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Abstract

There is a significant disparity between theoretical and empirical models of the Specialist's adjustment for inventory risk. Whereas theoretical work has shown that Specialist inventory rebalancing through the quoted prices is important to the functioning of the market, empiricists have failed to identify any evidence of this action intradaily. By partitioning the Specialist actions as active or passive, conditioned on the Price Continuity Rule, this study shows that the Specialist engages in active inventory rebalancing throughout the trading day. The paper finds that the Specialist's obligations -set by the NYSE- of achieving price continuity and smooth price changes come at a significant cost for the Specialist. However, he manages to mitigate this cost through his own actions when the rules are not binding. The implications of this paper have direct bearing on the current debate as to whether the NYSE design should be restructured.

JEL Classification: G10, G14

Key words: Quoted Prices; Specialist; Limit Order Book; Price Continuity Rule;

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1 Introduction

The debate in the market microstructure literature over financial market design and in particular over the process of determining transaction prices has intensified in recent years. The NYSE structure is based on the existence of a centralized Market Maker (the Specialist) as the provider of a "fair and orderly market" NYSE (1999, Rule 104).[1] He is the unique human intermediary who: 1) as a **centralized auctioneer** matches buyers and sellers and comes up with the fair stock price and 2) as a **liquidity provider** provides the necessary liquidity when there is a temporal disparity between supply and demand. The Specialist performs this dual role primarily through the continuous announcement of quotes. This paper looks at how the Specialist's own profits are affected by his duty to provide liquidity and the risks that are involved. This will shed light regarding the ongoing debate about restructuring the NYSE's design and the "black box" that exists concerning the Specialist and the Specialist system.[2] His unique centralized position gives him the monopolistic ability to observe market demands and act quickly. This is the source of his importance to the functioning of the market, but it is also an enormous potential source of personal gain. Do the rules of the exchange that ask him to provide liquidity have any effect in constraining him from taking advantage of his immediacy and information advantage?

Looking from a macro level of the market, we can see that the Specialist firms are profitable (annual reports) and that the Specialist makes money intradaily (Hasbrouck and Sofianos (1993) and Sofianos (1995)). However, the Specialist incurs inventory risks. Early theoretical work by Garman (1976) suggests that the Specialist should relate the posted quotes to his inventory, in order to avoid excessive inventory. Based on Garman's work, Amihud and Mendelson (1980) and Ho and Stoll (1981) examine bid-ask prices and spreads. Both papers' models imply that quoted prices are affected by the dealer's inventory position. In particular, they find that when inventory increases, both the bid price and ask price decline and the converse is true when inventory decreases. Thus,

[1] A detailed description of the NYSE structure can be found in Hasbrouck et al. (1993) and O'Hara (1995, Chapter 1).

[2] Numerous articles have appeared in the press questioning the centralized market making system of the NYSE: a) recent accusations of "front-running" by the Specialist appearing prominently in the Wall Street Journal and Business Week, b) the intervention of Ex-CEO of the NYSE Dick Grasso on the Specialist moves (WSJ 10/3/03) and c) Fidelity's announcement of the need to change the NYSE design.

both the macro level and theoretical results indicate that the Specialist is adjusting intradaily for inventory risks.

Looking at the micro level however, the empirical literature has failed to identify such a result.[3] Hasbrouck (1991) constructs a vector autoregressive model (VAR) of securities' trades and quoted price revisions to address the asymmetric information effect of trades as well as issues of inventory control behavior. The VAR model is used in an empirical study of transaction data by Hasbrouck and Sofianos (1993) who find that the Specialists do quote prices that induce reversion towards their mean inventory value (an estimate of a time-invariant target inventory). However, the expected movement towards the target inventory at any time is small. Similar results of slow inventory control on the quoted prices are also shown empirically by Madhavan and Smidt (1993). Recently Harris and Panchapagesan (2000) and Kavajecz and Odders-White (2001a) look at the quote revision process by adding the effect of the Limit Order Book. Harris and Panchapagesan (2000) find that the book order imbalances (as measured by the difference of weighted order sizes in the buy and sell side of the book) are informative in predicting quote revisions. They find that if the buy side has more pending orders in volume, then the quotes are revised upwards, and vice versa for a larger volume sell side. No inventory effect is present in their results. Kavajecz and Odders-White (2001a) look at the limit book best buy and sell price changes and find that the changes significantly explain the bid quote and ask quote revision respectively. Importantly, they also fail to find a significant inventory effect on updating either the buy or sell quotes. However, they do observe that the Specialist does not simply reflect the interest on the limit order book in his quotes but rather that he is actively smoothing the quote price changes. This result is also found in another paper by Kavajecz and Odders-White (2001b) where they show that the Specialist reduces the volatility of the limit order book best prices when he is posting the bid and ask prices. Thus, the current empirical literature regarding quote revision has shown evidence of some Specialist participation, although that participation is not clearly identified and does not coincide with the macro level theoretical results of inventory adjustment.

We look more closely at the determinants of the Specialist provision of liquidity through the quote process. We accomplish this by examining the different types of Specialist involvement and investigate possible causes for his moves. The NYSE is governed by rules that characterize the

[3] The micro effects do not add up to the macro effects. We look at this puzzle in great detail.

market and control the Specialist's moves. The degree to which the Specialist is influenced by these rules has not yet been systematically examined. In this paper, we take a step in this direction. Focusing on the principal rule of the Exchange -the **Price Continuity rule**- we investigate the extent to which this rule can control the Specialist quote actions and the quote revision process.

By employing a sample of the six largest companies in the Torq database, we observe a significant predictability of the quoted price revision from the limit order book. In particular, at any one time the limit order book contains a best buy and sell price. Not surprisingly, we find that changes to the best buy (sell) prices change the quoted midpoint. However, what is surprising is that the impact of a change in best buy price differs substantially from a change in the best sell price. This difference is not accounted for by commonly proposed explanations such as an information effect (Gulf war), or the stock's return (stock price trend).[4] *In this paper we call this difference the limit order book asymmetry*. The existence of the asymmetry helps us identify the Specialist's active role in the quote process. More specifically, our evidence suggests that he does not passively reflect the book information in the quotes, nor does he smooth prices evenly; rather he preferentially improves one or the other side of the best book prices.

We identify possible causes of differential improvement on the book quotes in combination with the Price Continuity rule. This rule is used extensively by the NYSE (Hearing Panel Decisions) for monitoring the Specialist current actions and for evaluating his overall performance for future stock allocation. In this paper, we argue that the Specialist improves the best buy price of the book when the current book price is discontinuous with respect to previous transaction price and similarly for the the best sell price. The Specialist is bound by the Price Continuity rule to improve

[4]Recent empirical literature has shown that the price trend affects the limit order book orders. Ahn et al. (2001) and Kavajecz and Odders-White (2003) find that whenever the prices are moving into a new higher (lower) level then the sell side limit order prices are closer (farther away) to the midpoint and buy side price farther away (closer). In particular, Ahn et al. (2001) find that when the price moves up (down), investors submit market buy (sell) orders instead of limit buy (sell) orders. Their explanation is that limit orders have greater risk of not been executed within a specified period of time when the prices move in the opposite direction, thus the traders cancel the limit orders and submit market orders. Harris and Hasbrouck (1996) in order to investigate empirically the performance of market and limit order, decide to remove the "sample artifact" of the price trend by taking a matched subsample of days with equal number of negative open-to-close return with days of positive return of similar magnitude. We also use their approach when we investigate whether the price returns are related to the book asymmetry.

and remedy any such discontinuities stemming from the current order book best prices. The empirical literature (Kavajecz (1999), Kavajecz and Odders-White (2001a) and Chung et al. (2001)) has identified such price smoothing behavior by the specialist, but this assertion has not been shown empirically. We find that the Price Continuity rule, as the primary source of the Specialist's price smoothing behavior, is a significant factor in forming the Specialist quoted prices.

Importantly, this is the first paper to show that the Specialist is rebalancing his inventory intradaily and also that he is using the quoted prices in order to make his daily profits. However, we also show that the rules of the exchange -Price Continuity Rule- constrain the Specialist actions and that the costs of this constraint are significant to the Specialist. We investigate the initial continuity and find that the Specialist's active, differential improvement of the limit order book can be explained in part by inventory imbalances and knowledge of the stock's future price change.

The economic interpretation of these results are significant. By partitioning the Specialist's action into *Active participation* (which are the actions when the Price Continuity rule is not binding) and *Passive participation* (when the rule is binding), we prove that the Specialist loses money and incurs inventory imbalances when he is passive *but* that the Specialist makes money and rebalances his inventory when he is active intradaily. In particular, using a sample of the 35 highly active companies in the Torq database we find that the Specialist's aggregate mean daily average total profits are $2,336. The positive total profits are clearly produced from the Specialist's active actions as those have a mean daily average profits of $6,160, compared with a loss of $3,824 when the Specialist is constrained by the rules. The Specialist's obligations -set by the NYSE- of achieving price continuity and smooth price changes come with significant costs. He can cover these costs with his own actions when the rules are not binding. Our results show further that the instances when the Specialist is passive balance out those instances when he is actively trading for his own interest. That is, in the aggregate, without partitioning his actions, it is difficult to detect any Specialist inventory adjustments. Therefore, we manage to explain the discrepancy in empirical models that have had difficulty identifying active specialist participation.

These findings represent two major contributions to the understanding of market microstructure price formation and financial markets. First, they specify how the market's design (rules of the exchange) affects the price discovery process and in particular the Specialist's quotes. From our novel characterization and partition of the Specialist improvements of the quotes into 1) those actions that are constrained by the rules and 2) the actions that he can take freely, we provide evidence that inventory and forecasting factors affect the Specialist's actions on an intraday basis. These results represent an important step in bridging the gap between theoretical and empirical work in the field of market microstructure. Previous empirical work has shown little evidence of either an inventory or informational signal effect of the Specialist's actions on the quoted prices– a result that would have been expected from theoretical work. Secondly, our findings provide evidence for academics that the regulations of the exchange should be included as an important factor in modeling the market making decisions. Little evidence is shown in current theoretical work on that aspect (Madhavan and Panchapagesan (2000)).

The remainder of the article is organized as follows. Section 2 discusses our Torq data sample and the initial findings of the asymmetric explanatory power of the book on the quote revision. Section 3 introduces the Price Continuity rule of the exchange and the partition of the Specialist actions. The methodology and models are discussed. Section 4 looks at the Specialist participation in explaining the asymmetry and examines factors of the Specialist's active, differential improvement of the order book and the changes in the quoted prices. A brief summary concludes the paper in Section 5. A detailed description of the algorithm created to identify the Specialist inventory in the Torq database is shown in the Appendix.

2 Data Description - Initial Findings

There are three central actors influencing the quote revision process: Electronic Orders, Floor Brokers and the Specialist. We look into the interactions of these participants under the rules and procedures of the exchange, using the TORQ database. The database covers intraday activity for 144 NYSE listed companies from November 1, 1990 to January 31, 1991.[5] In this paper we are using two samples. The initial investigation is done using the the six most frequently traded stocks in Torq (IBM, AT&T, Exxon, Phillip Morris, Boeing and General Electric). The main results are shown in an aggregated form for a larger sample of the 35 highly active companies in the database.[6]

[5]This data set was produced by Prof. Joel Hasbrouck (1992) while he was a visiting economist at the NYSE.

[6]The use of two samples was necessary to investigate in more detail the individual company's time series without cross-sectional aggregation. Once the initial investigation was conducted, we generalized our results using the aggregated regression and 35 companied instead of only 6.

The Torq database consists of four individual files:

- The Consolidated Transaction file (CT) contains one record per transaction at the exchange's reported time.

- The Consolidated Quotes file (CQ) contains one record per quote change. Quotes can change immediately after a transaction,[7] or with the cancellation or arrival of new orders.

- The System Order Database (SOD) covers all the SuperDot and ITS orders as they are shown in the Specialist Display Book. Thus, using the SOD we can reconstruct the Limit Order Book at any time and have a full image of "the electronic participant". Kavajecz (1999) has a detailed description of the Limit Book reconstruction.

- The Consolidated Audit Trail file (CD) provides information on the number and type of parties in a trade. This data set provides us with the necessary information to identify the two other key participants: Specialist and floor brokers.

