Participation Strategy of the NYSE Specialists to the Trades

Bülent, Köksal

Fatih University - Department of Economics

2008

Participation Strategy of the NYSE Specialists to the Trades

Bülent Köksal
Fatih University

October, 2007

Abstract. Using 2001 NYSE system order data in the decimal pricing environment, we analyze how the specialists react to the changes in market variables while making participation decisions to the trades. We analyze the following options that are available to the specialist before he trades: don't participate; participate at the quoted price; participate and improve the price. We find that the specialist uses information in the limit order book as summarized by the limit order book asymmetry. The specialist increases the probability that he participates to the trade when a market order arrives if he is able to step in front of the heavy side of the LOB. If the relative size of the market order, as described by the ratio of the market order size to the posted depth at the relevant side of the market, is high, the specialist chooses not to participate and let the market order trade with the limit order book. Consistent with the theoretical results in the previous literature, specialists trade more aggressively when the spread is large. We find that specialist trading strategies in stocks from different volume and price categories vary substantially. Finally, we also find significant inventory effects. The specialist trades more aggressively, if the trade with the incoming market order restores his inventory.

JEL Classification Code: G20
Keywords: NYSE specialists; Dealer Trading; Market Makers; Limit Order Book.

Address for correspondence: Bulent Koksal (bkoksal@fatih.edu.tr), Department of Economics, Fatih University, Buyukcekmece, 34500, Istanbul, Turkey.

Acknowledgements: This paper is based on my dissertation at Indiana University. I gratefully acknowledge the helpful comments from Craig Holden, Robert Jennings and Konstantin Tyurin. I thank Robert Jennings for providing the SOD data. This work was supported in part by Shared University Research grants from IBM, Inc. to Indiana University. Any remaining errors are my own.

New York Stock Exchange (NYSE) specialists are responsible for making markets for the stocks assigned to them. Their primary obligation is to ensure that there exists a fair and orderly market in their stocks. They should be willing to trade when other traders are unwilling to trade and the bid-ask spread should not be too wide. Also the specialists should intervene to prevent large price jumps, i.e., they should create price continuity. The NYSE uses the average width of the quoted bid/ask spread, the average depth of the quotes, the number of large price jumps, and the average size of price reversals to evaluate specialists' performances. The specialists' also have "negative obligations" that restrict their trading. Specialists cannot trade for their own accounts if there exist public orders at the same price or better. Also they should not trade with limit orders in order not to take the liquidity available to public traders. [1]

In this paper, we investigate the following issues by analyzing the participation decisions of the specialists to trades on the NYSE. First, what affects the participation strategy of a specialist to trades over time in an individual stock? Specifically, does he trade according to his affirmative obligations? Does he use information from the Limit Order Book (LOB) to predict the future returns of the stocks? Does he manage his inventory by using trades as inventory theories suggest? What is his reaction to the possibility of informed trading? Does he increase his participation to the trades to smooth prices when prices are volatile or does he avoid trading to stay away from risks inherent in volatile markets? Second, how do specialists' trading strategies vary across stocks? Specifically, what is the effect of volume on specialists' decisions? Does the specialist trade aggressively or defensively as the price volatility increases across stocks? Is the

[1] See Harris (2003) p.494 for an extensive description of specialists' roles and how they can act against the interests of the public investors on the NYSE.

relative tick size, as defined by the ratio of the minimum tick to stock price, important in trading strategy of the specialists?

The answers to these questions are very important because NYSE specialists make markets for a huge trading volume. On the NYSE, the dollar value of average monthly trading volume that the specialists oversee was $968.18 billion and average specialist volume as percentage of the NYSE total volume was around 20% in 2004.[2] Therefore, the average dollar volume that the specialists traded for their own accounts per month can be approximated as $193.64 billion. Specialists take one side of this huge trading activity and there are potential conflict of interests between the specialists desire to make profits for themselves and their obligation to be fair to all public traders. There has been an important debate going on about the role of the specialists and whether their contributions are valuable in the overall trading activity. Recently, as a result of an investigation by the U.S. Securities and Exchange Commission into floor trading practices, five largest specialist firms at the New York Stock Exchange were required to pay a combined $241.8 million to settle charges of improper trading.[3] More recently, the New York Times reported that the United States attorney's office was investigating individual specialists for executing proprietary orders before customer orders, and getting involved in a trade that should be carried out automatically with no intervention.[4]

---

[2] See "Market Activity" in the NYSE fact book that can be found at http://www.nysedata.com/factbook/. Generally, the specialist participation rate mentioned in the literature is the specialist volume as percent of NYSE 2x total volume which was approximately 10% in 2004. If one wants to calculate the total volume that the specialists traded for their own accounts, specialist volume as percent of NYSE total volume is the correct figure to use.

[3] See for example, *Wall Street Journal* (October 16, 2003) "NYSE to Punish Five Specialists In Trading Inquiry".

[4] "A New Inquiry Into Big Board Specialists", *New York Times*, February 7, 2005. Our paper does not address the issue of improper trading.

The NYSE claims that investors get the best available price most of the time in the specialist system. But many institutional investors prefer faster executions and believe that the human-based system for auctioning stocks does not allow this.[5] To address these concerns, the NYSE is planning to allow investors to execute more stock orders automatically.[6]

Despite the important role played by the NYSE specialists, one can find little or no analysis of their trading strategy. One reason for this lack of analysis in the previous literature is the lack of the data. To provide a meaningful analysis of specialist behavior, one needs detailed data about orders. Publicly available TAQ database contains information about volume and prices of individual transactions on the NYSE. However, this transaction data provides no information about specialist participation in individual trades. In addition to TAQ, the NYSE provided researchers with TORQ (Trades, Orders, Reports, and Quotes) database that contains transactions, quotes, order processing data, and audit trail data for a sample of 144 stocks for three months: November 1990 through January 1991.[7] This database can be used to partition posted depth into the specialist's contribution and the LOB's contribution (which is necessary for our analysis). Since the specialist IDs are removed from the TORQ database, one should rely on algorithms similar to the one provided in Panchapagesan (2000) to infer the trades with the specialist participation.

Considering the numerous changes in the trading system and procedures that occurred on the NYSE since 1991, TORQ database cannot provide much information

[5] See "Fidelity Urges NYSE to Revamp Trading Operation", *Wall Street Journal*, October 14, 2003.
[6] See"NYSE's Automatic Transition", *Wall Street Journal,* June 22, 2004 and the "Hybrid Market" information posted under http://www.nyse.com/pdfs/hm_booklet.pdf and http://www.nyse.com/productservices/nyseequities/1167694947683.html on the NYSE website.
[7] See Hasbrouck (1992) for a detailed description of TORQ database.

about the recent behavior of quotes and transactions.[8] Because of the public order precedence rule, the specialist has to better the quotes in the LOB if he wants to trade. The trading strategy of the specialists changed considerably after the decimalization in the NYSE, because undercutting the LOB became less costly now. [9]

When a market or marketable order arrives, the specialist faces the decision of choosing between the following strategies: i. Do not participate; ii. Participate at the quoted price; and iii. Participate and improve the price. Using 2001 NYSE system order data in the decimal pricing environment, we analyze how the specialist reacts to the changes in the market variables while choosing one of the three strategies above. To complete this analysis, it is important to determine the position of the specialist in the posted quotes, because this position is a constraint on specialist's strategy. For example, if a market buy order of size 100 arrives and the posted ask depth of 200 is coming from the specialist *only*, the specialist has no option but to trade with this market buy order unless another trading interest appears at the same time that can be matched with this market buy. In our example, if we did not look at the position of the specialist in the posted ask, we would incorrectly think that the specialist took the contra side of this market buy strategically, reacting to changes in market variables, where in fact he did not have any choice other than trading with the market buy. Accordingly, for each trade, we determine the position of the specialist in the posted quotes and determine his feasible strategies that do not contradict his affirmative obligations. Analyzing trading decisions of the specialists allows us to see if their trades are consistent with their market making

---

[8] The most important change is the switch to decimal pricing. For a list of other rule changes since 1997, visit http://apps.nyse.com/commdata/PubInfoMemos.nsf/AllPubRuleChanges?openview&count=500 .
[9] See Coughenour and Harris (2003) and references therein. Also see Ready (1999).

obligations as described above, or if they take away liquidity from the market for their own profits.

This work is related to a number of papers in the previous literature. Madhavan and Sofianos (1998) analyze specialist participation in the total transaction volume. Harris and Panchapagesan (2005) show that LOB is informative about future prices and specialists use this information. In this paper, we extend and complement their analysis in a number of ways. First, as described above, we take the position of the specialist in the posted quotes as given. So we are able to answer the question that "given his position in the posted quotes, i.e., given his participation strategy to the posted quotes, how does the specialist participate to the trades?". Second, we analyze the trading strategies of the specialists in the decimal pricing environment. The decimalization had many effects on the market variables including the profits of the specialists.[10] Therefore, our study also contributes to the previous literature by showing how the strategies of the specialists changed after the decimalization.

Our results from analyzing individual stocks over time indicate that the primary variables that the specialist looks at are the "Excess Spread", defined as spread minus minimum tick, and the "Relative Order Size", defined as the ratio of the market order size to the posted depth at the relevant side of the market. As the excess spread increases, more room is available for the specialist to undercut the LOB, and he trades more aggressively. This aggressiveness can also be the result of the specialists market making obligations. Since an increase in the spread is an indication of a weak market, the specialist might simply be trading because he has an obligation to trade when no one else is willing to trade. When the size of the market order relative to the posted bid size

[10] See Coughenour and Harris (2003) and references therein.

increases, the specialist increases the probability that he lets the market order trade with the LOB to protect himself from the possibility of informed trading.

