Public Trades	# of dealers	Avg. Inside Spread	Avg. $\beta_{j,k}$ TEI_FW	Avg. $\beta_{j,k}$ UEI_FW	Avg. $\beta_{j,k}$ TEI_ID	Avg. $\beta_{j,k}$ UEI_ID	# of Stocks	Market model R-square
High liquidity stocks											
NatWest Bank	30057	16257	172	15	59	0.29	0.45	0.44	0.16	9	62.5%
ASDA Group	12870	6399	68	15	67	0.25	0.38	0.23	0.13	16	12.2%
De La Rue	12047	6733	76	13	67	0.57	0.49	0.19	0.18	7	36.9%
Enterprise Oil	8896	4926	46	13	96	0.38	0.34	0.15	0.11	14	30.8%
North West Water	8295	7367	21	9	238	0.24	0.45	0.44	0.43	11	30.9%
Sun Alliance	7427	5030	19	14	94	0.29	0.37	0.34	0.22	8	49.5%
Wellcome	6468	4143	121	14	173	0.24	0.29	0.17	0.13	10	13.1%
AAH	5230	3383	94	9	55	0.48	0.41	0.21	0.20	21	37.0%
APV	5200	3719	47	10	61	0.15	0.14	0.03	0.02	7	47.5%
BUNZL	4940	2851	29	12	61	0.34	0.38	0.10	0.10	6	47.4%
Medium liquidity stocks											
FKI	4502	2992	42	12	140	0.37	0.32	0.32	0.14	14	37.2%
London & Manchester	4322	2924	21	8	92	0.41	0.46	0.17	0.15	39	33.0%
Spirax-Sarco Engg.	2381	1856	10	8	150	0.86	0.89	0.33	0.32	8	55.7%
Wassall	2068	1488	14	8	98	0.37	0.27	0.19	0.10	23	28.1%
Land Securities	1668	997	20	8	216	0.41	0.58	0.16	0.15	22	50.6%
Guardian Royal Exchange	1189	973	10	6	113	0.26	0.28	0.10	0.08	22	35.8%
RMC Group	889	656	9	7	118	0.43	0.49	0.09	0.10	21	42.6%
First Leisure Corp	661	556	4	7	99	0.68	0.73	0.29	0.29	9	41.5%
T & N	559	542	4	5	75	0.23	0.22	0.17	0.16	8	41.4%
WPP Group	439	331	7	5	117	0.19	0.28	0.05	0.03	6	4.3%

Table 2 Mean reversion in ordinary and equivalent inventories

This table reports the results of the regression

$$\Delta I_t = \alpha + \phi_1 D^1 I_{t-1} + \phi_2 D^2 I_{t-1} + \phi_3 D^3 I_{t-1} + \phi_4 D^4 I_{t-1} + \phi_5 D^5 I_{t-1} + \psi_t$$

where $D^l (l = 1, 2, .., 5)$ are dummy variables that equal 1 if the relative inventory lies within or beyond a given number of standard deviations (σ), D^1 = *1* if $I_{t-1} \geq 2\sigma$, otherwise zero; D^2 = 1 if $2\sigma > I_{t-1} \geq \sigma$, otherwise zero; D^3 = *1* if $\sigma > I_{t-1} > -\sigma$, otherwise zero; D^4 = *1* if $-\sigma \geq I_{t-1} > -2\sigma$, otherwise zero, and D^5 = *1* if $-2\sigma > I_{t-1}$, otherwise zero, $\phi_l (l = 1, 2, .., 5)$ represents the intensity of mean reversion which depends on the relative inventory level, and ψ_t is a white noise error term.