In particular, the last data file comes from the Equity Consolidated Audit Trade file (CAUD) which is the NYSE trading record that supports its surveillance department's operations. The CAUD file is included in the TORQ database albeit in an incomplete form with the identification of the Specialist removed. We rely on the algorithm of Prof. Panchapagesan (1997) to restore the missing information. The algorithm uses filters based on the NYSE's policies and procedures to identify Specialist participation.

In order to combine the four data sets and reconstruct an accurate picture of the transactions, quotes, and orders activity, we must determine the correct transaction and quote reporting times. As Lee and Ready (1991), Hasbrouck et al. (1993) and Odders-White (2000) point out, the quotes' and transactions' time-stamps that are reported in their individual data sets (TTIME variable in CT, and QTIME variable in CQ) are not accurate due to validation checks and reporting delays. We settle the transaction time problem by assigning the trading time of all trades that included a SuperDot executed order, to be the reported time of execution for those orders (RTIME) in the SOD database. Because of instantaneous computerized recordings and the lack of human intervention

[7] The Specialist is obligated by exchange rules to announce new quotes when a transaction occurs.

delays, this is a more accurate measurement of the transaction time than TTIME in the CT file.[8,9] In order to specify a time-stamp for those trades that did not include a SuperDot order, we relied heavily on Rule 128 of the NYSE (1999, Rule 128(A)(10)), that requires the seller to report the trade and the time of the transaction. We estimate the correct time for all trades without a SuperDot order to be the reported time of execution from the seller (SELLTIME) in the CAUD file.[10] In this way, we were able to estimate the correct transaction time for all trades in the data set taking into account the reporting delays (SELLTIME) and human intervention (RTIME).

Based on our estimated transaction time, we followed the procedure of Lee and Ready (1991) in order to discover the prevailing quote. After investigation, we decided to record the quote that was present for transaction time t to be the prevailing quote at t-3, 3 seconds earlier as Lee and Ready (1991). However, our final transaction level pictures differ from Lee and Ready (1991) as both the transactions and the prevailing quotes are reordered with respect to our estimated transaction time.[11]

We use the TORQ database and Panchapagesan's (1997) algorithm, to identify the Specialist participation in the trades. An additional variable that must be considered for explaining the quote revision process and the Specialist actions is his inventory. Researchers that have used the TORQ database, used either the change in the Specialist inventory or the accumulated inventory over a period of time and looked at its effect. This can be misleading, not only because the specialist inventory can change significantly during the after hours,[12] but also as Hasbrouck and Sofianos

[8] Hasbrouck (1992) mentions that "the time-stamp on the report is a useful indication of when the transaction really took place".

[9] The main reason of inaccurate trades time stamps is manual reporting of trades by floor reporters.

[10] For the correct identification of the trade time we constructed a simple algorithm to identify the correct transaction time based on SELLTIME. In particular, for the cases where we had multiple sell times, we took the closest one to the transaction reported time (TTIME) in CAUD. However, whenever the SELLTIME was zero or later than TTIME, we took the closest reported time of execution from the buyer (BUYTIME) in CAUD less than or equal to TTIME as the estimated transaction time. Otherwise we took TTIME. This procedure gave us a time that was earlier or equal to TTIME. More details on the Time variables can be found in Hasbrouck et al. (1993).

[11] For IBM company for example, only 58% of the transactions have retained their order. Looking at our estimated transaction time picture, the transactions were frequently reordered by one or two places that the original TTIME transaction picture.

[12] Therefore, using the total number of shares that the Specialist bought and sold during a trading period, can be proved to be a false estimate of his total total inventory.

(1993) point out, the excess inventory levels and not the changes in inventory are of interest in relating any inventory effect to Specialist actions. We create an estimate of the actual inventory levels in the TORQ database by using an algorithm based on the NYSE exchange rules 104.10(5) and 104.10(6). These rules prohibit the Specialist from buying stock on a direct plus tick or from selling on a direct minus tick based on his inventory position. Thus, following his transactions under the assumption that the rules of the exchange are not violated, we are able to approximate the Specialist inventory position at the beginning of each day. A more detailed description of the algorithm can be found in the appendix along with some comparisons between our estimates and the true inventory values. Therefore, we are now in a position to test the actual inventory effect in the quote revision model directly.

Harris and Panchapagesan (2000) and Kavajecz and Odders-White (2001a) have previously studied the relationship of the quote revision process to the limit order book. We use somewhat different variables to describe the limit order book effect and we also add proxy variables for the floor participation, Specialist inventory levels and Specialist information signal of future price moves.[13]

In particular, we estimate a linear regression model of predicting the quoted prices midpoint revision (midquote revision) based on a number of variables as described in Table 1. These include the change in the best book buy and sell sides,[14] lag variables of midquote revisions,[15] the current change in the transaction price,[16] the market order arrival rate,[17] the Specialist's inventory,[18] a

[13]As Sofianos and Werner (2000) mention "it is misleading to make inferences concerning liquidity based solely on the limit order book as represented by the SOD file in TORQ without considering floor participation".

[14]Kavajecz and Odders-White (2001a) find in a similar regression framework that these variables are highly predictive in explaining the bid and ask price change respectively

[15]These variables are included in the regression due to the autoregressive nature of our midquote time series. In particular, after investigation we conclude that both the use of first order differences for the midquote and also the inclusion of lag variables in the regression remedy the problem of autocorrelation in the residuals.

[16]We account for Hasbrouck (1991) who finds that the sign of a trade is informative in the simultaneous quote and trade revision processes (VAR model).

[17]Kaniel and Liu (2002) find empirically that market orders do convey information that the Specialist is using when updating the quotes. They do find however, that the Specialist perceives limit orders as been more informative that market orders.

[18]We are using the standardized estimated inventory calculated algorithmically. This way we assume that the mean inventory value is the Specialist target inventory level similarly to Hasbrouck and Sofianos (1993). However, we do

forecasting variable,[19] and lastly a group of variables that are used as a proxy for the floor brokers' "hidden limit order book".[20] This last group of variables is intended to estimate the floor brokers' pending orders. We are able to infer the floor brokers' limit order book from the current floor brokers' transactions (at transaction time t). This approximation assumes that the Specialist knows the floor broker participation in a transaction before he quotes prices.

Variable	:Description
$\triangle Midquote$	:Change in the Quote midpoint (midquote) from transaction time t-1 to t
$\triangle BestBuy$	:Change in the Limit order Book best price from transaction time t-1 to t
$FloorBuyVol$	:Mean value of the floor brokers' buy volume in the previous 10 transactions, i.e. transaction times t-9 to t
$\triangle FloorBuyPrice$	:Change in the last two floor brokers transaction buy prices up (and including) transaction time t
$\triangle FloorDotBuy$	:Difference between the Floor brokers' buy and limit order book best buy prices at transaction time t
$\triangle PreviousPrice$	:Change between transaction prices t-1 and t. If the change is zero we take the last non zero change
$MarketBuyPrc$	:Mean value of the transaction size percentage attributed to market buy orders at transactions t-2 and t-1
$MarketBuyVol$	:Mean value of the transaction volume attributed to market buy orders at transactions t-2 and t-1
$Inventory$	:The standardized estimated Specialist inventory position for transaction time t-1 using our algorithm
$Forecast$	:First non-zero change in the transaction price after the quote is announced at transaction time t

Table 1: **Variable Definitions** (the sell variables are defined in a similar manner).

The regression results are presented in Table 2. For each company the coefficient estimate is provided along with its t-value. Significant t-values are shown in bold.

not expect to see a significant explanatory power on the intraday level as previous research finds little evidence on this matter.

[19]This variable is intended to show the effect of any private signal-information that the Specialist has on the quotes. We take the first non-zero change between present and future transaction price as a proxy for the forecasting signal.

[20]The floor brokers may participate passively in the transaction process, by leaving their orders at the Specialist post (either percentage or limit orders). These orders are typically included in the display book as if they were coming from the limit order book. Most frequently though, the floor brokers are standing at the Specialist post and request information from him about the limit order book sides. They also reveal to the Specialist their intentions to buy or sell at particular prices that the Specialist can only display as part of his quotes. Therefore, the Specialist has the knowledge of the floor brokers' pending orders. This dual form of information, i.e. the electronic limit order book as well as an unobservable (hidden) floor limit book influences all of the specialist actions.

Variables	IBM $R^2 = 0.58$ Coef.	t-val	EXXON $R^2 = 0.60$ Coef.	t-val	MO $R^2 = 0.67$ Coef.	t-val	GE $R^2 = 0.68$ Coef.	t-val	BA $R^2 = 0.66$ Coef.	t-val	AT&T $R^2 = 0.67$ Coef.	t-val
$Intercept$	-0.0000	0	0.0001	0	0.0001	1	-0.0001	-1	-0.0000	-1	0.0000	0
$\triangle BestBuy$	0.1552	**57**	0.2958	**66**	0.3448	**119**	0.3574	**125**	0.4021	**94**	0.4357	**164**
$\triangle BestSell$	0.4545	**131**	0.4366	**87**	0.4674	**160**	0.4228	**156**	0.3379	**87**	0.3373	**133**
$\triangle lag1.Midquote$	-0.1684	**-36**	-0.0917	**-14**	-0.087	**-23**	-0.0888	**-24**	-0.0961	**-18**	-0.0571	**-15**
$\triangle lag2.Midquote$	-0.0503	**-11**	-0.0429	**-7**	-0.033	**-9**	-0.0302	**-8**	-0.0290	**-5**	-0.0185	**-5**
$\triangle lag3.Midquote$	-0.0358	**-8**	-0.0196	**-3**	-0.020	**-6**	-0.0084	**-2**	-0.0158	**-3**	-0.0080	**-2**
$\triangle lag4.Midquote$	0.0031	0	-0.0312	**-5**	-0.019	**-5**	-0.0045	-1	-0.0200	**-4**	-0.0077	**-2**
$FloorBuyVol$	-0.0005	-2	-0.0004	-2	-0.0006	**-4**	-0.0004	**-3**	-0.0003	-1	-0.0001	-2
$FloorSellVol$	0.0001	0	0.0006	**3**	0.0005	**3**	0.0002	2	0.0004	1	0.0002	**2**
$\triangle FloorBuyPrice$	0.0055	**20**	0.0023	**10**	0.0011	**8**	0.0013	**9**	0.0028	**11**	0.0007	**10**
$\triangle FloorSellPrice$	0.0042	**15**	0.0017	**8**	0.0013	**11**	0.0016	**12**	0.0023	**9**	0.0003	**4**
$\triangle FloorDotBuy$	0.0000	0	-0.0006	**-3**	-0.0002	-2	-0.0002	1	-0.0001	-0	0.0000	1
$\triangle FloorDotSell$	-0.0000	0	0.0001	1	0.0001	1	0.0001	-1	-0.0000	-0	-0.0000	-1
$\triangle PreviousPrice$	0.0059	**20**	0.0011	**5**	0.0006	**5**	0.0016	**11**	0.0020	**7**	0.0002	**2**
$MarketBuyPrc$	0.0008	**3**	0.0003	1	-0.0002	-2	-0.0001	-0	0.0006	**2**	0.0002	**2**
$MarketSellPrc$	-0.0005	-2	-0.0002	-1	-0.0003	**-2**	-0.0003	**-2**	-0.0004	-2	0.0000	0
$MarketBuyVol$	0.0004	1	0.0006	1	0.0015	**3**	-0.0001	-0	0.0003	1	0.0000	0
$MarketSellVol$	-0.0005	-2	-0.0006	-1	-0.0015	**-3**	-0.0002	-1	-0.0002	-1	-0.0001	-1
$Inventory$	-0.0002	-1	0.0002	1	0.0000	0	0.0000	0	-0.0003	-1	0.0000	1
$Forecast$	0.0004	2	0.0007	**3**	0.0004	**3**	0.0005	**4**	0.0011	**5**	0.0004	**6**

Table 2: **Linear regression model of future quotation midpoint returns ($\triangle Midquote$).** For each explanatory variable, the coefficient estimate is provided along with the t-value. Bold t-values show significance at a 5% level.