The specialist increases the probability that he participates to the trade when a market order arrives if he is able to step in front of the heavy side of the LOB. In addition, the specialist uses information from the cumulative order imbalance since the last trade to update his beliefs about the true value of the stock. If the order imbalance, defined as cumulative buy volume minus sell volume during the last 15 minutes or 15 trades increases (decreases), the specialist increases the probability that he undercuts the LOB when a market sell (buy) arrives.

We also find significant inventory effects. The specialist trades more aggressively, if the trade with the incoming market order restores his inventory.

The effects of other variables seem to be secondary. There is some evidence that when the size of the arriving market order is medium, the specialist decreases the probability of participating in the trade, which supports the finding of Barclay and Warner (1993) that informed traders prefer medium sized orders.

The rest of the paper is organized as follows. Section 1 describes the determinants of the specialist trading strategy predicted by the previous literature and states the hypotheses. Section 2 describes the data. Empirical methodology is discussed in section 3. Section 4 presents the results from our analysis and Section 5 concludes.

1. Hypotheses

1.1. The determinants of specialist participation to the trades over time

As first analyzed by Stoll (1978), Ho and Stoll (1981, 1983), the risk of carrying inventory induces a positive bid-ask spread. However, many previous studies (e.g.

Madhavan and Smidt (1993), Hasbrouck and Sofianos (1993), Kavajecz and Odders-White (2001)) find weak inventory effects. Madhavan and Sofianos (1998) provide evidence that specialists manage their inventories through the timing and direction of their trades rather than adjusting bid and ask quotes. Therefore, we expect a risk averse specialist to increase (decrease) the probability of taking the contra side of a market buy (sell) order when he has a long inventory position and, inversely, to decrease (increase) the probability of taking the contra side of a market buy (sell) order when he has a short inventory position.

Seppi (1997) models the competition between limit order traders and a strategic specialist. He shows that when the bid-ask spread is greater than the minimum tick, the specialist undercuts the LOB for small trades. As the spread increases, there will be more price points that the specialist can use to undercut the LOB and make profits. Also, a wide spread might cause large jumps in the prices. Therefore, a large spread may induce the specialist to increase his participation because he has the market making obligation to maintain price continuity. Accordingly, we expect that the specialist increases the probability that he participates in a trade when the bid-ask spread is large.

Easley and O'Hara (1992) shows that time between trades can be correlated with the factors related to the value of the asset. In their model, the frequency of trades is positively correlated with the occurrence of an information event. If no trade occurs in some time interval, the market maker raises his probability that no information event has occurred. Accordingly, he moves his bid and ask quotes closer to the true value of the stock, which is between bid and ask prices, because the probability of trading with an informed trader is low. This implies that the spread will be smaller as the time between trades increases.[11] In the context of our model, we expect that as no-activity time increases, the specialist increases the probability that he participates to the next trade.

The state of the LOB is an important factor considered by the specialist while determining his strategy to participate in the trades. During our sample period, the specialists were required to share the general information about the LOB with the floor brokers when asked.[12] However, this information was not available to most traders in the market, so the specialist had considerable advantage in having access to the LOB. In Seppi (1997) model, limit order traders are the primary source of competition that the specialist faces. Harris and Panchapagesan (2005) find that specialist uses information from the LOB in ways that favor him. They argue, for example, that an asymmetry in the LOB predicts the likely direction of future price changes.

Specialists may also use quote-matching strategies.[13] As described in Harris (2003), quote matching is a front-running strategy in which quote matchers try to trade in front of large patient traders. For example, when a quote matcher trades (buys) in front of a large buy limit order, and prices move against him, he limits his losses by trading with the standing buy limit order. When a specialist buys in a similar situation, and the prices move against him, he should not trade with the limit buy order (a negative obligation) but at least he does not need to be on the contra side of upcoming market sells until the liquidity on the buy side of the LOB is exhausted.

---

[11] For a similar result, see Easley, Kiefer and O'Hara (1997). For evidence of transaction clustering, see Admati and Pfleiderer (1989) and Engle and Russell (1998).

[12] Recently, the NYSE started selling real-time aggregate order book volume at each price point through its new system called the NYSE OpenBook™. This reduces but not eliminates the advantage of the specialists because they still have the exclusive access to *individual* orders. For more information, visit http://www.nysedata.com/openbook/. For the effects of the NYSE OpenBook™, see Boehmer, Saar and Yu (2005).

[13] See Harris (2003), p.248 and p.502.

If the specialist exploits the information in the LOB, we would expect that when the LOB is heavy on the buy (sell) side, he increases the probability that he participates to the trade when a market sell (buy) arrives. There are two reasons for this. One of them is quote matching as described above. The second one is having information about the direction of future price changes. On the other hand, if the specialist trades according to his affirmative obligations, he would increase the probability that he participates to the trade when a market buy (sell) arrives at times when the LOB is heavy on the buy (sell) side to maintain price continuity. The effect of LOB asymmetry on the specialist's participation strategy to the trades is therefore an empirically open question.

In Kyle (1985) model, the market maker revises his expectations about the value of the stock upwards (downwards) and increases (decreases) the stock price as result of buy (sell) orders which possibly includes orders coming from informed traders. Although there are no bid and ask prices in the Kyle model, the idea is that the market maker updates his belief of what the stock is worth and adjusts the price so as to minimize his loss to informed traders. Obviously, this updated belief about the value of the stock will be crucial for the specialist when he has to decide whether to take the contra side of a market order. We expect that, as the buy (sell) transaction volume since the last trade increases, the specialist increases (decreases) the probability that he participates when a market sell order arrives, and decreases (increases) the probability that he participates when a market buy order arrives.

Barclay and Warner (1993) shows that most of the cumulative stock-price change is due to medium-size trades providing evidence consistent with the hypothesis that informed trades are concentrated in the medium-size category. Following Madhavan and

Sofianos (1998), we define a trade as medium if it is between 50th and 99th percentile in size. We expect that, the specialist decreases the probability of his participation if the size of the market order is medium.

Dupont (2000) shows that the market maker reduces depth when the volatility of the asset value is high. Intuitively, high volatility increases the risks associated with carrying inventory which will result in less specialist contribution to depth. On the other hand, Madhavan and Sofianos (1998) state that "Price continuity rules require specialists to trade to stabilize prices, suggesting that participation will be higher in stocks whose intraday return volatility is large." In a cross sectional analysis of specialist participation, they find a positive relationship between their volatility variable and the specialist participation rate. Bondarenko and Sung (2003) theoretically show that when the price volatility is high, the optimal strategy of the specialist is to increase his participation even when he is not constrained by the rules imposed by the exchange. The effect of volatility on the specialist's quoting decision is therefore an empirically open question.

Peterson and Sirri (2002) find that "marketable limit orders are used proportionally more often: i) for larger orders, ii) by non-individual investors, iii) when the order size exceeds quoted depth, iv) when quote imbalances exist, v) when the depth is relatively low, and vi) when spreads are narrow." Therefore it is more difficult and less profitable to execute a marketable limit order for the specialist. We expect that, if the arriving order is a marketable limit order, the specialist decreases the probability that he chooses strategy 3, i.e., strategy of undercutting the LOB.

1.2. Cross-sectional determinants of specialist participation to posted quotes

Previous theoretical literature shows that specialists' services are more valuable for illiquid stocks. We expect that specialist percentage participation to trades should decline as the liquidity of the assigned stock increases. Trading volume and market capitalization can be used as proxies for liquidity. So there should be an inverse relationship between specialist's participation and these proxies.

As discussed in detail in the previous section, when volatility is high, the specialist might reduce depth because of the risks associated with carrying inventory, or he might increase depth to stabilize the prices. Madhavan and Sofianos (1998) find a positive relationship between the volatility as measured by the standard deviation of the midquote to midquote transaction returns, and the specialist participation rate in a cross sectional analysis of specialist participation. The effect of volatility on the specialist's participation decision to quotes is an empirically open question.

Seppi (1997) analyzes a model in which specialists face direct competition from public limit orders that have precedence under the NYSE rules. He shows that specialist's profits are maximized as the tick size goes to zero. The reason is that as the tick size approaches to zero, it becomes less costly for the specialist to undercut the LOB. The tick size on the NYSE switched from eights to sixteenths on June 24, 1997 and to pennies for a number of stocks on August 28, 2000. Finally, on January 29, 2001, all NYSE stocks started being traded in pennies.[14] This decrease effectively relaxed the public order precedence rule and increased the set of prices over which the specialist can choose to undercut the limit orders. As predicted by the Seppi model, Coughenour and Harris (2003) find empirically that participation rates and high frequency trading profits

[14] See the "trading" column in NYSE timeline at http://www.nyse.com/about/timeline/TimeLine.html.

increased for specialists making markets for low price stocks as a result of decimalization. In the context of our model, it is more costly for the specialist to undercut the LOB for low price stocks which implies that the specialist participation to the trades will be inversely related to the "Relative Tick" defined as the ratio of the minimum tick ($0.01) to the stock price.