Mean Reversion Coefficients	Ordinary Inventory OI	Total Equiv. Inventory Firm-Wide TEI_FW	Total Equiv. Inventory Industry-Desk TEI_ID	Unhedgeable Equiv. Inv. Firm-Wide UEI_FW	Unhedgeable Equiv. Inv. Industry-Desk UEI_ID	OI minus TEI_FW	OI minus TEI_ID	OI minus UEI_FW	OI minus UEI_ID
Inventory level is greater than or equal to two standard deviations									
High &Med. Liquidity stocks	**-0.561** (-53.28)	**-0.490** (-50.30)	**-0.301** (-24.99)	**-0.326** (-38.22)	**-0.343** (-27.50)	**-0.072** (-5.00)	**-0.261** (-16.31)	**-0.235** (-17.37)	**-0.219** (-13.40)
Inventory level greater than or equal to one standard deviation but less than two standard deviations									
High &Med. Liquidity stocks	**-0.214** (-21.75)	**-0.160** (-17.56)	**-0.162** (-22.89)	**-0.204** (-23.15)	**-0.187** (-22.18)	**-0.053** (-3.96)	**-0.051** (-4.25)	-0.009 (-0.71)	**-0.027** (-2.05)
Inventory level lying between plus one to minus one standard deviations									
High &Med. Liquidity stocks	**-0.151** (-16.79)	**-0.122** (-14.09)	**-0.106** (-16.10)	**-0.124** (-14.69)	**-0.143** (-17.71)	**-0.029** (-2.31)	**-0.045** (-4.03)	**-0.027** (-2.22)	-0.009 (-0.72)
Inventory level less than or equal to minus one standard deviation but greater than minus two standard deviations									
High &Med. Liquidity stocks	**-0.234** (-24.81)	**-0.188** (-20.74)	**-0.165** (-23.03)	**-0.156** (-18.11)	**-0.199** (-23.77)	**-0.046** (-3.50)	**-0.069** (-5.82)	**-0.078** (-6.11)	**-0.035** (-2.78)
Inventory level is less than or equal to minus two standard deviations									
High &Med. Liquidity stocks	**-0.548** (-41.17)	**-0.392** (-31.86)	**-0.360** (-26.07)	**-0.361** (-26.67)	**-0.471** (-41.30)	**-0.155** (-8.58)	**-0.188** (-9.79)	**-0.187** (-9.83)	**-0.077** (-4.37)

Table 3 Quote changes and expected inventory changes

This table summarizes the six quote change possibilities and the associated inventory changes. *Ask* denotes a quote equal to the lowest ask, *Bid* denotes a quote equal to the highest bid, *Straddle* denotes a straddling position, i.e., neither quote is competitive. Since we are analyzing quote changes, the three diagonal cells state 'not applicable' indicating that these cells do not pertain to any *change* in quote position.

Inventory change associated with quote change			
Quote Change	To Bid	To Ask	To Straddle
From Bid	Not Applicable	Large Positive	Small Positive
From Ask	Large Negative	Not Applicable	Small Negative
From Straddle	Small Negative	Small Positive	Not Applicable

Table 4 Quote changes and actual inventory changes

This table shows quote changes and the associated changes in the dealers' standardized ordinary and different measures of equivalent inventories. *Ask* denotes a quote equal to the lowest ask quote, *Bid* denotes a quote equal to the highest bid quote, *Straddle* denotes a straddling position, i.e., neither quote is competitive. Figures are in units of standard deviations of dealers' standardized inventories. Figures in bold face (italics) indicates that the values are significant at five (ten) percent level.