As expected, the two most important variables in explaining the midquote revision are the changes in the limit order book best buy and sell prices ($\triangle BestBuy$ and $\triangle BestSell$). The significant explanatory power of these variables is indicated by their large t-values. There is also a clear autoregressive time series effect that is captured by the significant lag variables of the midquote change ($\triangle lag1.Midquote$...$\triangle lag4.Midquote$). Notice the mean revision (negative correlation of the lag variables), that is also noted in Hasbrouck (1991). The floor brokers' effect is statistically significantly captured by the floor price buy and sell differences as proxies of the change in "hidden floor limit order book" best prices ($\triangle FloorBuyPrice$ and $\triangle FloorSellPrice$). However, their explanatory power is small with coefficients of order 10^{-2} lower than their respective limit order book coeficients. The other two variables that have significant explanatory power in all companies of our sample are the non-zero previous transaction price change ($\triangle PreviousPrice$) and the non-zero future transaction price change ($Forecast$). The $\triangle PreviousPrice$ effect is expected as the variable serves as a proxy for the classification of the previous transaction as a buyer-initiated or seller-initiated, which is shown in the current empirical literature to be positively correlated with the quote price changes. The $Forecast$ variable significance explanatory power shows that the Specialist is moving the quotes in the right direction of new price levels. This indicates that the Specialist has a private information signal, a result also shown in Kavajecz (1999).

A striking observation that comes out of the regression results of Table 2 and that motivates our current investigation is the significant asymmetry in the prediction of the quote change from the limit order book. The limit order book best buy price change contribution to the prediction of the quote revision process differs substantially from the best sell price change contribution. What are the reasons behind this asymmetry in prediction?

One possible explanation is that the asymmetry is a result of information events and stock trend returns. More precisely, our sample period of three months covers the market reaction to the unanticipated Gulf War Crisis.[21] We conducted a number of tests which exclude these explanations, however using the same subsample (52 days) as Harris and Hasbrouck (1996). This sample matches the 26 days of the TORQ database with a negative return on the day to the same number of days with positive returns. For this sample the asymmetry in the regression coefficient of the sell

[21] The S&P Index had a significant change.(13.1% increase)

side and buy side of the book have similar magnitudes as in the overall sample.[22] In addition, we partitioned each individual company price series into intervals of positive, negative and insignificant change of the stock returns based on a partitioning mechanism that we created.[23] For each subsample we obtained regression results on the limit book effect for each company. More than 95 percent of the time, the trend effect did not cause any change in the direction or significance of the asymmetry shown in Table 2. For a graphical description of the asymmetry we also include Figure 1 which shows the IBM company for the first 6 days in our sample. The quotes announced by the Specialist usually follow closely the best book buy and sell prices. However, we also observe that there are lengthy periods of time when the quotes do not reflect the book (3^{rd} and 5^{th} graph of Figure 1, i.e. 5^{th} and 7^{th} of November). In particular, the quoted actions of the Specialist cut the buy book side adrift from the trend in the midquote time series.

Having eliminated these competing explanations for the asymmetry, we now turn to the Active Specialist Participation hypothesis. We find that the Specialist does not passively reflect the book information, but rather he differentially improves one or the other side of the quotes. His price smoothing behavior to establish continuity -the Price Continuity rule- is only partly responsible for the above asymmetry, however. The Specialist's differential improvement of the quotes when he is not required to do so by the exchange rules –we define this action to be the *Active Specialist participation*– is another significant cause of the asymmetry. The Active Specialist Participation which the asymmetry identifies, is hidden in the overall Specialist participation, and is partly predictable from both inventory and forecasting signal inferred variables. As Madhavan and Sofianos (1998) find, the Specialist is selectively timing his trades. We expand their findings to incorporate selective participation in the quoted prices improvement when no rules of the exchange are in force. Section 3 describes in detail the models that we use in investigating the Specialist involvement in the quoted prices revision process and shows our initial results.

[22] In particular, we also constructed different subsamples for each company. The results remained intact.

[23] The actual statistical procedure for partitioning the stock path is available from the author upon request.

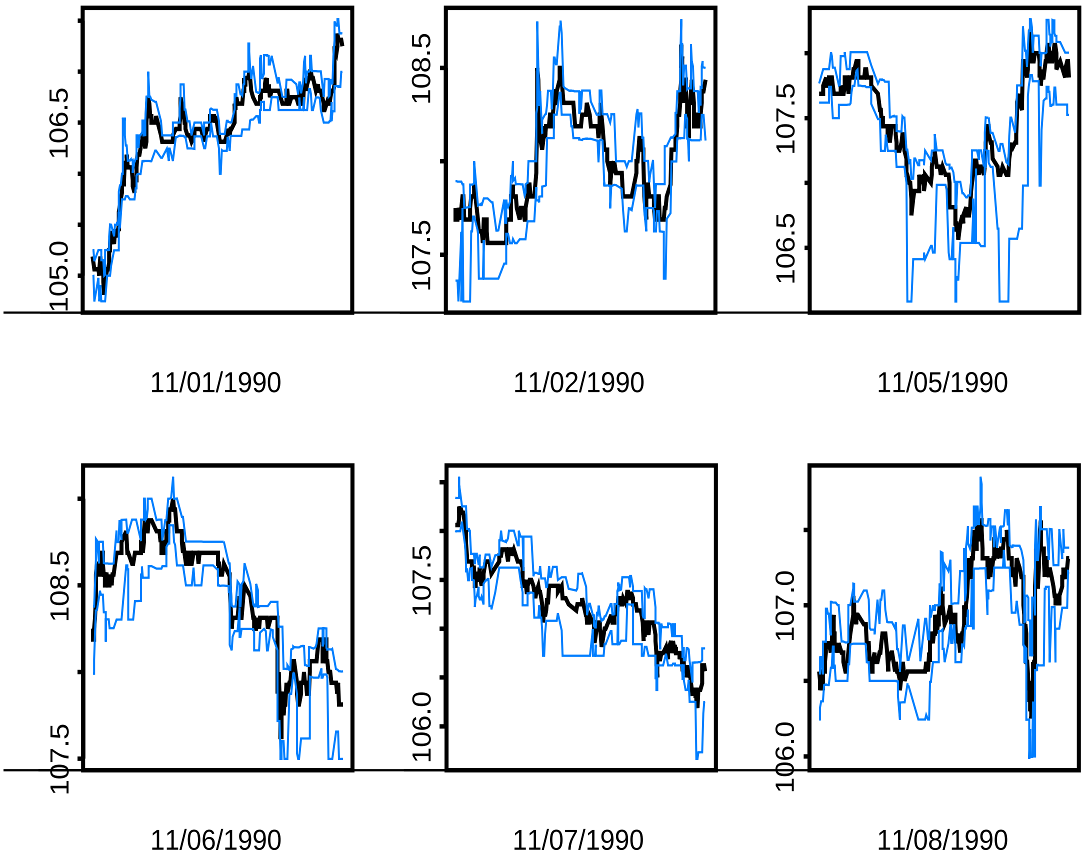

Figure 1: **The book prices and the midquote**. The figure shows the book best sell and buy prices time series (the two times series in light dark color) along with the middle of the quotes variable time series i.e. midquote (in heavy dark color). Each graph represents one day for the first 6 days in our sample (first 6 trading days of November 1990). The company is IBM. The Sell variable which is above the midquote follows it closely whereas the Buy variable which is below the midquote has periods of gaps. These gaps appears irrespective of the midquote time series trend of the stock.

3 Partition of the Specialist Actions - Models, Methodology, Initial Results

There are a number of rules that constrain the Specialist's moves when he is either assigning the quotes or when he is acting as a dealer (transacting for his personal account).[24] We will focus on the **Price Continuity rule**-NYSE (1999, Rule 104.10(3)). That is, we will look at the difference between the best book prices and the quoted prices and determine whether our regression asymmetry is due to the Specialist improving the book prices according to the Price Continuity rule. Among the rules that regulate the Specialist actions, the Price Continuity rule is of primary importance to the exchange; the majority of the hearings on Specialist violations up to 1990 (Torq data set) dealt with that rule. We expect the rule to promote a Specialist intervention when there is a large gap from the previous transaction price to either the best buy or sell prices in the book. In such situations, he will act in order to avoid a large quoted spread and price discontinuity. We define the one sided Gaps as follows:

- **Buy Gap**. We define the occurrence of a Buy Gap whenever the book best buy price at transaction time t is more that one tick ($\$\frac{1}{8}$) lower from the last transaction price and when the spread between the book best buy and sell prices at transaction time t is greater than one tick.

$$BuyGap = \{p_{Transaction,t-1} - p_{BestBookBuy,t} > 1/8\}\{p_{BestBookSell,t} - p_{BestBookBuy,t} > 1/8\}$$

- **Sell Gap**. We define similarly the occurrence of a Sell Gap whenever the best sell price at transaction time t is more than a tick higher from the last transaction price and when the

[24] We reviewed all NYSE Hearing panel decisions from 1976 to 1990 on Specialist disciplinary proceedings. We then conducted interviews with both Specialists on the Floor and Senior Officials of the NYSE (Market Surveillance) and confirmed that Specialists are primarily evaluated based on the extent to which they adhere to the following rules: the **Price Continuity rule**-NYSE (1999, Rule 104.10(3))-, the **Quotation rule**-NYSE (1999, Rule 104.10(4))-, and the **Price Stabilization rule** in connection with the **Destabilizing Transactions (establishing or increasing a position)**-NYSE (1999, Rule 104.10(5))- and **Destabilizing Transactions (liquidating or decreasing a position)**-NYSE (1999, Rule 104.10(6))-. From these rules we expect both the Price Continuity rule and Quotation rule to affect the Specialist quote revision process. We combine them and see how much they influence the asymmetry of our regression coefficient results.

spread between the book best buy and sell prices at transaction time t is greater than a tick.

$$SellGap = \{p_{BestBookSell,t} - p_{Transaction,t-1} > 1/8\}\{p_{BestBookSell,t} - p_{BestBookBuy,t} > 1/8\}$$

In the above definition of the Gap, the choice of one tick ($\$\frac{1}{8}$) as a threshold is related to NYSE Hearing panel Decisions.[25] Also, the definitions of the Buy and Sell Gap include only those cases of larger than a tick book spread, where the Specialist has the option of book price improvement.

Companies:	IBM		EXXON		MO	
Variable	Before Specialist Involvement(%)	After Specialist Involvement(%)	Before Specialist Involvement(%)	After Specialist Involvement(%)	Before Specialist Involvement(%)	After Specialist Involvement(%)
Buy Distance	33.12 (BuyGap)	4.12	9.25 (BuyGap)	1.59	7.17 (BuyGap)	2.03
Sell Distance	13.87 (SellGap)	4.75	6.5 (SellGap)	2.02	5.56 (SellGap)	3.00
Companies:	GE		BA		AT&T	
Variable	Before Specialist Involvement(%)	After Specialist Involvement(%)	Before Specialist Involvement(%)	After Specialist Involvement(%)	Before Specialist Involvement(%)	After Specialist Involvement(%)
Buy Distance	9.87 (BuyGap)	2.93	13.37 (BuyGap)	6.23	2.41 (BuyGap)	1.57
Sell Distance	7.28 (SellGap)	2.86	11.98 (SellGap)	5.50	3.83 (SellGap)	1.39

Table 3: **Buy and Sell Distance before and after the Specialist intervention.** Buy and Sell Distances are defined to be the indicator variables of greater than one-tick distance ($\$\frac{1}{8}$) of the Transaction Price at time t-1 to either the best book price or Specialist Quote price (best book buy price defines the Buy Gap and Specialist Bid Quote distance defines the distance after the Specialist Involvement, relevant for the sell side). We look at the percentages of the Buy and Sell Gaps that are greater than one tick before the Specialist Involvement (first column of every company) and the percentage of the relevant buy or sell distance after the Specialist announces the quotes for our six companies sample. The one-tick threshold was chosen after reviewing NYSE Hearing Panel decisions.