2. Data

Our data is from the NYSE System Order Database (SOD). Because of the volume of the data, it is necessary to select a sample of NYSE-listed securities. The original sample is selected as follows: Initially, 50 most actively traded NYSE stocks during the 20 trading days prior to January 29, 2001 are chosen. Also 25 stocks from each of four Volume-Price groups are randomly selected. To pick the 100-stock random sample, NYSE-listed securities are ranked on share trading volume and, separately, on average NYSE trade price during the 20 trading days prior to January 29, 2001. Each security is placed into one of four categories after comparing its share price to the median NYSE share price and its trading volume to the median NYSE volume. These groups (of unequal numbers of stocks) are a high-volume:high-price group, a high-volume:low-price group, a low-volume:high-price group, and, a low-volume:low-price group. Within each group, securities are arranged alphabetically (by symbol) and every Nth security is chosen, where N is chosen to select 25 securities from that group. Because two of the 50 stocks with the highest trading volume also are randomly chosen as part of the high volume groups, the final sample has 148 securities for the period April 2nd, 2001 – June 29th, 2001.

NYSE's System Order Database (SOD) gives detailed information on the entry and processing of orders. Order data include security, order type, a buy-sell indicator, order size, order date and time, limit price (if the order is a limit order), and the identity of the member firm submitting the order. Execution data include the trade's date and time, the execution price, the number of shares executing, and cancellation information. Orders, executions and cancellations are time-stamped to the second.

To determine the available strategies to the specialist when a market order arrives, we have to determine his position in the posted quotes. For example, as discussed in detail in Section 3.2.1 below, if the specialist represents all depth in the posted bid quote which is equal to 1000 shares, and if a market sell order of size less than 1000 arrives, the specialist has no choice but to take the other side of this trade (assuming that there does not exist a simultaneously arriving public order that could be matched with this market sell). [15] Since the posted quotes reflect trading interests of the limit order traders, floor brokers and the specialist, we need to estimate the LOB to separate the portion of the posted depth coming from the LOB. The LOBs are estimated by using the method described in Kavajecz (1999). First, the limit order book at the beginning of the sample period is estimated by searching for all execution and cancellation records that refer to orders placed before the sample period. Second, initial and each limit order book after that is updated sequentially depending on the placed orders, executions and cancellations. The result is the estimate of the LOBs at each point in time. After the LOBs are estimated, if the posted bid (ask) price is the same as the best limit bid (ask) price, then the LOB bid (ask) depth is subtracted from the posted bid (ask) depth. The *residual* depth comes from the specialist's trading interest and the orders left by the floor brokers with

[15] Our sample also contains marketable limit orders.

the specialist for the specialist to execute (passive floor broker participation). We call this residual as the "specialist's participation to the posted quotes" and use it to determine the position of the specialist in the posted quotes.[16] Sofianos and Werner (2000) estimate by using data from January 1997 to February 1997 that passive floor broker participation rate is 10.6% of buy plus sell volume of all purchases and sales. The remaining trade volume belongs to the specialist (10.8%), system orders (44.9%), and orders actively represented by the floor brokers (33.7%).

To calculate the transaction volume used in our analysis, we use Lee and Ready (1991) method to classify transactions in the TAQ database of the NYSE as buyer- or seller-initiated.

3. Empirical Methodology

3.1. Stock by Stock Analysis (Specialist participation over time)

When a market or marketable order arrives, the specialist faces the decision of choosing between the following strategies:

1. Do not participate,
2. Participate at the quoted price,
3. Participate and improve the price.[17]

Not all of above strategies are available to the specialist for all incoming market orders. Availability of the above strategies depends on the position of the specialist in the posted quotes. As an example consider the following scenario: The posted bid size is 1000 shares all of which comes from the LOB. Then, a market order to sell 500 shares

[16] Our dataset does not allow us to split out the passive floor broker participation.

[17] In their analysis of specialist trading decisions, Harris and Panchapagesan (2003) add one more case which is to "stop the order". The percentage of stopped orders in our sample is around 0.01%. Accordingly, we exclude this choice from our analysis.

arrives. In this case, only the choices 1 and 3 are available to the specialist. The specialist cannot participate at the quoted price because of the public order precedence rule.

[Insert Table 1.]

Table 1 reports the percentage of each quote case for different volume and price categories of stocks. If a stock's mean daily volume (price) is above the median of our sample, then it is in the high-volume (price) category, otherwise it is in the low-volume (price) category. We observe from the table that specialists quote more aggressively for low-volume stocks on the bid-side. Average percentage of bid quotes in which specialists undercut the LOB for low-volume (high-volume) stocks is 16.78 % (12.21 %). One reason might be that low-volume stocks have thin LOBs and they need more specialist participation. Another observation is that the specialists quote more aggressively for high-price stocks. A possible explanation consistent with the discussion in Section 1.2 is that as the relative tick size approaches zero, it becomes less costly for the specialist to undercut the LOB.

We determine the strategies for different cases as follows. Let's partition the posted bid depth into two parts that come from the specialist and the LOB. [18] So posted bid depth equals $S_B + L_B$, where S_B comes from the specialist, and L_B comes from the LOB. Let M_S denote the size of the incoming market sell. There exist three possible quote conditions according to the values that S_B and L_B take and for each quote condition there are two possible cases depending on the size of the incoming market sell order, M_S.[19] Therefore we have the following 6 cases for bid quotes (mirror image holds for the ask quotes).

[18] We only discuss the cases for the bid quotes, as the cases for the ask quotes are the mirror image.
[19] Koksal (2007a) analyzes specialist's decision of how much depth to add to the posted quotes in addition to the LOB.

Case 1. $S_B = 0; L_B > 0; M_S > L_B;$ LOB provides all depth; Market sell size > bid depth.

Case 2. $S_B = 0; L_B > 0; M_S \leq L_B;$ LOB provides all depth; Market sell size ≤ bid depth.

Case 3. $S_B > 0; L_B > 0; M_S > L_B;$ Mixed Case ; Market sell size > bid depth.

Case 4. $S_B > 0; L_B > 0; M_S > L_B;$ Mixed Case; Market sell size ≤ bid depth.

Case 5. $S_B > 0; L_B = 0; M_S > L_B;$ Specialist provides all depth; Market sell size > bid depth.

Case 6. $S_B > 0; L_B = 0; M_S \leq L_B;$ Specialist provides all depth; Market sell size ≤ bid depth.

Below, we discuss the strategies available to the specialist for each of the 6 cases.

Case 1: $S_B = 0; L_B > 0; M_S > L_B$

If the size of the incoming market order is greater than the posted bid depth, i.e., if $M_S > L_B$, then all three strategies are available to the specialist. Specifically, he may let the market order trade with the LOB; he may participate at the quoted price since the size of the market order is greater than the posted bid depth; or he may participate and improve the price and trade with the market order alone. This quote case provides the specialist with the highest degree of freedom, because since the size of the market order is greater than the corresponding depth coming from the LOB, the specialist can implement his strategy by choosing strategy 2 or strategy 3.

In this paper, we only analyze the initial decision of the specialist when the market order arrives. For example, the specialist may choose to fill *part* of the market order by participating and improving the price and he may let the remaining part filled by the LOB. We do not distinguish between filling the orders partially or completely.

[Insert Table 2.]

Case 2: $S_B = 0; L_B > 0; M_S \leq L_B$

If the size of the incoming market order is less than or equal to the posted bid depth, i.e., if $M_S \leq L_B$, then the specialist has the option to do nothing and let the market order trade with the LOB, or he can participate and improve the price. Hence, only the first and third strategies are available.

Case 3: $S_B > 0; L_B > 0; M_S > L_B$

In this case, the specialist cannot choose strategy 1, i.e., the choice of "not participating". He has to choose either strategy 2 and participate to the trade at the quoted price, or he can undercut the LOB and fill this order completely for his own account. Therefore, the available strategy set is {Strategy 2, Strategy 3}.

Case 4: $S_B > 0; L_B > 0; M_S \leq L_B$

In this case, the specialist cannot participate at the quoted price because of the public order precedence rule; hence second strategy is not available to the specialist. The available strategy set is {Strategy 1, Strategy 3}.

Case 5: $S_B > 0; L_B = 0; M_S > S_B,$

In this case the specialist has no choice but to trade with the market order. Therefore, we don't analyze this case.

Case 6: $S_B > 0; L_B = 0; M_S \leq S_B,$

Similar to Case 5 above, the specialist does not have any strategies to choose.

Table 2 lists all possible quote cases, and the available strategies of the specialist. In this table, S_B and S_A also include some orders left by the floor brokers with the specialist.

Given that a particular quote condition is $S_B = 0; L_B > 0$ or $S_B > 0; L_B > 0$, we use a multinominal logit framework to analyze Case 1, where all three strategies are available, and a logit framework to analyze the Cases 2, 3, and 4, where only two strategies are available.

3.2. *Explanatory variables for stock by stock analysis*

We use a multinominal logit model for our time series analysis of the specialist participation to the trades. This model will be discussed in more detail in Section 3.3 below. To test the hypotheses formulated in the first section we use the following variables for the time series analysis.