Quote Change From	**Ordinary Inventory OI**	**Total Equiv. Inventory Firm-Wide TEI_FW**	**Total Equiv. Inventory Industry-Desk TEI_ID**	**Unhedgeable Equiv. Inv. Firm-Wide UEI_FW**	**Unhedgeable Equiv. Inv. Industry-Desk UEI_ID**
Bid to Ask	**0.138**	-0.013	0.043	-0.01	-0.005
	(7.24)	(-0.21)	(0.98)	(-1.3)	(-0.87)
Bid to Straddle	**0.067**	-0.014	-0.02	0.00	0.003
	(3.78)	(-0.81)	(-0.15)	(0.22)	(0.28)
Ask to Bid	**-0.129**	-0.035	0.00	-0.00	0.01
	(-6.86)	(-0.61)	(0.24)	(-0.15)	(0.43)
Ask to Straddle	**-0.058**	0.036	0.02	0.00	-0.00
	(-4.41)	(0.19)	(0.19)	(0.37)	(-0.18)
Straddle to Bid	**0.027**	-0.021	0.00	-0.00	0.001
	(1.98)	(-0.69)	(0.23)	(-0.13)	(0.45)
Straddle to Ask	*-0.018*	0.043	0.00	0.01	-0.001
	(-1.69)	(0.42)	(0.32)	(0.27)	(-0.48)

Table 5 Inventory and trade execution

This table reports the mean difference of standardized inventories between the dealer executing the trade and the median market maker, together with corresponding t-statistics. It reports the results separately for public trades and for inter-dealer trades, and within each category, it reports the mean difference separately for for large-size trades (trades greater than or equal to three NMS), medium-size trades (trades greater than one NMS but less than three NMS) and small-size trades (trades less than or equal to one NMS).

Inventory Distance Difference DD_τ^j with	Public trades					Inter-dealer trades				
	Ordinary Inventory OI	**TotalEquiv Inventory FirmWide TEI_FW**	**Total Equiv. Inventory IndustryDesk TEI_ID**	**Unhedgeable Equiv. Inv. Firm Wide UEI_FW**	**Unhedgeable Equiv. Inv. IndustryDesk UEI_ID**	**Ordinary Inventory OI**	**TotalEquiv Inventory FirmWide TEI_FW**	**Total Equiv. Inventory IndustryDesk TEI_ID**	**Unhedgeable Equiv. Inv. Firm Wide UEI_FW**	**Unhedgeable Equiv. Inv. IndustryDesk UEI_ID**
	Large-size public trades					**Large-size inter-dealer trades**				
High Liquidity	**0.74** (8.32)	0.06 (0.86)	-0.03 (-0.74)	0.04 (0.71)	0.05 (0.90)	**0.39** (4.55)	0.03 (0.53)	0.06 (1.44)	-0.02 (-0.36)	-0.06 (-1.12)
Medium Liquidity	**0.56** (9.39)	-0.04 (-0.98)	-0.01 (0.12)	-0.01 (-0.21)	0.07 (0.44)	**0.45** (6.37)	-0.05 (-0.84)	-0.06 (-1.19)	0.03 (0.61)	0.02 (0.52)
All Stocks	**0.61** (12.32)	0.01 (0.32)	-0.02 (-0.41)	0.01 (0.19)	0.03 (0.84)	**0.42** (7.79)	-0.02 (-0.38)	0.01 (0.23)	0.00 (0.21)	-0.01 (-0.31)
	Medium-size public trades					**Medium-size inter-dealer trades**				
High Liquidity	**0.25** (12.07)	-0.01 (-0.60)	0.00 (0.38)	0.00 (0.02)	0.02 (0.89)	**0.41** (14.43)	0.03 (1.37)	-0.02 (-1.12)	-0.03 (-1.45)	0.02 (0.85)
Medium Liquidity	**0.22** (7.17)	0.01 (0.37)	0.05 (1.66)	0.08 (2.91)	0.00 (0.27)	**0.27** (6.26)	0.02 (0.40)	-0.11 (-3.23)	-0.05 (-1.43)	0.03 (0.83)
All Stocks	**0.24** (14.03)	-0.00 (-0.27)	0.02 (1.45)	0.03 (1.62)	0.01 (0.90)	**0.37** (15.59)	0.03 (1.35)	-0.04 (-2.86)	-0.04 (-1.16)	0.02 (1.16)
	Small-size public trades					**Small-size inter-dealer trades**				
High Liquidity	**0.02** (3.29)	0.00 (0.55)	0.00 (0.25)	-0.00 (-0.25)	-0.00 (0.93)	**0.25** (23.79)	-0.02 (-1.79)	-0.00 (-0.83)	-0.02 (-2.21)	-0.02 (-2.10)
Medium Liquidity	**0.05** (3.95)	0.01 (0.98)	-0.02 (-1.16)	-0.03 (-1.16)	-0.00 (-0.14)	**0.06** (2.13)	-0.01 (0.58)	-0.06 (-2.97)	-0.05 (-2.26)	-0.00 (-0.27)
All Stocks	**0.03** (4.44)	0.00 (0.86)	-0.01 (-0.96)	0.01 (0.96)	-0.00 (-0.92)	**0.23** (22.92)	-0.01 (-1.87)	-0.02 (-2.05)	-0.03 (-2.84)	-0.01 (-2.07)