A percentage summary of the Buy and Sell Gaps before the Specialist involvement and the relevant distance after the Specialist announcement of the quotes for our six-company sample is shown in Table 3. We observe a large asymmetric one sided-gap between the transaction price at

[25]The choice of one tick ($\$\frac{1}{8}$) is related to NYSE Hearing Panel Decisions penalizing price changes greater than two ticks. In addition, as Hasbrouck and Sofianos (1993) point out “Specialists are required to maintain price continuity, which in practise limits most successive intraday price changes to one tick”.

transaction time t-1 and the book best prices at transaction time t ("Before Specialist Involvement" column) that is "fixed" by the Specialist ("After Specialist Involvement" column). In particular, Table 3 shows that the Specialist is not only trying to lower the gap, i.e. the book spread and instances of price discontinuity, but he is also trying to balance out the buy and sell gaps. He provides the necessary liquidity at that price so as to "maintain a fair market and minimize the effect of temporary disparity between supply and demand" NYSE (1999, Rule 104.10(1)). Note that our observations do not contradict the findings by Chung et al. (1999), where they show that the Specialist quoted spreads that have a Specialist price improvement are wider than the Specialist quoted spreads that reflect the book best prices. They indirectly agree with our result that the Specialist involvement is indeed needed and implemented for price continuity when there are large book spreads (gaps). We therefore must conclude from Table 4 that the Specialist is indeed affected by the Price Continuity rule and is involved in lowering the "Gaps" when needed.

Three scenarios that are related to the Specialist improvement of the book best prices warrant investigation: the effect of the Price Continuity rule actions of the Specialist on the quote asymmetry; his moves when the Price Continuity rule is not in force; and cases in which the rule does need to be implemented but the Specialist is "illegally" active against the rule. To facilitate this inquiry, we partitioned the Specialist actions into three categories. These are:

- **Active Specialist Participation**. The Specialist improves the book buy or sell side of the quotes in a No Gap scenario.[26] (Gaps are defined above, page (13)).
- **Price Continuity rule actions**. The Specialist reduces the Buy or Sell Gaps. He follows the exchange rule in these cases.
- **Price Discontinuity actions**. These actions take place in Gap scenarios, though the Specialist improves the other side of the book from the Gap. We consider these actions to be "illegal", even if his moves serve to lower the book spread.

Table 4 gives a summary of the Specialist actions in percentages as defined above. We observe that his behavior is mainly classified as either Active Participation or Price Continuity actions. The

[26]The No Gap scenario is described as follows: the current (at transaction time t) book spread is two ticks ($\$\frac{2}{8}$) and the previous transaction price (at transaction time t-1) was at the middle of the spread. When the Specialist is improving either the buy or sell side of the spread, he is essentially supporting the no transaction price change.

Specialist Price Discontinuity actions take place less than 5% of the time for all the companies in our sample except BA that reaches 8%. As expected, the Specialist hardly ever strays from his responsibility to follow the Price Continuity rule. Table 4 also depicts the Specialist's overall participation in the quote price process. This participation is defined as the percentage increase in the bid or ask best price of the book when a transaction occurs as shown in the prevailing quotes. As the table shows, the Specialist has a significant presence in the quote process over our three month period. The large value for the IBM participation (49%) is clearly related to the large percentage of Buy and Sell Gaps for that company (as seen in Table 3).

Specialist Actions	IBM (%)	EXXON (%)	MO (%)	GE (%)	BA (%)	AT&T (%)
Overall Participation	49	23	18	21	24	8
Active Participation	30	51	57	46	37	60
Price Continuity	67	45	39	49	55	36
Price Discontinuity	3	4	4	5	8	4

Table 4: **The partition of Specialist actions.** The Specialist overall participation in the Quotes is shown in percentages. We also show: the **Active Specialist Participation**, **Price Continuity rule actions** and **Price Discontinuity actions** percentage of his overall participation for each company.

In order to investigate the effect of each type of Specialist action on the book asymmetric information, we proceed with a regression analysis. We introduce each time the particular Specialist action variable, while keeping all other predicting variables in the regression, and examine the change in the asymmetry for our two book covariates. More specifically, in order to test the statistical significance of both the initial and final asymmetries (when the Specialist variable is introduced), as well as the decrease in the asymmetry, we proceed using the two-stage regression shown below:

$$\triangle Midquote = \alpha_1 + \alpha_2(\triangle BestBuy - \triangle BestSell) + \alpha_3(\triangle BestBuy + \triangle BestSell) + others + e \quad (1)$$

$$\hat{e} = \alpha_1^* + \alpha_2^*(\triangle BestBuy - \triangle BestSell) + \alpha_3^*(\triangle BestBuy + \triangle BestSell) + \alpha_4^*(\triangle SpecialistAction) + others + e^* \quad (2)$$

where $\triangle$ denotes the difference in the variable for transaction time t and t-1 and the $others$ are the rest of the variables that appear in our initial regression on Table 2. $\hat{e}$ is the estimated residual from the first-stage regression and $\triangle SpecialistAction$ is each time the Specialist action as classified above.

The idea behind the two-stage regression is straight forward. Our goal is to test the significance of the asymmetry. This is done with the first-stage regression, as $2\alpha_2$ equals the change in the coefficients of $\triangle BestBuy$ and $\triangle BestSell$ in our initial regression on Table 2.[27] We use the second-stage regression because $2\alpha_2^*$ equals the change between the initial asymmetry and the asymmetry when $(\triangle SpecialistAction)$ is introduced. Accordingly, we test the statistical significance of the remaining asymmetry, i.e. each time $(\triangle SpecialistAction)$ is introduced, using the first-stage regression. Table 5 shows the estimated value $2\hat{\alpha}_2$ and the t-statistic for the absence and presence of the Specialist action variables and the t-statistic of $2\hat{\alpha}_2^*$ for the percentage explained variable.

We observe that the initial asymmetry that we have also pointed out in Table 2 is significantly different from zero in all six companies and especially highly significant for IBM. Of the three Specialist classification actions, the Price Continuity rule is significant in explaining the asymmetry for five out of six companies. Similarly, the Active Specialist Participation is significant in explaining the asymmetry in four companies. The Specialist Discontinuity participation alone has little effect on the initial asymmetry and is insignificant in all but one of the companies in our sample.[28]

[27]Similarly, $2\alpha_3$ equals the joint effect of the book variables $\triangle BestBuy + \triangle BestSell$. We create both the difference and the addition of the two book variables as explanatory variables, even if we only care about the statistical significance of $2\hat{\alpha}_2$, as we want to have a similar regression to the initial one (same power), and the first-stage regressions is identical with respect to the book covariates as our original one of Table 2.

[28]For IBM company, the Specialist Discontinuity is actually increasing the asymmetry. This shows that compared with the other two Specialist actions, Price Discontinuity actions have the opposite effect. In particular, the Specialist improves the sell side of the book more than the buy side. However, due to the relatively low frequency of these actions compared with the other two groups (Table 4), we do not investigate these actions further in this paper.

Variables	IBM	EXXON	MO	GE	BA	AT&T
Original Regression BestBuyDif and BestSellDif asymmetry, (t-value)						
|Difference|	0.299 (63.8)	0.141 (19.6)	0.122 (27.5)	0.068 (15.9)	0.064 (10.1)	0.099 (25.9)
Original Regressions with Change in Specialist Improvement as added variables, (t-value)						
NoGap/Specialist Buy and Sell Imprs and lags: **Active Specialist Participation**						
|Difference|	0.295 (66.8)	0.121 (19.1)	0.093 (25.0)	0.058 (15.7)	0.078 (13.0)	0.076 (24.3)
Percent Explained	1% (0.7)	14% (3.1)	24% (7.9)	15% (2.8)	-22% (-2.3)	23% (7.2)
BuyGap/Specialist Buy and SellGap/Specialist Sell Imprs and lags: **Price Continuity rule**						
|Difference|	0.137 (28.4)	0.108 (15.9)	0.107 (24.8)	0.057 (13.9)	0.001 (0.1)	0.093 (25.2)
Percent Explained	54% (33.6)	23% (4.9)	12% (3.7)	16% (2.8)	98% (10.7)	6% (1.5)
SellGap/Specialist Buy and BuyGap/Specialist Sell Imprs and lags: **Price Discontinuity**						
|Difference|	0.334 (69.8)	0.127 (17.3)	0.117 (25.9)	0.065 (15.1)	0.063 (9.9)	0.097 (25.4)
Percent Explained	-12% (-7.2)	10% (1.9)	4% (1.4)	4% (0.7)	2% (0.2)	2% (0.4)

Table 5: **Explaining the Asymmetry.** The table depicts the Specialist different roles' as variables in explaining the regression coefficient difference between the Buy and Sell Sides of the Limit Order Book (|Difference|). The coefficient estimates are predictors for the Specialist future quotation midpoint revision. The t-statistics are shown in parentheses.

4 Investigating the partition of the Specialist Actions - Main Results

Although we have that the Active Specialist Participation and Price Continuity rule each explain part of the asymmetry, in all companies except BA, the asymmetry that remains after using either one of these variables as covariate is still significant (Table 5). Additional two-stage regressions (not shown on Table 5) reveal that the remaining asymmetry is insignificantly different from zero when we introduce both the Price Continuity and Active Participation as covariates in the regression. However, as more than 90% of the Specialist actions are specified by these two variables (Table 4), it seems that a more informative variable in explaining the asymmetry is a carefully chosen combination of the Active Specialist Participation and the Price Continuity rule.

More specifically, because the Price Continuity rule implementation is conditioned on the existence of either a Buy or Sell Gap as defined in the previous section, we investigate whether the creation of these Gaps is related to the Active Specialist Participation. To do this we look at the moment when the Gaps first appear at transaction time t, i.e. the $NoGap^{t-1} => Gap^{t}$ instances. According to our definition, the $NoGap^{t-1}$ occurs either when there is a one-tick book spread at transaction time t-1, or when there is a two-ticks book spread at transaction time t-1 and the transaction price at t-2 occurred at the middle of this spread.

In the first scenario of $NoGap^{t-1}_{\frac{1}{8}}$ with a one-tick (\$$\frac{1}{8}$) book spread, the Specialist cannot act to change any book prices. The only action he can take is to improve the depth of the book according to the floor crowd and his beliefs. For those instances in which a Buy or Sell Gap appears just after this No Gap scenario, we have Figure 2 were we portrait the possible positions of the limit order book best buy and sell prices at times t-1 and t relative to the transaction price position at t-1. We have four different cases depending on the transaction at time t-1 (either at the bid or ask) and the nature of the Gap (either Buy or Sell Gaps). The activity is also summarized on Table 6 were we tabulate (percentage wise) each one of the four cases. We observe that for IBM we have a significantly greater percentage of Buy Gaps created than Sell Gaps (64.8% compare with 36.4%), whereas for the other companies we do not observe such a difference (last column of Table 6).