Excess Spread is the current quote spread minus the minimum tick in cents;

Relative Order Size is the log ratio of the market buy (sell) order size to the posted ask (bid) depth;

LOB Asymmetry is the total size of the sell limit orders minus the total size of the buy limit orders in the LOB multiplied by –1 if the incoming market order is a sell order;[20]

Near LOB Asymmetry is the total sell limit orders minus total buy limit orders within 20 cents of the best limit prices multiplied by –1 if the incoming market order is a sell order;

Signed Cumulative Order Imbalance is the total buy volume minus sell volume in all exchanges during the last 15 minutes or 15 trades whichever is shorter multiplied by -1 if the incoming market order is a buy order;[21]

Specialist's Signed Inventory cumulative inventory of the specialist preceding the trade multiplied by -1 if the incoming market order is a sell order;[22]

---

[20] If the specialist use information from the LOB as Harris and Panchapagesan (2005) found, they will trade more aggressively when they can step in front of the heavy side of the book

[21] We expect that the specialist will take the contra side of a market sell (buy) order more aggressively if the cumulative order imbalance preceding the trade is positive (negative), i.e., he updates his belief about the security value upwards (downwards) if the buy (sell) volume preceding the trade is greater than the sell (buy) volume. To calculate the transaction volume used in our analysis, we use Lee and Ready (1991) method to classify transactions in the TAQ database of the NYSE as buyer- or seller-initiated.

Medium Trade Dummy takes the value of 1 if the trade size is between 50th and 99th percentile and 0 otherwise;

Order Type Dummy takes the value of 1 for the marketable limit orders and 0 otherwise.

Volatility is the standard deviation of the transaction prices during the last ten minutes before the current quote;

Trade idle time is the normalized time in seconds since the arrival of the last market order.

3.3. Cross sectional analysis

We estimate the following cross-sectional regression model to analyze how the participation of the specialists varies across stocks:

$$\begin{aligned} SpecPart_i = \beta_0 + \beta_1 LogMeanDailyVol_i + \beta_2 RelTick_i + \beta_3 LogMarketCap_i \\ + \beta_4 Volatility_i + \beta_5 AvePercentageSpread_i + \varepsilon_i \end{aligned} \tag{1}$$

where, for stock i, $SpecPart_i$ is the percentage of the trades that the specialist participated (at the quote or by improving the price), $LogMeanDailyVol_i$ is the log of average daily volume, $RelTick_i$ is the minimum tick size (=$0.01) divided by the average stock price over the sample period, $LogMarketCap_i$ is the log of shares outstanding times average stock price, $Volatility_i$ is the average of the volatility variable from the time series analysis, $AvePercentageSpread_i$ is the average percentage quoted spread over the sample period and ε_i is the error term.

---

[22] We assume that the inventory of the specialist is equal to zero at the beginning of the period and ignore overnight changes in the inventory. Harris and Panchapagesan (2005) use this variable too. If the specialists manage inventory, they will trade more aggressively, i.e., increase the probability that they choose strategy 2 or 3, if trading would restore their inventories.

4. Results

4.1. Stock by Stock analysis

As discussed in Ellul, Holden, Jain and Jennings (2007), the exogenous variables affect the probability of choosing base case strategy, but because of the multinominal logit estimation, this effect can't be determined directly from the coefficients. In addition, occasionally, the signs of the coefficients of the non-base case variables can be different from the signs of their impact on the choices. To solve this problem, following Ellul, Holden, Jain and Jennings (2007), we calculate what they refer to as impulse sensitivities. "Impulse sensitivity" is defined as the change in the probability of an event caused by a one standard deviation increase in an explanatory variable. The benchmark probability of each event is calculated by using the estimated logistic function evaluated at the mean of each of the explanatory variables. The significance of an impulse sensitivity is calculated by the method described in Ellul, Holden, Jain and Jennings (2007).

In this paper, we don't distinguish between the market sells and market buys. Hence all the discussion below applies to both market buys and sells, since the 6 different cases are mirror images of each other for market buys and sells.

Tables 3 through 6 report the results for each of the four quote cases. Panel A of these tables report the impulse sensitivity of the exogenous variables. We will discuss and interpret the mean impulse sensitivities. In all tables, the percentages of significant impulse sensitivities at the 5% level of significance range from 89.41% to 100%.

The percentage probability changes in a row in the impulse sensitivity tables allow us to determine how the *net* effect of a one standard deviation increase in an explanatory variable from its mean is distributed among the strategies available to the specialist. This distribution allows us to determine the strategies that the specialist leans towards, by looking at the overall change in predicted probabilities. It is important to note that these numbers are not *levels*, i.e., they are not overall probabilities of selecting the strategies.

Case 1. $S_B = 0; L_B > 0; M_S > L_B$ or $S_A = 0; L_A > 0; M_B > L_A$

Table 3, Panel A reports the mean impulse sensitivities along with the percentage of impulse sensitivities that are significant at the 5% level for each stock. In this quote case, if the specialist wants to participate in a trade, he does not need to improve the price, because the size of the market order is large enough. The specialist will improve the price if the remaining size of the market order is not sufficient for the size he wants to trade.

[Insert Table 3.]

Specialists can use the (possible) information in the buy (sell) transaction volume in two ways. For example, when there is a large buy (sell) transaction volume, this may indicate that the stock price will increase (decrease). Accordingly, first, the specialists can protect themselves by not participating in a trade when a large market buy (sell) order arrives. Second, they can be more aggressive in participating a trade when a market sell (buy) order arrives. The impulse sensitivities for Strategies 1, 2 and 3 are -1.43 %, 0.64 % and 0.80%, respectively, when the "Cumulative Order Imbalance" increases by one standard deviation. As a result of one standard deviation increase in the "Cumulative Order Imbalance", the specialist increases the probability that he chooses strategy 3 (participate and improve price) by 0.80 %, increases the probability of strategy 2 by 0.64% and decreases the probability that he chooses the first strategy by 1.43%. Therefore, the specialist acts more aggressively to buy (sell) the stock, when he infers from "Cumulative Order Imbalance" that the stock price will increase (decrease). Hence, consistent with the Kyle (1985) model, he updates his belief of what the stock is worth and adjusts the price so as to minimize his loss to informed traders.

The effect of a one standard deviation in “Excess Spread” is to increase the probability of choosing strategy 3 by 5.57% on average. Probability of choosing other strategies decreases. Consistent with prediction of Seppi (1997), when excess spread increases, the specialist has more room to undercut the LOB, and he acts aggressively when a market order arrives. As discussed before, this result is also consistent with market making obligations of the specialists that they should be ready to trade when nobody else is willing to do so.

In their analysis of specialist strategies, Harris and Panchapagesan (2005) show that the LOB is informative about future price changes and the specialist uses this information. One of the variables that they use as measure of informativeness of the LOB is the overall LOB asymmetry. If the specialist uses information from the LOB, he would try to step in front of the heavy side of the LOB, i.e. he would be more aggressive and increase the probability that he chooses strategy 3. A one standard deviation disturbance to the “LOB Asymmetry” variable causes the specialist to increase his probability of choosing strategy 3 (stepping in front of the heavy side of the LOB) on average by 0.40%. Hence, the specialist uses the information in the LOB to predict future price changes but this effect seems small.

When the “Near LOB Asymmetry” increases by one standard deviation, the specialist interestingly increases the probability of strategy 2 by 0.56%. This is in contrast to the results for the overall LOB asymmetry. It seems that the specialists use information from the LOB by using the overall asymmetry, however, they are constrained by their market making obligations and are not always able to step in front of the heavy side of the LOB.[23]

Our results provide some evidence along the lines of the findings of Barclay and Warner (1993) that informed trades are concentrated in the medium-size category. When the size of the market order is medium, the specialist decreases the probability of participating and increases the probability of choosing the most defensive strategy by 1.25%

The impulse sensitivity of strategy 3 for "Order Type Dummy" is -0.68%. The specialist decreases the probability of aggressive participation which is consistent with the implications of Peterson and Sirri (2002) analysis that it is more difficult and less profitable to execute marketable limit orders.

"Relative Order Size" is one of the most important variables for the specialist while deciding whether to participate to a trade. When the size of the arriving market sell (buy) order relative to the posted bid (ask) depth increases by one standard deviation, the specialist decreases his probability of participating to a trade (i.e., choosing strategies 2 or 3) by 7.14%. Hence, the specialist is less willing to participate to a relatively large order, possibly coming from an informed trader.

The total impulse sensitivity of choosing strategies 2 and 3 associated with the specialist's inventory is 1.31%. Hence, the specialist becomes more aggressive in participating to a trade, if the trade would restore his inventory. This supports the results

[23] Koksal (2007a) shows that the asymmetry in the LOB close to the best limit prices is more informative in predicting the short term price changes.

in Madhavan and Sofianos (1998) that specialists selectively participate to trades to manage the inventory.[24]

As the time since the last trade increases, the specialist increases the probability of participating by 0.72%. This is consistent with finding of Easley and O'Hara (1992) that, if no trade occurs in some time interval, the market maker raises his probability that no information event has occurred. In our model, as no-activity time increases, the specialist increases the probability that he participates to the next trade.

Finally, as stock price volatility increases, the specialist decreases the probability of becoming more aggressive by 0.65% because the risks of carrying inventory is higher when the volatility of the stock increases.

Case 2. $S_B = 0; L_B > 0; M_S \leq L_B$ or $S_A = 0; L_A > 0; M_B \leq L_A$

In this case, the strategy of participating at the quoted price is not available because of the public order precedence rule. Therefore, the specialist must improve the price if he wants to trade. One implication is that, when the specialist wants to restore his inventory for example, he has to be more aggressive. The mean impulse sensitivities from the logit analysis are reported in Table 4 along with overall significance of impulse sensitivities at the 5% level.

[Insert Table 4.]

Similar to the previous case, the specialist revises his belief about the stock value by using the "Cumulative Order Imbalance". The impulse sensitivity of strategy 3 associated with cumulative order imbalance is 2.80%. Therefore, if the buy (sell) volume relative to the sell (buy) volume has been higher, the specialist increases the probability of

[24] Koksal (2007a)provides some evidence that the specialists also use posted quotes to manage their inventories.

participating to a trade when a market sell (buy) order arrives, to minimize his losses and make profits.

