Liquidity Provision, Information, and Inventory Management in Limit Order Markets: An Analysis of Order Revisions

by

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Abstract

Limit order revisions, which involve decisions about when and how to modify or cancel prevailing limit orders, account for a significant proportion of limit order activity in exchanges around the world. This paper examines the determinants of traders' decisions to revise orders, and the profitability of traders' order revision strategies using a unique dataset which provides complete information on trades, orders, trader identification codes, and trader categories. The analysis provides three important results. One, informed traders and traders who function as voluntary market makers revise orders most intensely. Two, along with changes in market prices and other market conditions, changes in traders' inventories, including inventories of correlated stocks, influence order revision strategies. Three, informed traders reduce the execution costs of their order portfolios through active order revisions; the benefit is especially pronounced on earnings announcement days, when the value of private information is high. That traders employ revisions to mitigate their order submission, inventory, and adverse selection risks indicates that order revisions are a valuable feature of the rapidly proliferating electronic limit order markets.

Keywords: Limit Order Revisions, Inventory Management, Informed Traders, Limit Order Trading

JEL classification: G11, G14, G20

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1. Introduction

The largest exchanges around the world operate as electronic limit order book markets or at least allow for public limit orders.[1] A unique feature of electronic limit order book (LOB) markets is that liquidity is provided by a pool of voluntary market participants who strategically place limit orders, not by designated market makers. Consequently, examinations of limit order trading strategies employed by such voluntary liquidity providers are integral to our understanding of the evolution of prices and liquidity in LOB markets. This paper focuses on a prominent class of limit order strategies: order revisions. These are dynamic strategies that involve decisions about when and how to modify or cancel prevailing limit orders.[2] Few limit order strategies are as ubiquitous as order revisions. Almost half of all limit orders submitted on the NYSE, the London Securities and Derivatives Exchange, and the Australian Securities Exchange are revised.[3] Further, due to innovations in information technology, the incidence of order revisions has been increasing in recent years at an alarming rate. Hasbrouck and Saar (2009) document that, in 2004, the rate of 'fleeting orders' — order cancellations within two seconds of submission — on INET was 36% of submitted limit orders, twice its value in 1999.[4] Similarly, Hendershott et al. (2011) find that when the NYSE automated the dissemination of the inside quote in 2003, the orders-to-trades ratio, which proxies for the intensity of order cancellations, increased manifold.

The increasing incidence of order revisions, especially cancellations, has recently attracted regulatory scrutiny. Market regulators such as the Commodity Futures Trading Commission (CFTC) and the Securities Exchange Commission (SEC) in the US, the Financial Services Authority (FSA) in the UK, and the Securities and Exchange Board of India (SEBI) have filed charges against numerous market participants for having employed manipulative order cancellation strategies.[5] Even the recently passed Dodd-Frank act specifically discusses manipulative order cancellations, and has added the same to the list of unlawful "Disruptive Practices".[6] Order

[1] See Jain (2005) and Swann and Westerholm (2006)
[2] We collectively refer to order cancellations and modifications, wherein the limit price and/or quantity specifications of the order are changed, as order revisions. Order cancellation is effectively a revision of the quoted volume to zero.
[3] Coppejans and Domowitz (2002) , Yeo (2005), and Fong and Liu (2010).
[4] INET is an electronic communications network (ECN) LOB market. See Hasbrouck and Saar (2009) for further details.
[5] For example, see CFTC press release PR6007-11: http://www.cftc.gov/PressRoom/PressReleases/pr6007-11; SEC press release 2001-129: http://www.sec.gov/news/press/2001-129.txt; SEBI press release 254: http://www.sebi.gov.in/Index.jsp? &sub_sec_id=25.
[6] ‘‘Dodd-Frank Wall Street Reform and Consumer Protection Act’’: www.sec.gov/about/laws/wallstreetreform-cpa.pdf

cancellations are also suspected of having played a significant role during the infamous 'Flash Crash' of May 6, 2010 — when the Dow Jones Industrial Average lost and gained 9% within minutes. Consequently, regulators are considering various actions to discourage order revisions. The SEC is debating the introduction of an order cancellation fee, and the European Commission (EC) has proposed imposing a minimum resting period before an order can be revised and/or limiting traders' order cancellations rates to a pre-specified level.[7]