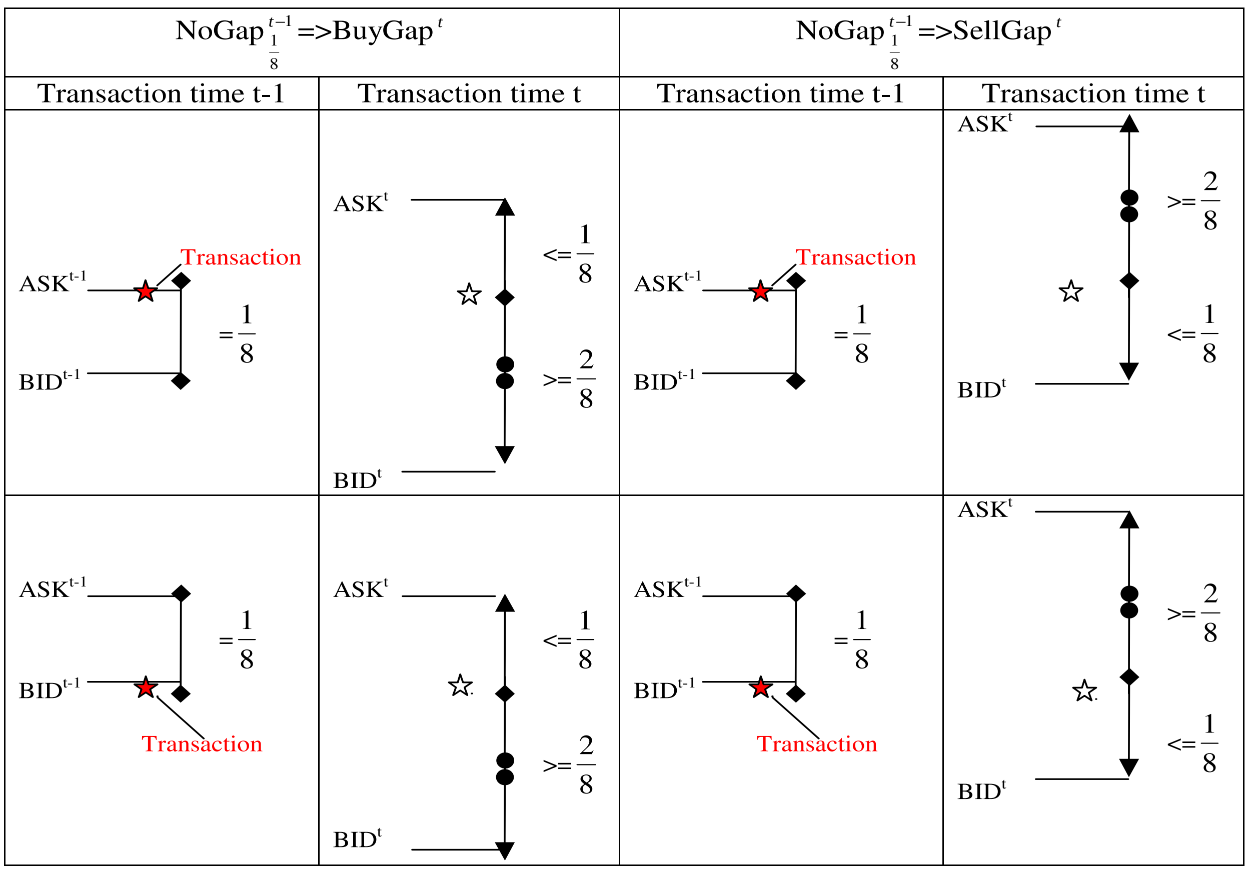

Figure 2: **Creation of Gaps: The one-tick case.** The figure shows all the possible book best sell and buy prices at transaction times t-1 and t for the $NoGap^{t-1}_{\frac{1}{8}} => Gap^{t}$ scenario. We also have the position of the transaction that occurred at time t-1 as the Gap creations are conditioned on both the transaction position at time t-1 and the position of the book at time t.

Company	Total Number of $NoGap^{t-1}_{\frac{1}{8}} => Gap^t$	Nature of the Gap	Transaction(t-1) at the Bid(%)	Transaction(t-1) at the Ask(%)	Total (%)
IBM	691	Buy Gap	49.5	15.3	64.8
		Sell Gap	14.3	22.1	36.4
EXXON	199	Buy Gap	21.1	31.2	52.3
		Sell Gap	35.2	13.1	48.3
MO	443	Buy Gap	9.7	38.4	48.1
		Sell Gap	46.7	5.2	51.9
GE	414	Buy Gap	19.8	29.5	49.3
		Sell Gap	27.3	23.9	51.2
BA	383	Buy Gap	11.2	41.3	52.5
		Sell Gap	31.3	16.4	47.7
AT&T	177	Buy Gap	2.3	45.2	47.5
		Sell Gap	48	5.1	53.1

Table 6: **Creation of Gaps: the one-tick case.** The table summarizes the activity the led to the creation of the Gaps and their percentages for the one-tick ($\$\frac{1}{8}$) scenario of the book quote spread. It gives the percentages of Buy and Sell Gaps that were created when the one-tick spread was hit at either the book bid (first column) or the book ask (second column). It also gives the percentages of total Buy and Sell Gaps created. Notice that except for IBM, the other percentages are not shown to be significantly different.

In particular, the majority of the Gaps created for IBM happened on the same side of the book as the transaction at t-1 (columns "Transaction at the Bid" and "Transactions at the Ask" of Table 6) . That is, there are at least three times more Buy Gaps created when the transaction hits the bid side of the book than the ask side. Similarly, there are more Sell Gaps created when the transaction hits the ask side of the book than the bid side. By hitting the book quote, the quote order is discharged, and in order for the Gap to be created at the same side as the book quote, the second best order must be at least two ticks away. This shows a non-dense IBM limit order book with the second best limit order prices more than a tick away from the best prices. These cases are also described graphically in the diagram of Figure 2 (in row 1 columns 3-4 and in row 2 columns 1-2).

By contrast, the creation of Gaps at the opposite side of the transaction – i.e second column of Table 6 where Buy Gaps are created when the ask side is hit – shows cancellations of the book's best price orders. These are the prevailing scenarios for the other five companies in our sample. In general, we find that except for the thin IBM book Gap creations, the rest of the Gaps are mainly created from the book best price order cancellations and are almost evenly distributed among the Buy and Sell side of the Book.

The second scenario of No Gap that can lead to a Buy or Sell Gap at transaction time t, is a two-ticks ($\$\frac{2}{8}$) book spread at time t-1 with the transaction price at the midquote of the book's best sell and best buy prices at time t-2 (i.e. middle of the spread). We again identify those times in which we get a No Gap to a Gap picture. In contrast to the previous scenario, now the Specialist has the ability to improve either the buy or sell sides. Notice that he is not obliged to do so, as there are no cases of price discontinuity. Thus, his quote movement will be mainly based on his own interest. Table 7 shows the $NoGap^{t-1}_{\frac{2}{8}} => Gap^t$ instances and the Specialist improvement on the book quotes, whereas Figure 3 and Figure 4 are diagrams of the book best prices' moves for the different gap creation cases (Figure 3 is without any Specialist participation, and Figure 4 is with a Specialist improvement of either the book best buy or sell prices at time t-1). In particular, in Figure 3 we show the 6 different cases of Gap creations and book movements based on the position of the transaction at time t-1 (either at the bid, midquote or ask) and the Gap that is created (either Buy or Sell Gap). Figure 4 depicts the 8 possible cases depending on the Specialist improvement at transaction time t (either improvement of the book bid or ask), the transaction position at time t-1 (either at the bid or ask) and the Gap creation (either Buy or Sell Gap).

Notice that the differences in the total percentages of Buy-Sell Gaps in Panel 1 and Panel 2 of Table 7 are not the same. The asymmetry in the Gap creations is much higher when the Specialist improves one side of the book, than when he is reflecting the book prices. For example, for the IBM Gap creations, the Specialist is improving the buy side disproportionately to the sell side and as a result, 66% out of the 70% Buy Gaps created after Specialist improvement, are produced by improvements of the book best buy prices. Similarly, out of 28% Sell Gaps created, 21% are produced by Specialist improvements of the book best sell prices.

[29]We are using the "Improvement at the Bid" instead of "Transaction at the Ask" – and similarly at the Ask – instances, as practically these instances are the same for the $NoGap^{t-1}_{\frac{2}{8}} => Gap^t$ subsample. In particular for all the companies, 99% of the Specialist improved quotes are hit.

Table 7: **Creation of Gaps: The two-ticks case.** The table summarizes the activity that led to the creation of the Gaps and their percentages for the two-ticks ($\$\frac{2}{8}$) scenario of the book quote spread. Panel 1 shows the NoGap$\frac{2}{8}$ =>Gap case for no Specialist improvement of the book quotes whereas Panel 2 shows the Specialist involvement that creates a Gap.

Panel 1: No Specialist Quote Improvement

Company	Number of $NoGap^{t-1}_{\frac{2}{8}} => Gap^t$	Nature of the Gap	Transaction(t-1) at the Bid(%)	Transaction(t-1) at the Midquote(%)	Transaction(t-1) at the Ask(%)	Total (%)
IBM	630	Buy Gap	4.9	15.6	36.5	56.5
		Sell Gap	32.7	12.1	2.7	47.5
EXXON	126	Buy Gap	1.6	23.8	23.8	49.2
		Sell Gap	19.8	30.2	1.6	51.6
MO	520	Buy Gap	0.4	5.4	35.6	41.4
		Sell Gap	53.1	5.6	0.2	58.9
GE	641	Buy Gap	0.9	5.1	40.6	46.6
		Sell Gap	46	7.2	0.8	54
BA	535	Buy Gap	1.7	13.1	35.7	50.5
		Sell Gap	33.1	16.6	1.1	50.8
AT&T	329	Buy Gap	0	7	43.2	50.2
		Sell Gap	42.2	7.6	0.3	50.1

Panel 2: Specialist Quote Improvement

Company	Number of $NoGap^{t-1}_{\frac{2}{8}} => Gap^t$	Nature of the Gap	Improvement(t-1)[29] of the Bid(%)	Improvement(t-1)[29] of the Ask(%)	Total (%)
IBM	725	Buy Gap	66.1	3.6	69.7
		Sell Gap	6.5	21.1	27.6
EXXON	309	Buy Gap	57.6	2.3	59.9
		Sell Gap	7.4	32.3	39.7
MO	686	Buy Gap	63.8	1.7	65.5
		Sell Gap	3.4	29.7	33.1
GE	629	Buy Gap	59.5	1.4	60.9
		Sell Gap	2.1	35	37.1
BA	295	Buy Gap	41.4	6.8	48.2
		Sell Gap	7.1	42.7	49.8
AT&T	263	Buy Gap	23.6	4.2	27.8
		Sell Gap	1.5	70.7	72.2

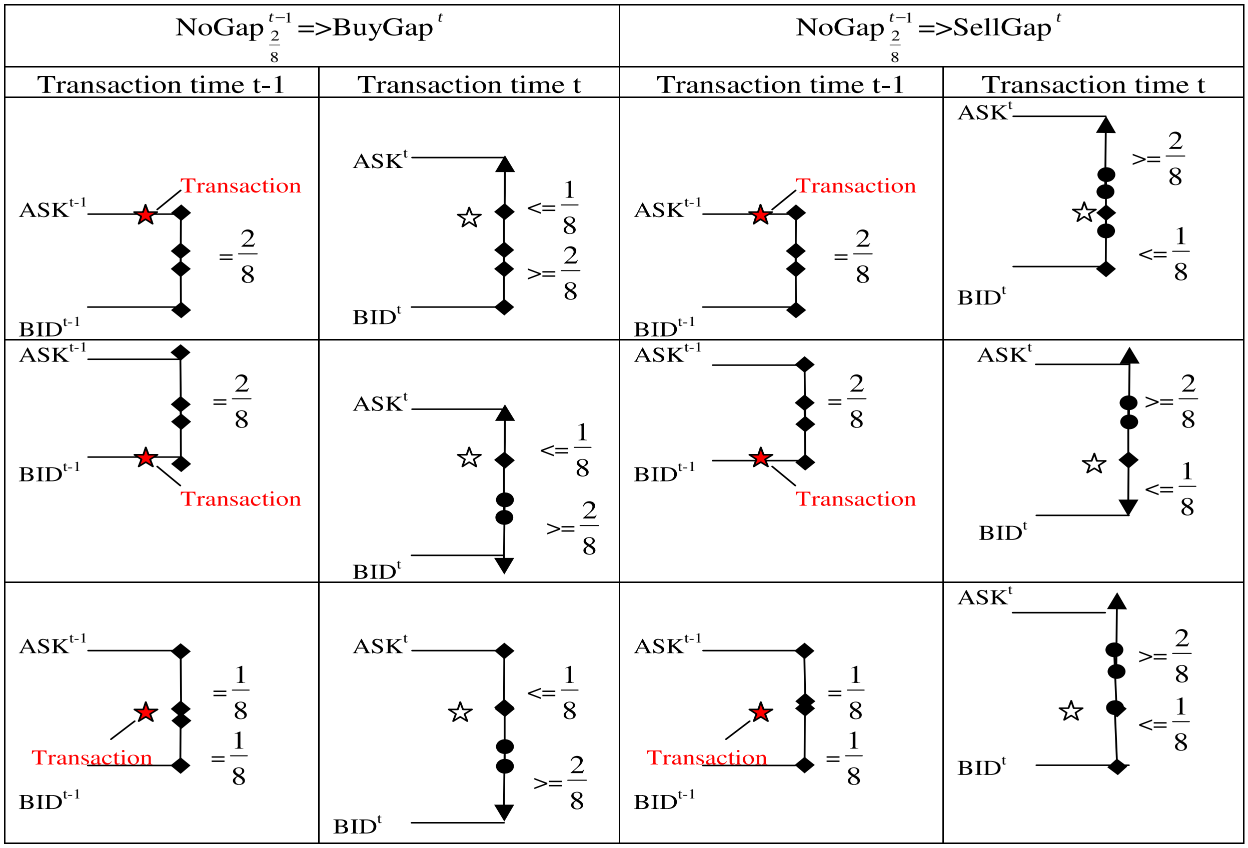

Figure 3: **Creation of Gaps: The two-ticks case-No Specialist Participation.** The figure shows all the possible book best sell and buy prices at transaction times t-1 and t for the $NoGap_{\frac{2}{8}}^{t-1} => Gap^t$ scenario without any Specialist price involvement. We also have the transaction that occurred at time t-1 as the Gap creations are conditioned on both the transaction position at time t-1 and the position of the book at time t.