The "Excess Spread" has the most significant impact on specialist's choice of undercutting the LOB. The impulse sensitivity of Strategy 3 associated with excess spread is 10.01%. This number is almost twice as high as that of the same impulse sensitivity in the previous quote case. Since the size of, say, a market sell order is less than the corresponding bid size in the posted quotes coming from the LOB, when the specialist trades with this market sell, and the prices move against him, he does not need to be on the contra side of upcoming market sells until the liquidity on the buy side of the LOB is exhausted. This is a type of quote-matching strategy discussed in Section 1. On the other hand, the reason why the specialists are more aggressive when the spread is large might be the price smoothing obligation of the specialists. They may be improving the price to smooth the prices which otherwise would be more volatile because of the large spread.

The effect of an increase in the total asymmetry in the LOB is an increase in the probability of specialist being more aggressive. Since the LOB asymmetry may be informative for the future price movements as shown by Koksal (2007a), and Harris and Panchapagesan (2005), the specialist increases the probability of being more aggressive if he can step in front of the heavy side of the LOB.

Similar to the previous case, the specialist is less likely to take the contra side of a marketable limit order because since the price is fixed, it might be less profitable to trade with this order.

The impulse sensitivity of strategy 3 associated with specialist's inventory is 0.44% indicating that the specialist increases the probability of participating to a trade that will restore his inventory. This effect seems to be small though. This results is consistent with the findings of Madhavan and Smidt (1993) who find that the specialist inventories exhibit slow mean reversion, with a half-life of seven and three-tenths days.

The impulse sensitivity of the strategy 3 associated with "Relative Order Size" is negative, i.e., as the relative size of the market order increases the specialist decreases the probability of being aggressive. In the previous quote case, the size of the market order is greater than the posted depth coming from the LOB. Therefore, the size of the market order is relatively larger than the market order in this quote case. Accordingly, the specialist is more aggressive in *not* participating to a trade with the arriving market order in quote case 1 when compared to quote case2.

Case 3: $S_B > 0; L_B > 0; M_S > L_B$ or $S_A > 0; L_A > 0; M_B > L_A$

Table 5 reports the results for quote case 3. This case is similar to case 1 except, the specialist has some depth in the posted quotes now. The specialist's positive depth in the posted bid (ask) quotes indicates that he is trying to increase (decrease) his holdings of the stocks. Accordingly, we can expect that, when compared to quote case 1, the specialist will be more aggressive in undercutting the LOB, while participating to trades with upcoming market orders. This conjecture is indeed correct. For example, the impulse sensitivity of strategy 3 associated with "Cumulative Order Imbalance" for quote case 3 is 1.69%, which is higher than the combined impulse sensitivities of strategies 2 and 3 for the same variable in quote case 1. Similar finding is true for the impulse sensitivity of strategy 3 for the "Excess Spread". The impulse sensitivity of strategy 3 associated with the excess spread in quote case 3 is 22.19%, whereas the same number for quote case 1 is only 5.57%.

[Insert Table 5.]

As the relative market order size increases by one standard deviation, the probability of choosing strategy 2 increases by 8.93%. This increase is similar to the previous quote cases, where the specialist increases the probability of not participating as a result of an increase in relative order size. In quote case 3, however, strategy 1 is not an available strategy; hence the specialist increases the probability of the most defensive strategy that he can choose, i.e., strategy 2.

The impulse sensitivities associated with the asymmetry in the LOB is consistent with the previous quote cases. The results suggest that the specialist has some tendency to increase the probability that he participates to a trade, if he can trade in front of the heavy side of the LOB.

The impulse sensitivity of strategy 3 related to specialist's inventory is 0.69%. As discussed above, in this quote case, the positive depth coming from the specialist in the posted quotes might be an indication that the specialist wants to trade. If this depth is related to inventory concerns, we would expect to see that the specialist would be more aggressive in taking the other side of the incoming market order, which is the case here.

Case 4: $S_B > 0; L_B > 0; M_S \leq L_B$ or $S_A > 0; L_A > 0; M_B \leq L_A$

Case 4 is very similar to Case 2, in that the strategies available to the specialist are same. Since the size of the arriving market order is less then the depth coming from the LOB, the positive depth that the specialist adds is not very relevant. If he would like to trade, he has to undercut the LOB. There is one difference, however, similar to the difference between quote cases 1 and 3. The positive specialist depth in the quotes indicates that the specialist wants or needs to trade. To increase the probability that he trades, he adds some depth in the relevant side of the posted depth. Accordingly, we expect that the specialist will be more aggressive in participating to the trades in quote case 4, when compared to the quote case 2. The results reported in Table 6 are similar, however, suggesting that these two quote cases are similar to each other.

[Insert Table 6.]

4.1.1.Trading Volume Effects

There is considerable heterogeneity across stocks as reflected by distribution of estimated coefficients (not reported). Previous literature (e.g. Easley and et al. (1996)) finds that the specialists handle frequently traded stocks and infrequently traded stocks differently. The services of the specialists are mostly needed in thinly traded stocks. In their analysis of posted quote changes, Kavajecz and Odders-White (2001) find that there exist significant differences between high- and low-volume stocks.

To investigate the effect of volume on the strategy of the specialist, we divide the stocks in our sample into two volume categories based on average daily volume. If the average daily volume of a stock is greater than the median, it is considered a high-volume stock; otherwise it is a low-volume stock. The results are presented in Table 7. We report and discuss the impulse sensitivities only.

[Insert Table 7.]

The impulse sensitivity of the strategy 1 associated with the “Cumulative Order Imbalance” is higher in absolute value for low volume stocks for all quote cases except for quote case 3. The effect of this variable is higher for low volume stocks, possibly because order imbalance carries more information for illiquid stocks.

The effect of "Excess Spread" is higher for high volume stocks for quote cases 1 and 3, where the size of the market order is greater than the LOB depth in the posted quotes, and higher for low volume stocks for quote cases 2 and 4, where the size of the market order is less than the LOB depth in the posted quotes. This result has two implications. First, the specialist has more information than anyone about an illiquid stock that he oversees, because infrequently traded stocks are not closely followed by investors. In addition, the depth coming from the LOB for illiquid stocks is generally low, resulting in higher frequency of undercutting the LOB by the specialists consistent with their market making obligations to maintain price continuity.

In all quote cases except for quote case 2, the impulse sensitivity of undercutting the LOB associated with the specialist's inventory is higher for low volume stocks. Specialists increase the probability of undercutting the LOB more for low volume stocks if the trade would restore their inventories because inventory management is more difficult for illiquid stocks. Therefore, whenever they get the chance, they aggressively try to restore their inventory.

4.1.2.Trading Price Effects

Trading price of a stock can be important for the specialists because for the same number of shares, they have to use more capital for high-price stocks. Also, relative tick size, as defined by the ratio of the tick size to stock price, is smaller for the high-price stocks making the public order precedence rule less binding. In their analysis of specialist profits and the tick size, Coughenour and Harris (2003) find that after the decimalization, participation rates and high frequency trading profits increased for specialists handling low-price stocks.

To see if the strategies of the specialists depend on the price of the stocks, we divide the stocks into two price categories. If the mean price of a stock is greater than the median in our sample, it is in the high-price category; otherwise it is in the low-price category. Table 8 reports the mean impulse sensitivities according to the price categories.

[Insert Table 8.]

The effect of inventory on choosing strategy 3 is generally higher for low-price stocks. This implies that the specialists might be concerned more about the dollar value of their inventories. Since they have to trade more for low-price stocks to restore their inventories in dollar terms, the impulse sensitivity of strategy 3 related to inventory is higher for low-price stocks.

A similar effect can be seen in the impulse sensitivity of strategy 3 related to "Cumulative Order Imbalance". It is higher for low-price stocks for quote cases 2 and 4, because higher number of shares is required to implement a particular trading strategy.

4.2. Cross Sectional Analysis

Coefficient of *logarithm of mean daily volume* is negative and significant at the 1% level. Specialist participation to trades decreases as transaction volume increases. This might indicate either that specialist services are needed more for thinly traded, illiquid stocks or participating to the trades for low-volume stocks is more profitable.

[Insert Table 9.]

Log of market capitalization has a positive significant coefficient. Therefore holding everything else like volume constant, the specialist participation is higher for larger firms. One explanation might be that better public information is available for larger firms and the possibility of informed trading is lower. Hence it is more profitable for the specialist to participate in the trades for these stocks to collect the bid ask spread.

In addition, there is a positive relationship between the volatility of the stock and the average percentage specialist participation providing evidence that specialists increase their participation to smooth prices for volatile stocks. Finally, estimated coefficient of the "Percentage Quoted Spread" provides a related result. As the percentage spread increases, the specialist has more price points to choose from, and accordingly, his participation increases.