Table 6 Inventories and effective spreads

This table reports the results of the following regression for public trades τ :

$$ES_\tau = \sum_{i=1}^{20} \gamma_j D_{j,\tau} + \delta_1 OI_\tau + \delta_2 EI_\tau + \delta_3 InsideSpread_\tau + \delta_4 PI_\tau + \delta_5 PNI_\tau + \delta_6 NPI_\tau + \xi_\tau$$

where D_j *(j=1, 2, ...20)* are stock specific dummy variables which take value of one for that stock and zero otherwise, γ_j *(j=1, 2, ... 20)* are stock specific intercept terms; OI_τ and EI_τ are respectively the ordinary inventory level and the equivalent inventory level of the dealer executing that public trade a second before the trade; $InsideSpread_\tau$ is the inside spread at the time of the public trade (defined as best ask minus best bid divided by the mid-price); PI_τ is a dummy variable for Preferenced & Internalized trades, PNI_τ is a dummy variable for Preferenced & Non-Internalized trades, NPI_τ is a dummy variable for Non-Preferenced & Internalized trades, and ξ_τ is a white noise error term. The parentheses contain t-statistics for hypotheses that the particular coefficient is equal to zero. Slope coefficients significant at the five (ten) percent level are indicated in bold face (italics).

Ordinary inventory combined with	**Large-size trades**				**Medium-size trades**				**Small-size trades**			
	Public Sells		**Public Buys**		**Public Sells**		**Public Buys**		**Public Sells**		**Public Buys**	
	δ_1	δ_2	δ_1	δ_2	δ_1	δ_2	δ_1	δ_2	δ_1	δ_2	δ_1	δ_2
TEI_FW	**20.82**	2.93	*-9.41*	-2.31	**24.70**	-3.31	-1.12	1.75	**3.58**	-0.34	-0.91	0.13
	(4.31)	(0.31)	*(-1.71)*	(-0.33)	(7.56)	(-0.91)	(-0.36)	(0.43)	(4.70)	(-0.40)	(-0.99)	(0.13)
TEI_ID	**20.72**	2.82	*-9.75*	-7.18	**25.16**	**14.61**	-1.04	3.31	**3.58**	0.25	-0.88	0.57
	(4.21)	(0.38)	*(-1.74)*	(-0.64)	(7.70)	(3.15)	(-0.34)	(0.63)	(4.71)	(0.25)	(-0.96)	(0.49)
UEI_FW	**20.74**	4.27	*-8.81*	-7.08	**24.59**	0.91	-0.99	-1.83	**3.60**	-0.37	-1.10	1.89
	(4.19)	(0.58)	*(-1.69)*	(-0.66)	(7.50)	(0.22)	(-0.31)	(-0.43)	(4.72)	(-0.44)	(-1.19)	(0.84)
UEI_ID	**20.51**	5.33	*-9.51*	-4.97	**23.84**	**12.41**	-1.15	3.17	**3.65**	-0.56	-0.91	0.06
	(4.21)	(0.46)	*(-1.72)*	(-0.44)	(7.30)	(3.31)	(-0.36)	(0.77)	(4.76)	(-0.70)	(-0.98)	(0.06)