In general, the majority of the Gap creations for the Specialist improvements for all the companies are taking place as depicted in the diagram of Figure 4 in row 2 columns 3-4 and in row 4 columns 1-2, i.e. the Specialist is improving the one side of the book and the other side gets hit by a transaction. The book side that was improved remains unchanged and as a result a gap is created. Therefore, we can deduce that the Specialist causes the book prices to drift away from the transaction prices (Active Participation), as the book is slow in following his moves.

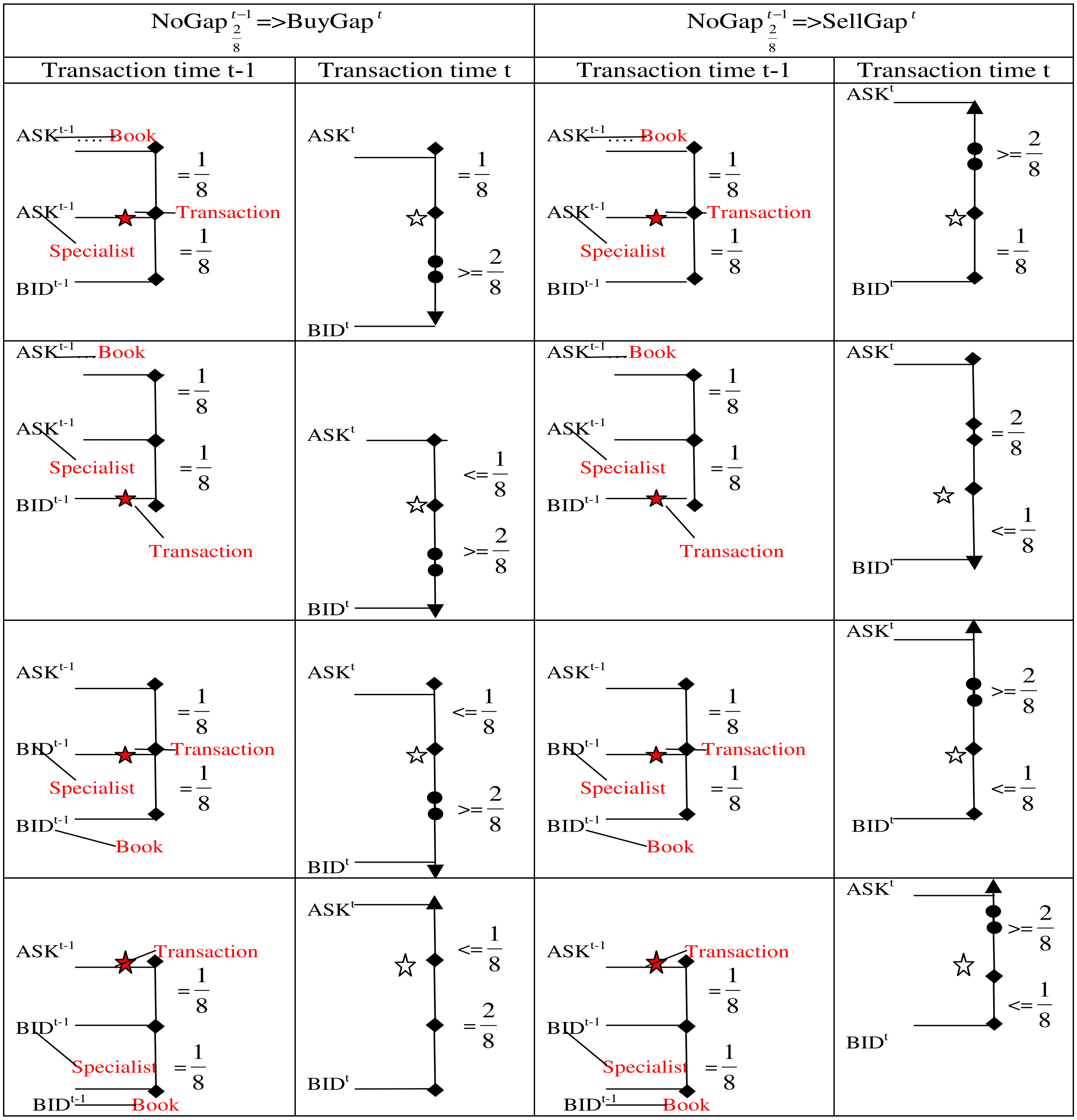

Figure 4: **Creation of Gaps: The two-ticks case - Active Specialist Participation.** The figure shows all the possible book best sell and buy prices at transaction times t-1 and t for the $NoGap_{\frac{2}{8}}^{t-1} \Rightarrow Gap^{t}$ scenario with a Specialist improvement of either the buy or sell side of the book. We also have the transaction that occurred at time t-1 as the Gap creations are conditioned on both the transaction position at time t-1 and the position of the book at time t.

Variables	IBM NoGap$\frac{2}{8}$ cases:7456	EXXON NoGap$\frac{2}{8}$ cases:3531	MO NoGap$\frac{2}{8}$ cases:6836	GE NoGap$\frac{2}{8}$ cases:8124	BA NoGap$\frac{2}{8}$ cases:4762	AT&T NoGap$\frac{2}{8}$ cases:7000
Buy Improvement(%)	33.2	27.6	28.3	18.6	11.5	4.3
Sell Improvement(%)	11.4	9.9	12.5	14.5	13.7	14

Table 8: **Active Specialist Buy and Sell percentages.** The table shows the Specialist actions for the NoGap$\frac{2}{8}$ cases, i.e. a book spread of two ticks at time t and a transaction price at the middle of the Spread at time t-1. The Specialist improves either the buy or sell price of the book quote when he is announcing his quotes. The table gives the percentages of Specialist price improvement for each one of the companies in the No Gap scenario.

The Specialist's disproportionate improvement of the two book sides for the No Gap($\frac{2}{8}$) case is also verified in Table 8. This is a larger sample of all the two-ticks No Gap cases with no condition on what follows (i.e. both the $NoGap^{t-1}_{\frac{2}{8}} => Gap^t$ and $NoGap^{t-1}_{\frac{2}{8}} => NoGap^t$ cases). We observe that for the first four companies, the Specialist more frequently improves the book best buy price. However, the opposite is true for BA and AT&T were the Specialist more frequently improves the sell side of the book. Panel 2 of Table 7 shows the results in the Gap creation of this asymmetric Specialist behavior. As mentioned before, the Specialist is not required to act by the Price Continuity rule in the No Gap scenario, so his actions are in his own interest. However, his actions do create a difference in the number of Buy and Sell Gaps that is significant and much greater than the difference when there are no Specialist actions (Table 6 or Table 7 Panel 1).

In order to verify the above tabulations which show that the initial Gap asymmetries are primarily related to the Specialist participation and not as much to the limit order book change cancellations or the lack of a "heavy" book side, we proceed by predicting the first instances of the Specialist Price Continuity rule actions. To do this, we regress the Specialist Buy Improvement for a Buy Gap instance at transaction time t, conditioned on no Gap instance for transaction time t-1. We regress the Specialist Buy Improvement on all the explanatory variables used in Table 2. In order to see the predictive power of the Active Specialist Participation we also include the Specialist Buy and Sell improvements on the No Gap case at transaction time t-1. Similarly, we rerun the regression using the Specialist Sell Improvements for the first Sell Gap as a response variable.

Variables	IBM	EXXON	MO	GE	BA	AT&T
Conditional regression on NoGap=>Gap instances, (t-value)						
Response variable: SpecialistBuyImpr						
$\triangle BestBuy$	-0.749 (-52)	-0.475 (-10.9)	-0.251 (-10.0)	-0.311 (-14.8)	-0.352 (-16.1)	-0.0389 (-1.4)
$lag1.SpecialistBuyImpr$	0.687 (62.7)	0.603 (11.8)	0.757 (38.5)	0.752 (39.1)	0.706 (26.6)	0.818 (33.9)
$\triangle BestSell$	0.118 (6.4)	0.060 (1.3)	-0.059 (-2.4)	0.051 (2.5)	0.159 (7.2)	-0.075 (-2.8)
$lag1.SpecialistSellImpr$	0.038 (1.4)	0.018 (0.3)	0.035(1.7)	0.008 (0.4)	-0.009 (-0.3)	0.002 (0.1)
R^2	0.75	0.60	0.77	0.72	0.60	0.76
Response variable: SpecialistSellImpr						
$\triangle BestBuy$	0.029 (2.6)	0.071 (2.5)	0.020 (0.9)	-0.099 (-4.8)	-0.113 (-4.5)	0.003 (0.1)
$lag1.SpecialistBuyImpr$	-0.039 (-2.3)	-0.115 (-3.4)	-0.035 (-2.1)	-0.042 (-2.2)	-0.014 (-0.5)	0.011 (0.3)
$\triangle BestSell$	0.245 (16.9)	0.136 (4.6)	0.136 (6.5)	0.306 (15.5)	0.338 (13.3)	0.297 (7.8)
$lag1.SpecialistSellImpr$	0.536 (25.9)	0.650 (16.0)	0.726 (40.0)	0.710 (33.2)	0.698 (22.8)	0.816 (33.2)
R^2	0.48	0.69	0.70	0.63	0.54	0.78

Table 9: **Investigation of the "First" Specialist Price Continuity Action .** The tables shows the estimated values of the variables of interest for the regression of the Specialist Buy (Sell) Action under the condition of NoGap=>Gap instances (t-statistics are in parentheses). The coviariates of interest are the limit order book best buy and sell price changes information ($\triangle BestBuy$ and $\triangle BestSell$) and the Specialist Active Participation on the NoGap interval ($lag1.SpecialistBuyImpr$ and $lag1.SpecialistSellImpr$).

The results on the estimated coefficients of interest (Book and Active Specialist Participation) are shown in Table 9.

The results strongly indicate that the Active Specialist Participation is significantly predicting his moves on the first Gap instances. The limit order book covariates are also significant predictive factors, however, as clearly shown by the higher t-values, the Specialist variables are for most companies at least as powerful in the prediction as the book. Therefore, we can deduce that the NoGap=>Gap scenarios are caused primarily by the Specialist actions at the No Gap instances, a result that was also shown in Table 7.

The Specialist causality of the Price Continuity rule initial actions lead us to combine his Active Participation with the rule actions. We thus come up with an "adjusted" Active Participation

Variables	IBM	EXXON	MO	GE	BA	AT&T
Original Regression BestBuyDif and BestSellDif asymmetry, (t-value)						
|Difference|	0.299 (63.8)	0.141 (19.6)	0.122 (27.5)	0.068 (15.9)	0.064 (10.1)	0.099 (25.9)
Original Regressions with Change in Specialist Improvement as added variables,(t-value)						
NoGap-BuyGap/Specialist Buy and NoGap-SellGap/Specialist Sell Imprs: **Adjusted Active Participation**						
|Difference|	0.259 (62.7)	0.072 (13.9)	0.064 (23.1)	0.032 (10.3)	0.083 (15.4)	0.038 (16.7)
Percent Explained	13% (9.7)	49% (13.2)	48% (21.3)	53% (11.5)	-30% (-3.5)	62% (26.2)
BuyGap/Specialist Buy and SellGap/Specialist Sell Imprs: **Price Continuity rule Minus Adjusted Active Participation**						
|Difference|	0.153 (33.5)	0.112 (16.4)	0.100 (23.4)	0.064 (16.1)	0.007 (1.3)	0.082 (22.4)
Percent Explained	49% (32.2)	21% (4.3)	18% (5.2)	6% (1.0)	89% (12.2)	17% (4.5)

Table 10: **Explaining the Asymmetry-Adjusted variables.** The tables depicts our new variable of Adjusted Active Specialist Participation and the remaining Price Continuity rule factor in explaining the regression coefficient difference between the Buy and Sell Sides of the Limit Order Book (|Difference|). The coefficient estimates are predictors for the Specialist future quotation midpoint revision. The t-statistics are shown in parentheses.

classification of the Specialist that includes also the instances where the rule was forced after an active Specialist move on a NoGap scenario. We recalculate the regressions (1) & (2) with the change in the Adjusted Active Specialist Participation as the $(\triangle SpecialistAction)$ variable (results shown in Table 10). Comparing Table 10 to Table 5 we see a significant increase in the active Specialist role in explaining the difference in the best buy and sell book covariates (|Difference|). For four out of the six companies in our sample the asymmetry is decreased in half, with AT&T reaching 62% explained by our adjusted active Specialist variable. The 13% for IBM still gives the Price Continuity rule as the most significant explanatory variable. Similarly for BA company.