4.3. Are the participation strategies of the specialists to the trades informative about future price changes?

By using the TORQ database, Harris and Panchapagesan (2005) show that the LOB is informative about the future price movements, and that specialists use this information while making trading decisions. During the period of TORQ database the tick size was equal to \$1/8, and after decimalization the strategies of the specialists have changed considerably.[25]

We use a direct method to test if the specialist's trades are informative about future price changes. Specifically, we estimate the following model by using OLS for each security i:

$$R_{i,t+k} = \alpha_i + \beta_{0,i} R_{i,t-k} + \beta_{1,i} SpPart_{i,t} + \varepsilon_{i,t} \tag{2}$$

where subscript t denotes arrival time of the market order, $R_{i,t+k}$ is the transaction price return in basis points over k periods starting at time t, $R_{i,t-k}$ is the transaction price return in basis points over k periods ending at time t, $SpPart_{i,t}$ is a signed dummy

[25] See Coughenour and Harris (2003).

variable that is equal to 1, if the specialist chooses strategy 2 or 3 for case 1, and is equal to 1 if the specialist chooses strategy 3 for cases 2, 3 and 4, and zero otherwise, and it is multiplied by -1 if the incoming market order is a buy order and $\varepsilon_{i,t}$ is the random error term. The definition of $SpPart_{i,t}$ implies that, a positive estimated coefficient indicates a correct prediction of the future returns by the specialist. k equals 5 minutes, 1 hour or 1 day. The model captures the predictive power of the trades that the specialists have participated over different time horizons. We include the lagged return to model return mean reversion in short horizon transaction price returns documented in the previous literature.

[Insert Table 10.]

Table 10 reports the results from estimating equation (2) for all quote cases. A positive coefficient of specialist participation to the trades indicates that the specialist predicts the future return correctly. General conclusion from Table 10 is that, as the time horizon increases, the success of the specialists in predicting the direction of future price movement decreases.[26] Koksal (2007a) finds that the limit order book asymmetry close to the best limit prices is more informative about the future returns and this informativeness decreases as the time horizon increases. Accordingly, since this is the information that the specialists use, their success rate decreases with the time horizon as well. Overall, the specialists are not very successful in predicting future returns. Panel B of Table 10 shows that, overall success of specialists in predicting future returns is around 20%. Some specialists, however, are more successful in predicting future returns

[26] Koksal (2007a) shows that the participation of specialists in the posted quotes has some predictive power over future stock returns, this power being stronger for short-term returns.

than others. The results from individual regressions (not reported) show that there are some specialists who can predict the future returns correctly over all time horizons.

5. Conclusion

Using 2001 NYSE system order data in the decimal pricing environment, we analyze how the specialists react to the changes in market variables while making participation decisions to the trades. We analyze the following options that are available to the specialist before he trades: don't participate; participate at the quoted price; participate and improve the price. We find that the specialist uses information in the limit order book as summarized by the limit order book asymmetry. The specialist is more likely to participate to a trade with an arriving market order, if he can step in front of the LOB. If the relative size of the market order, as described by the ratio of the market order size to the posted depth at the relevant side of the market, is high, the specialist chooses not to participate and let the market order trade with the limit order book. Consistent with the theoretical results in the previous literature, specialists trade more aggressively when the spread is large. We find that specialist trading strategies in stocks from different volume and price categories differ. Finally, there is evidence that the specialists trade selectively to manage their inventories.

References

Admati, Anat R., and Paul Pfleiderer, 1989, Divide and Conquer: A Theory of Intraday and Day-of-the-Week Mean Effects, *Review of Financial Studies* 2, 189-223.

Barclay, Michael J., and Jerold B. Warner, 1993, Stealth Trading and Volatility: Which Trades Move Prices?, *Journal of Financial Economics* 34, 281-305.

Boehmer, Ekkehart, Gideon Saar, and Lei Yu, 2005, Lifting the Veil: An Analysis of Pre-trade Transparency at the NYSE, *Journal of Finance* 60, 783-815.

Bondarenko, Oleg, and Jaeyoung Sung, 2003, Specialist participation and limit orders, *Journal of Financial Markets* 6, 539-571.

Coughenour, Jay F., and Lawrence E. Harris, 2003, Specialist Profits and Minimum Price Increment, *Working Paper, University of Delaware*.

Dupont, Dominique, 2000, Market Making, Prices, and Quantity Limits, *Review of Financial Studies* 13, 1129-51.

Easley, David, and et al., 1996, Liquidity, Information, and Infrequently Traded Stocks, *Journal of Finance* 51, 1405-36.

Easley, David, Nicholas M. Kiefer, and Maureen O'Hara, 1997, One Day in the Life of a Very Common Stock, *Review of Financial Studies* 10, 805-35.

Easley, David, and Maureen O'Hara, 1992, Time and the Process of Security Price Adjustment, *Journal of Finance* 47, 576-605.

Ellul, Andrew, Craig W. Holden, Pankaj Jain, and Robert Jennings, 2007, Order Dynamics: Recent Evidence from the NYSE, *forthcoming in the Journal of Empirical Finance*.

Engle, Robert F., and Jeffrey R. Russell, 1998, Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data, *Econometrica* 66, 1127-62.

Harris, Larry, 2003. *Trading and Exchanges: Market Microstructure for Practitioners* (Oxford University Press).

Harris, Lawrence E., and Venkatesh Panchapagesan, 2005, The information content of the limit order book: evidence from NYSE specialist trading decisions, *Journal of Financial Markets* 8, 25-67.

Harris, Lawrence, and Venkatesh Panchapagesan, 2003, The Information-Content of the Limit Order Book: Evidence from NYSE Specialist Trading Decisions, *Working Paper, Washington University*.

Hasbrouck, Joel, 1992, Using the TORQ Database, *Working Paper, New York University*.

Hasbrouck, Joel, and George Sofianos, 1993, The Trades of Market Makers: An Empirical Analysis of NYSE Specialists, *Journal of Finance* 48, 1565-93.

Kavajecz, Kenneth A., 1999, A Specialist's Quoted Depth and the Limit Order Book, *Journal of Finance* 54, 747-71.

Kavajecz, Kenneth A., and Elizabeth R. Odders-White, 2001, An Examination of Changes in Specialists' Posted Price Schedules, *Review of Financial Studies* 14, 681-704.

Koksal, Bulent, 2007a, Participation Strategy of the NYSE Specialists to the Posted Quotes, *Working Paper, Fatih University*.

Kyle, Albert S., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315-35.

Lee, Charles M. C., and Mark J. Ready, 1991, Inferring Trade Direction from Intraday Data, *Journal of Finance* 46, 733-46.

Madhavan, Ananth, and Seymour Smidt, 1993, An Analysis of Changes in Specialist Inventories and Quotations, *Journal of Finance* 48, 1595-1628.

Madhavan, Ananth, and George Sofianos, 1998, An Empirical Analysis of NYSE Specialist Trading, *Journal of Financial Economics* 48, 189-210.

Panchapagesan, Venkatesh, 2000, Identifying Specialist Trades in the TORQ Data --- A Simple Algorithm, *Working Paper, Washington University*.

Peterson, Mark, and Erik Sirri, 2002, Order Submission Strategy and the Curious Case of Marketable Limit Orders, *Journal of Financial and Quantitative Analysis* 37, 221-41.

Ready, Mark J., 1999, The Specialist's Discretion: Stopped Orders and Price Improvement, *Review of Financial Studies* 12, 1075-1112.

Seppi, Duane J., 1997, Liquidity Provision with Limit Orders and a Strategic Specialist, *Review of Financial Studies* 10, 103-50.

Sofianos, George, and Ingrid M. Werner, 2000, The trades of NYSE floor brokers, *Journal of Financial Markets* 3, 139-176.

Stoll, Hans R., 1978, The Supply of Dealer Services in Securities Markets, *Journal of Finance* 33, 1133-51.

Table 1. Percentage participation by the NYSE specialists to the posted quotes

This table reports the percentage of bid side and ask side position of the specialists for the stocks in our sample according to volume and price categories. If mean daily volume (mean price) of a stock is higher than the median, then it is in "high" category, otherwise it is in "low" category. The three possible cases for the posted quotes are: LOB alone, LOB+Specialist, and Specialist alone. S_A and S_B denotes the depth contributed by the specialist to the posted bid and ask quotes, respectively. Similarly, L_A and L_B denotes the depth contributed by the LOB to the posted bid and ask quotes, respectively. The numbers in the rows sum up to 100% subject to rounding error.

Volume Categories	**LOB Alone**	**LOB+Specialist**	**Specialist Alone**
Bid-Side of the posted quotes	S_B=0; L_B>0	S_B>0; L_B>0	S_B>0; L_B=0
High	68.89	18.91	12.21
Low	72.40	10.82	16.78
Ask-Side of the posted quotes	S_A=0; L_A>0	S_A>0; L_A=0	S_A>0; L_A=0
High	53.95	23.80	22.25
Low	62.47	15.96	21.57

Price Categories	**LOB Alone**	**LOB+Specialist**	**Specialist Alone**
Bid-Side of the posted quotes	(S_B=0; L_B>0)	(S_B>0; L_B>0)	(S_B>0; L_B=0)
High	68.28	18.34	13.39
Low	70.89	19.95	9.17
Ask-Side of the posted quotes	S_A=0; L_A>0	S_A>0; L_A=0	S_A>0; L_A=0
High	52.92	23.30	23.78
Low	57.65	24.64	17.71

Table 2. Specialist's available choices for different cases.

This table reports possible quote cases at the time a market sell (buy) order of size M_S (M_B) arrives to the specialist. S_B and L_B are the contributions to the posted depth from the specialist and limit order book, respectively (similar for posted ask). Possible strategies of the specialist are 1 (Do not participate), 2 (Participate at the quoted price), and 3 (Participate and improve the price) depending on the quote condition.

		Possible Decisions
Posted Bid Depth Size	$= S_B+L_B$	**1.** Do not participate.
Posted Ask Depth Size	$= S_A+L_A$	**2.** Participate at the quoted price.
		3. Participate and improve the price.

Bid Side Quote Condition	Case	Size of the Incoming Market Sell (M_S)	Possible Decisions
$S_B=0; L_B>0$	1	$M_S > L_B$	1,2,3
	2	$M_S \leq L_B$	1,3
$S_B>0; L_B>0$	3	$M_S > L_B$	2,3
	4	$M_S \leq L_B$	1,3
$S_B>0; L_B=0$	5	$M_S > S_B$	No Decision
	6	$M_S \leq S_B$	No Decision

Ask Side Quote Condition	Case	Size of the Incoming Market Buy (M_B)	Possible Decisions
$S_A=0; L_A>0$	1	$M_B > L_A$	1,2,3
	2	$M_B \leq L_A$	1,3
$S_A>0; L_A>0$	3	$M_B > L_A$	2,3
	4	$M_B \leq L_A$	1,3
$S_A>0; L_A=0$	5	$M_B > S_A$	No Decision
	6	$M_B \leq S_A$	No Decision

Table 3. Multinominal Logit Model Results for stock by stock estimation for Quote Case 1

In Panel A, we report the mean impulse sensitivities defined as the change in the probability of an event caused by a one standard deviation shock to the explanatory variable. Available strategies of the specialist are as follows: 1 (Do not participate), 2 (Participate at the quoted price), and 3 (Participate and improve the price). Significance column in Panel A reports the percentage of significant impulse sensitivities at 5% level of significance. Panel B reports the percentage of negative and positive significant coefficients.

Panel A. Mean Impulse Sensitivites (%)

	3 Choices Available to the Specialist			Significance (%)		
Exogoneous Variables	**Str1**	**Str2**	**Str3**	**Str1**	**Str2**	**Str3**
Cumulative Order Imbalance	-1.43	0.64	0.80	98%	99%	98%
Excess Spread	-4.20	-1.32	5.57	100%	99%	99%
Medium Trade Dummy	1.25	-0.96	-0.29	95%	96%	97%
Trade Idle Time	-0.72	0.64	0.08	94%	96%	96%
Relative Order Size	7.12	-4.83	-2.31	100%	99%	99%
LOB Asymmetry	-0.42	0.02	0.40	98%	98%	98%
Near LOB Asymmetry	-0.57	0.56	0.00	97%	98%	96%
Order Type Dummy	-1.77	2.45	-0.68	98%	99%	97%
Specialist's Inventory	-1.31	0.66	0.66	98%	98%	97%
Volatility	0.64	-0.35	-0.30	98%	97%	97%

Panel B. Signs of Significant Impulse Sensitivities in Percentages

	Str1		Str2		Str3	
Exogoneous Variables	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**
Cumulative Order Imbalance	83	17	45	55	11	89
Excess Spread	90	10	67	33	1	99
Medium Trade Dummy	28	72	69	31	70	30
Trade Idle Time	78	22	26	74	39	61
Relative Order Size	0	100	97	3	100	0
LOB Asymmetry	56	44	48	52	41	59
Near LOB Asymmetry	58	42	41	59	54	46
Order Type Dummy	71	29	16	84	87	13
Specialist's Inventory	72	28	31	69	34	66
Volatility	31	69	68	32	63	37

Table 4. Multinominal Logit Model Results for stock by stock estimation for Quote Case 2

In Panel A, we report the mean impulse sensitivities defined as the change in the probability of an event caused by a one standard deviation shock to the explanatory variable. Available strategies of the specialist are as follows: 1 (Do not participate), and 3 (Participate and improve the price). Significance column in Panel A reports the percentage of significant impulse sensitivities at 5% level of significance. Panel B reports the percentage of negative and positive significant coefficients.

Panel A. Mean Impulse Sensitivites (%)

	2 Choices Available to the Specialist		Significance (5 %)	
Exogoneous Variables	**Str1**	**Str3**	**Str1**	**Str3**
Cumulative Order Imbalance	-2.80	2.80	97.32%	97.32%
Excess Spread	-10.01	10.01	100.00%	100.00%
Medium Trade Dummy	0.64	-0.64	95.54%	95.54%
Trade Idle Time	-1.03	1.03	94.64%	94.64%
Relative Order Size	2.15	-2.15	98.21%	98.21%
LOB Asymmetry	-1.03	1.03	98.21%	98.21%
Near LOB Asymmetry	0.23	-0.23	100.00%	100.00%
Order Type Dummy	0.97	-0.97	96.43%	96.43%
Specialist's Inventory	-0.44	0.44	98.21%	98.21%
Volatility	0.50	-0.50	99.11%	99.11%

Panel B. Signs of Significant Impulse Sensitivities in Percentages

	Str1		Str3	
Exogoneous Variables	**Negative**	**Positive**	**Negative**	**Positive**
Cumulative Order Imbalance	86.61	13.39	13.39	86.61
Excess Spread	99.95	0.05	5.36	94.64
Medium Trade Dummy	54.46	45.54	45.54	54.46
Trade Idle Time	89.29	10.71	61.61	38.39
Relative Order Size	10.71	89.29	89.29	10.71
LOB Asymmetry	60.71	39.29	39.29	60.71
Near LOB Asymmetry	38.39	61.61	61.61	38.39
Order Type Dummy	14.29	85.71	85.71	14.29
Specialist's Inventory	62.50	37.50	37.50	62.50
Volatility	32.14	67.86	67.86	32.14

Table 5. Multinominal Logit Model Results for stock by stock estimation for Quote Case 3

In Panel A, we report the mean impulse sensitivities defined as the change in the probability of an event caused by a one standard deviation shock to the explanatory variable. Available strategies of the specialist are as follows: 2 (Participate at the quoted price), and 3 (Participate and improve the price). Significance column in Panel A reports the percentage of significant impulse sensitivities at 5% level of significance. Panel B reports the percentage of negative and positive significant coefficients.

Panel A. Mean Impulse Sensitivites (%)

	2 Choices Available to the Specialist		Significance (5 %)	
Exogoneous Variables	**Str2**	**Str3**	**Str2**	**Str3**
Cumulative Order Imbalance	-1.69	1.69	91.76%	91.76%
Excess Spread	-22.19	22.19	98.82%	98.82%
Medium Trade Dummy	-1.86	1.86	97.65%	97.65%
Trade Idle Time	-0.16	0.16	94.12%	94.12%
Relative Order Size	8.93	-8.93	97.65%	97.65%
LOB Asymmetry	-1.43	1.43	95.29%	95.29%
Near LOB Asymmetry	1.17	-1.17	91.76%	91.76%
Order Type Dummy	2.73	-2.73	89.41%	89.41%
Specialist's Inventory	-0.69	0.69	96.47%	96.47%
Volatility	1.40	-1.40	96.47%	96.47%

Panel B. Signs of Significant Impulse Sensitivities in Percentages

	Str2		Str3	
Exogoneous Variables	**Negative**	**Positive**	**Negative**	**Positive**
Cumulative Order Imbalance	69.41	30.59	30.59	69.41
Excess Spread	100	0	0	100
Medium Trade Dummy	61.18	38.82	38.82	61.18
Trade Idle Time	49.41	50.59	50.59	49.41
Relative Order Size	1.18	98.82	98.82	1.18
LOB Asymmetry	55.29	44.71	44.71	55.29
Near LOB Asymmetry	42.35	57.65	57.65	42.35
Order Type Dummy	18.82	81.18	81.18	18.82
Specialist's Inventory	57.65	42.35	42.35	57.65
Volatility	37.65	62.35	62.35	37.65

Table 6. Multinominal Logit Model Results for stock by stock estimation for Quote Case 4

In Panel A, we report the mean impulse sensitivities defined as the change in the probability of an event caused by a one standard deviation shock to the explanatory variable. Available strategies of the specialist are as follows: 1 (Do not participate), and 3 (Participate and improve the price). Significance column in Panel A reports the percentage of significant impulse sensitivities at 5% level of significance. Panel B reports the percentage of negative and positive significant coefficients.

Panel A. Mean Impulse Sensitivites (%)

	2 Choices Available to the Specialist		Significance (5 %)	
Exogoneous Variables	**Str1**	**Str3**	**Str1**	**Str3**
Cumulative Order Imbalance	-1.11	1.11	96.70%	96.70%
Excess Spread	-5.37	5.37	97.80%	97.80%
Medium Trade Dummy	0.37	-0.37	98.90%	98.90%
Trade Idle Time	-0.19	0.19	95.60%	95.60%
Relative Order Size	-2.54	2.54	93.41%	93.41%
LOB Asymmetry	0.90	-0.90	93.41%	93.41%
Near LOB Asymmetry	-0.84	0.84	94.51%	94.51%
Order Type Dummy	0.73	-0.73	95.60%	95.60%
Specialist's Inventory	-0.51	0.51	97.80%	97.80%
Volatility	1.74	-1.74	95.60%	95.60%

Panel B. Signs of Significant Impulse Sensitivities in Percentages

	Str1		Str3	
Exogoneous Variables	**Negative**	**Positive**	**Negative**	**Positive**
Cumulative Order Imbalance	81.32	18.68	18.68	81.32
Excess Spread	96.70	3.30	3.30	96.70
Medium Trade Dummy	50.55	49.45	49.45	50.55
Trade Idle Time	76.92	23.08	23.08	76.92
Relative Order Size	75.82	24.18	24.18	75.82
LOB Asymmetry	36.26	63.74	63.74	36.26
Near LOB Asymmetry	49.45	50.55	50.55	49.45
Order Type Dummy	19.78	80.22	80.22	19.78
Specialist's Inventory	42.86	57.14	57.14	42.86
Volatility	26.37	73.63	73.63	26.37

Table 7. Logit Model Results for stock by stock estimation according to volume categories

This table reports report the mean impulse sensitivities defined as the change in the probability of an event caused by a one standard deviation shock in the explanatory variable from logistic regressions that converged for all quote cases by volume categories. If mean daily volume of a stock is above the median, then it is in the high-volume category, otherwise it is in the low-volume category.