4.1 Factors of the Specialist Improvement of the Book Quotes – Quote Revision process revisited

The Specialist decision to improve the buy or sell side of the book is partly explained by the Price Continuity Rule as seen from the detailed investigation of preferential improvement in the previous section and the limit order book asymmetry. Other possible factors for the Specialist improvement are of great interest, especially if they can be related to inventory or private information theoretical models that have not yet been in full agreement with current empirical investigations. As mentioned earlier, theoretical results of Garman (1976), Amihud and Mendelson (1980) and Ho and Stoll (1981) of intraday quoted prices adjustment due to inventory imbalances cannot be found be found by empiricists Hasbrouck and Sofianos (1993), Harris and Panchapagesan (2000), Kavajecz and Odders-White (2001a), to name a few.

We address this issue by looking at a larger sample of the Torq database that includes the six companies seen in the sections above. In particular, we use the highest quartile group of companies in the database, as they have adequate information (number of transactions, Specialist trades) for our investigation. We thus look more closely at the quote revision process of 35 companies cross sectionally as they relate to the Specialist inventory, his inferred forecasting ability, the Gap occurrence (which has already shown its significance through the Price Continuity rule) and lastly all the other variables as used in our original regression of Table 2 (the floor brokers' proxy variables, market order arrival rate, previous transaction price change and the book quote change). However, for the inventory and forecasting variables we look more closely at the interaction terms with the Gap indicators in order to identify different Specialist behavior with respect to the Gap and No Gap scenarios. We aggregate the independent variable coefficients and their individual standard errors in a Bayesian framework. In particular, for aggregating 35 time series regression results, we use the following model for each individual time series estimated coefficient $\hat{\beta}_i$ (i is the i-th time series):

$$\beta_i \; i.i.d. N(\beta, \sigma^2) - \text{independent over i}$$

and each

$$\hat{\beta}_i \mid \beta_i \; i.i.d. N(\beta_i, s_i^2) - \text{independent over i,}$$

where N is the Gaussian distribution. We estimate μ and σ^2 by maximum likelihood. Previous researchers have used different methods of aggregation of individual time series using crude measures of estimating the significance of the mean effect of each explanatory variable. For example, methods using either aggregated t-statistics or p-values, do not take into account the variability of the true β_i's. This paper, by using the Bayesian aggregation, captures the variation between companies in the predictive contribution of each individual $\hat{\beta}_i$ estimate.

Table 11 shows our results with aggregated covariates' estimates of interest for the two new regressions. We have clustered our explanatory variables into four groups that describe the Gap effect, the book effect and the Inventory:Gap and Forecasting:Gap interactions. In particular, we display the following explanatory variables: the Gap indicators ($BuyGap$, $SellGap$ and $NoGap$) when the Price Continuity rule is binding, (i.e. the Specialist is obliged to improve either the best book buy or sell price in order to achieve price continuity), the change in the book best prices ($\triangle BestBuy$, $\triangle BestSell$), the Specialist Inventory effect and its interaction in each one of the Gap subsamples ($Inventory$,$Invenstory : NoGap$, $Inventory : BuyGap$, $Inventory : SellGap$) and similarly a forecasting variable and its interaction with each subsample ($Forecast$, $Forecast : NoGap$, $Forecast : BuyGap$, $Forecast : SellGap$). We perform two regressions ("Gap Action" and "Adjusted") that differ only for the Specialist Participation ($NoGap$, $BuyGap$, $SellGap$ and interactions). In particular the second regression is using the Adjusted Active Specialist Participation as defined in section 3, i.e. the first $NoGap^{t-1}_{\frac{2}{8}} => Gap^t$ instances that occur due to a Specialist action are also considered Active Participation and included in the No Gap variable. We include the second regression as we investigate whether the Specialist is using the Price Continuity rule for his own interest while complying with the rules. Table 11 also shows the original regression results, as in Table 2, but now aggregated for the larger 35-companies sample than the six-companies individual sample.

Regressions	Gap Actions	t-value	Adjusted	t-value	Original	t-value
$BuyGap$	0.0082	4.6	0.0205	6.4		
$SellGap$	-0.0058	-3.2	-0.0226	-7.3		
$NoGap$	0.0008	1	0.0041	2.1		
$BestBuyDif$	0.2760	10.6	0.2860	11.3	0.2597	10.6
$BestSellDif$	0.3110	13.7	0.3229	14.9	0.2969	14.1
$Inventory$	-0.0001	-2	-0.0002	-1.7	-0.0001	-2.0
$Inventory : NoGap$	**-0.0006**	**-3.2**	**-0.0025**	**-2.5**		
$Inventory : BuyGap$	-0.0006	-1.2	-0.0045	-1.9		
$Inventory : SellGap$	-0.0001	-0.1	-0.0009	-0.5		
$Forecast$	0.0004	3.4	0.0004	3.6	0.0008	5.0
$Forecast : NoGap$	**0.0004**	**2.4**	**0.0003**	**0.6**		
$Forecast : BuyGap$	-0.0013	-2.3	-0.0021	-1.6		
$Forecast : SellGap$	-0.0005	-0.5	-0.0001	-0.1		

Table 11: **Bayesian aggregation regression results of the 35 most liquid companies in the Torq database.** The table shows the linear model results of the aggregated regressions in predicting the Specialist quote revision process in all 35 time series. The aggregations were done using the Bayesian framework. The first two regressions ("Gap Action" and "Adjusted") differ only for the Specialist participation ($NoGap$, $BuyGap$, $SellGap$ and interactions). In particular the second one is using the Adjusted Active Specialist Participation; that is the first $NoGap^{t-1}_{\frac{2}{8}} => Gap^t$ instances that occur due to a Specialist action are also considered an Active Participation and a $NoGap$ case. We use the following explanatory variables: the Gap indicators ($BuyGap$, $SellGap$ and $NoGap$) when the Price Continuity rule is binding, (i.e. the Specialist is obliged to improve either the best book buy or sell price in order to achieve Price Continuity), the change in the book best prices ($\triangle BestBuy$, $\triangle BestSell$), the Specialist Inventory effect and its interaction in each one of the Gap subsamples ($Inventory$, $Invenstory : NoGap$, $Inventory : SellGap$, $Inventory : BuyGap$) and similarly a forecasting variable and its interaction with each subsample ($Forecast$, $Forecast : NoGap$, $Forecast : SellGap$, $Forecast : BuyGap$). The last regression refers to the original regression that does not take into account any active/passive Specialist participation, similar to Table 2. T-values are shown next to the coefficients' estimates. Significant estimated coefficients of Specialist inventory or forecasting effect in the No Gap subsample (Active Specialist Participation) are in bold font.

There is clear evidence from the Gap group of Table 11 that the existence of Buy and Sell Gaps have a significantly different impact on the Specialist's decision to change the book quotes. As expected by the Price Continuity rule, the existence of a Buy Gap causes an upward quote change which reflects the Specialist adjustment of the buy side discontinuity, and vice versa for the existence of a Sell Gap. In general, the results verify the Price Continuity effect seeing in the previous section. Accounting for that effect, the last two groups of explanatory variables verify the "active" trading behavior of the Specialist on the quotes. For both aggregated regressions ("Gap Action" and "Adjusted"), we see an inventory rebalancing effect (significant negative sign) on the NoGap:Inventory interaction, which reflects the active Specialist participation (the Price Continuity rule is not binding). Such an effect is not present whenever the Specialist has to follow the rule in the Gap interactions. A similar forecasting effect is also significant in our regressions (significant positive coefficient in the NoGap case). We see that the forecasting effect is always much stronger for the No Gap than the Gap scenarios – the coefficients are decreasing and even taking significantly negative values in the gap subsamples (Buy Gap).[30] Comparing the two regressions ("Gap Action" and "Adjusted"), we do not observe any major differences in the coefficient estimates to indicate that the Specialist is using the Price Continuity Rule for his own interest. The last regression ("Original"), agrees with Table 2 (six companies sample) as the significant variables in those companies are verified in our aggregated regression. The weak significance of the inventory effect (t value of 2.1) agrees with previous empirical literature that failed to find strong intraday inventory adjustments by the Specialist.

In general, we conclude that there is supporting evidence that the Specialist is actively adjusting the quotes based on either an inventory imbalance or an information signal for future price changes. He is doing so when he is not obliged to follow the Price Continuity rule of the exchange. This rule is the driving force determining his quotes – when there is a but or sell gap – even if he acts against his knowledge of future prices or causes extremely slow balancing of his inventory. These results shed light to why the empirical literature has failed to identify strong inventory effect in the past –also shown from the weak significant effect of inventory in the "original" regression of

[30] This essentially means that the Specialist is acting (improving the quotes) on the opposite side than the future prices sign. In particular, he is improving the best book buy and the price goes down when he is dealing with the Price Continuity Rule

Table 11 and in Table 2. By the disentanglement of the Specialist actions into active and passive participation we manage to uncover the significance of inventory rebalancing on the quote revision process that is repeatedly described in theoretical work. The inventory effect is hidden when no interactions are present as the majority of Specialist actions follow the rule of the exchange which shows no inventory adjustments.

4.1.1 Economic interpretation of the factors

In order to develop economic measures of the consequences of the Specialist behavior shown in Table 11, we look at the Specialist profits as they are determined throughout the trading day. We are interested in the economic interpretation of the inventory rebalancing and forecasting effects of the Specialist actions that are achieved whenever the Price Continuity rule is not in effect, as seeing above. We calculate the intraday profits, similarly to Hasbrouck and Sofianos (1993) and Sofianos (1995), i.e. for each transaction at time t the profit is defined as $\Pi_t = I_{t-1}(p_t - p_{t-1})$, where I_{t-1} is the Specialist inventory before the transaction at time t and p the transaction price at both time t and t-1. In other words, the Specialist transaction profit is the price appreciation of his inventory position. We aggregate the Specialist transaction profits for:

1. **Overall Specialist profits**. All the transaction throughout the trading day.
2. **Passive Specialist profits**. Only those transactions intradaily that occur due to the Specialist passive participation of following the Price Continuity rule.
3. **Active Specialist profits**. Those transactions that occur due to the Specialist active participation when the rule is not binding.

Profits 2 and 3 refer to the NoGap and Gap subsamples of Specialist actions. Table 12 reports the mean and median of the daily average profits per company for our sample of the 35 highest active companies in the Torq database.

We thus can see from Table 12 the economic importance of the Active Specialist participation as the Specialist profits are clearly produced when he acts freely -the Price Continuity rule is not binding. In particular, we find that the Specialist aggregate mean daily average profits for the 35 most liquid companies in the Torq database are $2,336 and his Active Profits are $6,160. At the

Average Daily Specialist Profits ($)	Mean (t-value)	Median (t-value)
Overall Specialist Profits	2,336(4.0)	745(13.7)
Passive Specialist Profits	-3,824(-2.1)	-710(-2.1)
Active Specialist Profits	6,160(3.7)	1,560(2.5)

Table 12: **Specialist Profits and Price Continuity Rule.** The table shows summary statistics of the total average daily Specialist profits for the 35 companies in our sample. In addition, we have summary statistics for the Specialist profits as they are determined by either the Price Continuity rule actions- **Passive Specialist Profits-**, or his actions when the rule is not binding **-Active Specialist Profits**.

same time Table 12 shows that the cost to the Specialist of achieving price continuity and smooth price changes on the NYSE, is substantial – aggregate mean daily average passive Specialist profits of $3,824. The Specialist adjustment of his inventory position and use of forecasting, when the rule is not binding, creates the necessary gains for him to come up with positive profits.

5 Summary and Conclusion

This paper looks at the Specialist participation in the quoted prices and in particular the factors that drive him to update the quoted prices and improve either the buy or sell side of the limit order book.

What drives our investigation on the Specialist quoted prices is the significant disparity between theoretical and empirical models on the Specialist's adjustment of inventory risk. Whereas theoretical work has shown that Specialist inventory rebalancing through the quoted prices is important to the functioning of the market, empiricists have failed to identify evidence of this action intradaily. We look at this puzzle closely.

We initially identify and investigate what causes the difference in the predictive contribution of the buy and sell side of the limit order book on the quoted price revision process. For some stocks in our sample the buy side of the book is more informative while for others the sell side has more information. This difference is not accounted for by commonly proposed explanations like the stock trend or even the information signal of the unanticipated Gulf War (sample is from November of 1990 - January of 1991). We look at possible causes of the asymmetry by examining the Specialist involvement in the book best prices and in particular at the rules of the exchange that govern his actions. Focusing on the principal rule of the exchange -the Price Continuity rule- we look at the extent to which this rule can control the Specialist quote actions and the quote revision process. By defining as **Active Participation** the Specialist actions he can take freely, that is when the Price Continuity rule is not binding, and **Passive Participation** the Specialist's actions when the rule is binding, we investigate the extent to which each one can explain the asymmetry in the predictive power of the limit order book. We show that both the Active Specialist Participation and the Price Continuity rule (Passive Participation) individually are significant factors in causing the asymmetry.

We proceed by looking more closely at the novel partition of the Specialist actions in relation to the intraday inventory effect and Specialist profits. We find compelling evidence that the Specialist is rebalancing his inventory through the quoted prices and in addition he is using the quoted prices in order to make his daily profits. By employing a sample of the 35 highly active companies in Torq, we find that the aggregate mean daily total Specialist's profits of $2,336 are clearly produced from the Specialist active actions (mean daily average profits of $6,160) compared with a loss of $3,824 when the Specialist is obliged to act and follow the Price Continuity rule. These economically meaningful results show that the price smoothing achieved on the NYSE market does come with a cost for the market makers. However, the Specialists manage to cover that costs with their active inventory rebalancing and use of forecasting knowledge in the cases when they are not obliged to follow the exchange rules. These results have long been featured in theoretical models but have thus far eluded empirical studies.

In addition, our paper sheds light to the ongoing current debate of the Specialist role and the need of restructuring the NYSE design. We show that the rules are in effect and do affect the Specialist profits. However, further investigation is needed on the way the Price Continuity rule is currently implemented (after decimalization). Recent views point out to the fact that the rule's lack of discreteness – the gap scenarios discussed in this paper are more difficult to identify today – might lead to lesser "clear cuts" and more space for active Specialist participation.

Appendix

Inferring the Specialist Inventory using Rules 104.10(5) & 104.10(6).

The Torq database and Panchapagesan's algorithm (1997) are used in order to identify the Specialist's transactions intradaily. However, his inventory can change significantly during the afterhours ("intranightly") as well.[31] Therefore, the total number of shares that the Specialist bought and sold during the trading period can be shown to be a false estimate of his total inventory. Using NYSE exchange rules we construct a better estimate of his inventory position, thus having a better picture of his current status.

The exchange rule 104.10(5) and 104.10(6) relate the destabilizing transactions of the Specialist - buying on a plus or a zero plus tick (a positive transaction price change) and selling on a minus or a zero minus tick (a negative transaction price change) - with his inventory.[32] In particular, for increasing or establishing an inventory position (either long or short) the Specialist is not allowed to buy stocks on a direct plus tick or sell on a direct minus tick (Rule 104.10(5)). However, he is allowed to do so when he is decreasing or liquidating a position (Rule 104.10(6)). Therefore, assuming that the Specialist is following the rules of the exchange we can deduce that: **any direct plus tick purchases of stock from the Specialist can only happen when he has a negative inventory (decreasing a short position) and similarly any sells on a minus tick by the specialist can happen when he has a positive inventory (decreasing a long position)**.

Following the above rules we construct an algorithm for estimating the change in inventory that occurred outside exchange hours as follows: we choose the after hours change in inventory so that we have the least number of non-agreements ("illegal" Specialist Transactions) with rules 104.10(5 & 6) in the following trading day. We proceed by comparing our new estimate of **Adjusted Inventory** with a simpler estimate of inventory position defined as follows:

- **Total Inventory**. We take the specialist inventory to be the total number of shares that he bought minus the total number of shares that he sold, starting at zero at the first day of our

[31] Both Sofianos (1995) and Hasbrouck and Sofianos (1993) mention that the Specialists occasionally make adjustments to their inventories by trading in other markets outside exchange hours.

[32] The tick test definition NYSE (1999, Rule 112(d)(3)) refers to the change in prices between transactions i.e. $p^t - p^{t-1}$.

sample. This assumes no “intranightly” Specialist transactions.

Table 12 shows the two estimated Specialist inventory measures for IBM company. The calculated inventories are for the three months (November 1990 - January 1991). The table shows the extent to which these measures of inventory agree with Rules 104.10(5 & 6). We observe that the number of cases in our sample where the Specialist violates the two rules minimizes significantly with the adjusted definition for the inventory (Adjusted Inventory: 81 violations, Total Inventory: 189 violations, Rule agreement investigation-Number of Specialist destabilizing transactions: 373) and balance out the long and short violations. The two estimated transaction level time series of the inventories are also shown in Figure 5 for our sample period. We see that the mean reversion that is documented in the literature for the Specialist inventory is clearly more pronounced in the Adjusted Inventory than the Total Inventory measurement.

Specialist Inventory Definition	Inventory Position According to Rules 104.10(5) & 104.10(6)	Rule Agreements	
		Agreed	NotAgreed
Total Inventory	Long	47	157
	Short	137	32
Adjusted Inventory	Long	165	39
	Short	127	42

Table 13: **Estimating the Specialist Inventory.** The table shows the two estimated inventory measurements for IBM company (November 1990 to January 1991). Given each estimate, we calculate the number of violations of the NYSE exchange rules 104.10(6) & 104.10(6).

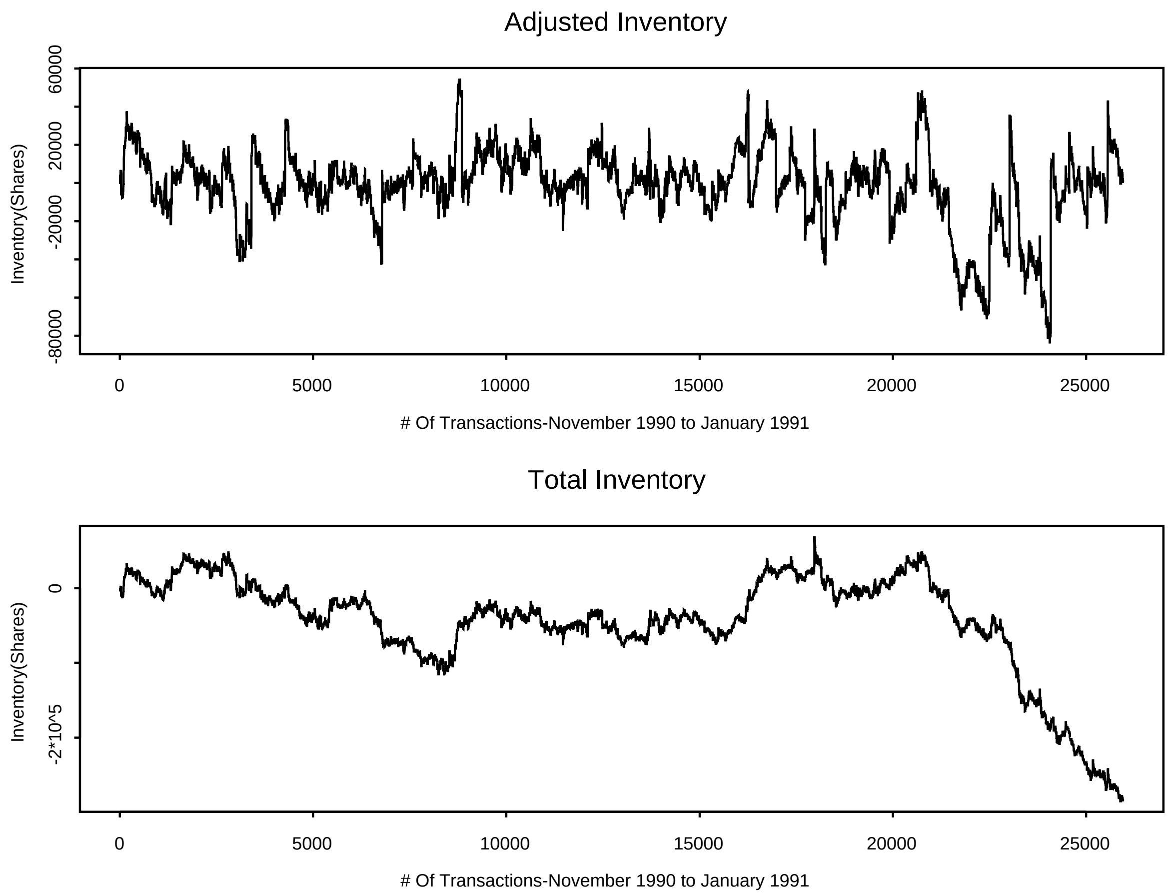

Figure 5: **Time Series of Inventory Measurements.** Figure 2 shows the time series of the two inventory measurements for IBM for the sample period of November 1990 to January 1991.

From the above analysis the question arises of whether the Adjusted Inventory is a better estimate for the true Specialist inventory position than the Total Inventory estimate. The argument (by construction), that with the Adjusted Inventory the exchange rules are violated significantly less, is one verification. Additional proof is given when we consider Hasbrouck and Sofianos (1993) with actual Inventory summary statistics for a sample of 138 Torq database companies from November 1988 to 1990. They report for the 4th highest quartile subsample (Average daily number of Transactions) two ratio measurements involving true inventory positions: The Average Absolute Closing Inventory over the Average Daily Volume and the Average Absolute Change in Inventory over the Average Daily Volume. For the same companies (largest quartile based on trading frequency), we calculate for the period of November 1990 to January 1991 the estimated ratio measures based on out two estimates of inventory position and present them on Table 13.[33]

	Hasbrouck and Sofianos (1993)	Our Sample	
Variable	True Inventory	Adjusted Inventory	Total Inventory
Number of Securities[34]	36	35	
$\frac{Avg.\lvert Inventory\rvert}{Avg.DailyVolume}$	0.13 (0.06)	0.15 (0.13)	0.55 (0.39)
$\frac{Avg.\lvert\triangle Inventory\rvert}{Avg.DailyVolume}$	0.06 (0.04)	0.08 (0.04)	0.07 (0.03)

Table 14: **Evaluating the Inventory Estimates.** The table shows the two estimated inventory measurements for the highest quartile sample (Average Daily number of Transactions) in the ratio estimates of Hasbrouck and Sofianos (1993) values. Standard deviations are in parentheses.

Looking at the first ratio variable of Table 13 ($\frac{Avg.\lvert Inventory\rvert}{Avg.DailyVolume}$) we observe that the Adjusted Inventory measurements are much closer to the true value that the Total Inventory estimate. By adding the overnight estimated adjustment to the intraday inventory we capture more closely the true inventory value than by assuming zero intranight Specialist trading. The second ratio of change in Inventory ($\frac{Avg.\lvert\triangle Inventory\rvert}{Avg.DailyVolume}$) estimates are both very close to the true values, depicting that the overnight estimated adjustments are not large in magnitude compared with the intraday Specialist transaction volume.

[33]It is our belief that Hasbrouck and Sofianos (1993) ratio variables, albeit in a earlier time period, can definitely characterize the true inventory positions in our sample period.

[34]In our sample we have 35 companies as we excluded one company which had very big values in both ratio variables (outlier). However, even if we include that company, the matching of the Adjusted Inventory and Total Inventory ratio estimates with the true values is also pronounced in favor of our adjusted measure. In particular, for the absolute Inventory ratio estimate we have values for Adjusted Inventory: 0.19 (0.28) and Total Inventory: 0.58 (0.43) and absolute difference in Inventory ratio estimate for Adjusted Inventory: 0.08 (0.04) and Total Inventory: 0.07 (0.03)

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