		Quote Case 1			Quote Case 2		Quote Case 3		Quote Case 4	
Variable	**Vol. Cat.**	**Str1**	**Str2**	**Str3**	**Str1**	**Str3**	**Str2**	**Str3**	**Str1**	**Str3**
Cumulative Order Imbalance	H	-1.12	0.32	0.81	-2.27	2.27	-2.57	2.57	-0.68	0.68
	L	-2.25	1.50	0.78	-3.80	3.80	3.20	-3.20	-2.74	2.74
Excess Spread	H	-3.46	-2.57	6.03	-7.17	7.17	-22.30	22.30	-4.39	4.39
	L	-6.21	2.08	4.29	-15.34	15.34	-21.59	21.59	-9.12	9.12
Medium Trade Dummy	H	0.79	-0.65	-0.14	-0.51	0.51	-0.78	0.78	0.09	-0.09
	L	2.49	-1.79	-0.72	2.81	-2.81	-7.78	7.78	1.44	-1.44
Relative Order Size	H	6.43	-4.04	-2.38	1.45	-1.45	8.61	-8.61	-1.27	1.27
	L	8.99	-6.95	-2.12	3.46	-3.46	10.72	-10.72	-7.37	7.37
LOB Asymmetry	H	-0.96	0.33	0.62	-0.27	0.27	-0.75	0.75	0.52	-0.52
	L	1.04	-0.81	-0.24	-2.45	2.45	-5.22	5.22	2.35	-2.35
Near LOB Asymmetry	H	-0.07	0.23	-0.16	-0.15	0.15	1.13	-1.13	-0.18	0.18
	L	-1.91	1.47	0.46	0.92	-0.92	1.38	-1.38	-3.34	3.34
Trade Idle Time	H	-0.91	0.66	0.25	-1.26	1.26	-0.32	0.32	-0.76	0.76
	L	-0.22	0.58	-0.38	-0.61	0.61	0.67	-0.67	1.97	-1.97
Order Type Dummy	H	-1.21	2.08	-0.87	1.01	-1.01	2.60	-2.60	0.73	-0.73
	L	-3.29	3.44	-0.16	0.89	-0.89	3.43	-3.43	0.71	-0.71
Specialist's Inventory	H	-1.19	0.70	0.49	-0.50	0.50	-0.37	0.37	0.04	-0.04
	L	-1.62	0.53	1.13	-0.33	0.33	-2.44	2.44	-2.57	2.57
Volatility	H	1.41	-0.94	-0.47	1.06	-1.06	1.35	-1.35	1.13	-1.13
	L	-1.42	1.24	0.19	-0.56	0.56	1.65	-1.65	4.06	-4.06

Table 8. Logit Model Results for stock by stock estimation according to price categories

This table reports report the mean impulse sensitivities defined as the change in the probability of an event caused by a one standard deviation shock in the explanatory variable from logistic regressions that converged for all quote cases by price categories. If mean daily price of a stock is above the median, then it is in the high-price category, otherwise it is in the low-price category.

		Quote Case 1			Quote Case 2		Quote Case 3		Quote Case 4	
Variable	**Price. Cat.**	**Str1**	**Str2**	**Str3**	**Str1**	**Str3**	**Str2**	**Str3**	**Str1**	**Str3**
Cumulative Order Imbalance	H	-1.67	0.77	0.90	-2.21	2.21	-1.92	1.92	-0.65	0.65
	L	-1.14	0.48	0.68	-3.49	3.49	-1.35	1.35	-1.79	1.79
Excess Spread	H	-4.18	-2.72	6.90	-8.57	8.57	-21.61	21.61	-5.07	5.07
	L	-4.23	0.33	3.99	-11.67	11.67	-23.03	23.03	-5.82	5.82
Medium Trade Dummy	H	0.46	-0.44	-0.01	-0.29	0.29	-1.92	1.92	0.37	-0.37
	L	2.18	-1.57	-0.62	1.72	-1.72	-1.76	1.76	0.38	-0.38
Relative Order Size	H	6.29	-3.76	-2.53	1.58	-1.58	9.71	-9.71	-2.30	2.30
	L	8.09	-6.09	-2.05	2.81	-2.81	7.82	-7.82	-2.89	2.89
LOB Asymmetry	H	-0.71	0.39	0.32	-1.21	1.21	-1.00	1.00	0.68	-0.68
	L	-0.07	-0.41	0.49	-0.83	0.83	-2.05	2.05	1.23	-1.23
Near LOB Asymmetry	H	-0.39	0.39	-0.01	0.68	-0.68	1.64	-1.64	-0.47	0.47
	L	-0.77	0.76	0.01	-0.29	0.29	0.49	-0.49	-1.37	1.37
Trade Idle Time	H	-0.90	0.72	0.18	-1.31	1.31	-0.92	0.92	-1.06	1.06
	L	-0.51	0.55	-0.04	-0.72	0.72	0.92	-0.92	1.08	-1.08
Order Type Dummy	H	-1.50	2.36	-0.86	1.28	-1.28	2.32	-2.32	0.66	-0.66
	L	-2.10	2.56	-0.47	0.61	-0.61	3.31	-3.31	0.83	-0.83
Specialist's Inventory	H	-0.89	0.40	0.50	-0.78	0.78	-0.67	0.67	0.26	-0.26
	L	-1.79	0.96	0.85	-0.05	0.05	-0.71	0.71	-1.63	1.63
Volatility	H	1.20	-0.65	-0.56	0.85	-0.85	2.05	-2.05	1.58	-1.58
	L	-0.01	0.00	0.01	0.09	-0.09	0.46	-0.46	1.97	-1.97

Table 9. OLS Results from Cross-sectional Regression of Specialist Participation

This table reports results from estimation of equation 1. Standard errors are reported in parantheses. ***, ** and * denotes significance levels at the 1%, 5% and 10% levels, respectively. Dependent variable is the percentage of trades that the specialist has chosen strategy 2 (participate at the quoted price) or strategy 3 (participate at the improved price).

Exogoneous Variables	**Coefficients**	
Intercept	0.344	***
	(0.118)	
Log Mean Daily Volume	-0.062	***
	(0.016)	
Log Market Capitalization	0.043	***
	(0.014)	
Relative Tick	9.915	
	(9.105)	
Volatility (Std. Dev. of Transaction Prices)	0.005	*
	(0.003)	
Average Percentage Quoted Spread	0.008	**
	(0.004)	
Sample Size	120	
Adj R^2	0.37	

Table 10. GMM Results from Time Series Regression of Future Returns

Panel A reports results from estimation of equation 2 for each of the 148 stocks in our sample. For each future return regression (k=5 minutes, 1 hour, or 1 day), mean and standard error of all coefficient estimates across stocks are reported. The last two columns report the number of significant positive and negative coefficients at the 10% level. A positive coefficient of specialist participation to the trades indicates that the specialist predicts the future return correctly. Panel B reports the percentage of correct predictions for each quote case calculated by dividing the frequency of positive coefficients in Panel A by the total number of stocks used in the analysis.

Panel A. Distribution of the coefficient estimates

	Quote Case 1				Quote Case 2				Quote Case 3				Quote Case 4			
	Mean	Std. Error	Neg.	Pos.	Mean	Std. Error	Neg.	Pos.	Mean	Std. Error	Neg.	Pos.	Mean	Std. Error	Neg.	Pos.
Variables	**k = 5 minutes**				**k = 5 minutes**				**k = 5 minutes**				**k = 5 minutes**			
Intercept	1.94	8.77	8	23	0.06	3.77	11	22	2.83	3.39	2	25	-1.54	5.28	18	10
Lagged Return	0.04	0.39	18	29	0.07	0.13	13	40	0.09	0.35	18	18	0.29	1.58	19	17
Specialist Participation	0.07	5.33	22	24	1.49	5.63	22	30	2.90	14.41	17	19	4.66	7.50	5	26
	k = 1 hour				**k = 1 hour**				**k = 1 hour**				**k = 1 hour**			
Intercept	4.69	28.26	10	26	1.52	12.66	14	26	6.50	16.55	3	16	-3.73	26.27	10	10
Lagged Return	0.08	0.82	22	17	0.03	0.35	29	21	-0.08	0.20	23	9	-0.01	0.25	14	13
Specialist Participation	8.94	20.40	10	25	18.84	71.34	13	26	19.50	53.41	6	18	4.64	33.12	6	14
	k = 1 day				**k = 1 day**				**k = 1 day**				**k = 1 day**			
Intercept	41.57	97.93	12	56	27.46	44.86	13	61	28.82	52.31	12	38	39.51	53.14	10	38
Lagged Return	-0.06	0.23	43	23	-0.07	0.17	55	23	-0.05	0.23	34	13	-0.05	0.24	34	13
Specialist Participation	10.74	60.54	13	26	-6.97	38.53	27	26	12.91	98.26	14	10	-13.05	111.24	12	11

Panel B. Percentage of correct predictions

k	QC1	QC2	QC3	QC4
5 minutes	18%	22%	19%	27%
1 hour	19%	19%	18%	14%
1 day	19%	19%	10%	11%