Despite the prevalence of order revision strategies in LOB markets around the world and the recent regulatory concern, few studies have empirically analyzed limit order revisions. Liu (2009), Hasbrouck and Saar (2009), and Fong and Liu (2010) provide valuable characterizations of order revisions. However, probably due to data limitations, our understanding of the rationale for, and the profitability of, order revisions remains incomplete. This paper employs a unique database drawn from one of the largest electronic LOB markets, the National Stock Exchange, India (NSE). The database provides complete information on trades, orders, trader identification codes, and trader classifications for a sample of 50 stocks, which constitute the Standard & Poor's CNX Nifty index, between April 1 and June 30, 2006.[8] The richness of the database enables the paper to answer three important and hitherto unaddressed questions. First, what type of traders revise orders? Second, how do trader inventories and market characteristics affect trader's decision to revise an order? And, third, do traders profit from the active management of their order portfolios through order revisions? Apart from adding to our understanding of order revisions, answers to the aforementioned questions also provide vital insight into the determinants of limit order trading and the role of informed traders in the rapidly evolving LOB markets.

The empirical analysis provides a number of new results. Traders who are members of the exchange (the voluntary dealers at the NSE), traders who curtail the size of their over-night inventories to a small fraction of their daily trading volume, and traders who regularly post a network of buy and sell orders around the mid-quote revise a significantly greater proportion of their orders than others. In sum, the de facto market makers or middlemen in the market prominently employ order revisions. That the de facto market makers greatly utilize order revisions supports the general implication of inventory management models that dealers with finite capital

[7] "SEC chief looks to fix market structure", *Reuters* (March 1, 2011).
Document titled "Consultation Document" dated December 8, 2010: http://ec.europa.eu/internal_market/consultations/2010/mifid_en.htm

[8] The index represents almost 60% of the exchange's market capitalization, and covers 21 sectors of the economy.

actively adjust their quotes to manage inventories.[9] Further, traders belonging to financial institutions, frequent traders, and traders who generally place large orders revise a significantly greater proportion of their orders than other traders. This result underlines the role of informed traders[10] in limit order trading; while it contradicts the traditional assumption that informed traders participate only through market orders, it adds to the emergent view[11] that informed traders strategically provide liquidity in LOB markets.

Results from the proportional hazards duration models show that traders closely monitor their outstanding limit orders and strategically respond to changes in their inventories and in market conditions through order revisions.[12] Specifically, consistent with the inventory control models, traders are more likely to cancel or negatively modify — move the limit price away from the prevailing mid-quote — a buy (sell) order when their inventory in the stock increases (decreases) after submitting the order. Similarly, traders are less likely to positively modify a buy (sell) order when their inventory in the stock increases (decreases) post its submission. The results are also consistent with the dynamic limit order models proposed by Harris (1998), Foucault et al. (2005), Goettler et al. (2005 and 2009), and Rosu (2011). These models imply that because inventory imbalances increase waiting costs (costs of delayed execution), traders, especially the de facto market makers, will place aggressive orders so as to correct their inventory imbalances. Furthermore, changes to trader inventories in correlated stocks also have a similar effect on order cancellations. For example, traders are more likely to cancel a buy order in stock *s* when their inventories in stocks that belong to the same industry (2 digit SIC) as stock *s* increase after submitting the buy order. This result supports the Ho and Stoll (1983) inventory management model, which implies that traders actively adjust their quotes in a stock to manage their 'equivalent' inventories — inventory in the stock corrected for inventory positions in all other stocks with correlated returns — and not just

[9] See, for example, Amihud and Mendelson (1980), O'Hara and Oldfield (1986), Madhavan and Smidt (1993).
[10] Kumar et al. (2009), who employ the same dataset as the current paper, find that orders placed by institutional traders, especially by financial institutional traders, are significantly more informed than those placed by individual traders. Numerous other studies have also found similar evidence in different settings. See, for example, Bartov et al. (2000) and Campbell et al. (2007), Chakravarty (2001), Anand et al. (2005), Boehmer and Kelly (2008), and Boehmer et al. (2008).
[11] See, for example, Bloomfield et al. (2005) and Anand et al. (2005).
[12] Similar to Hasbrouck and Saar (2009), we use hazard models to accommodate time varying covariates. While in their models only the best quotes are time varying, here we also introduce time varying inventory variables.

their ordinary inventory in the stock. The equivalent inventory effect is not statistically significant for order modifications.

Trader category matters. Hazards duration models also show that even after controlling for trader inventories, order characteristics ,and market conditions, an order is more likely to be revised if it is submitted by an institutional trader. This evidence adds further credence to the hypothesis that informed traders revise a greater proportion of their limit orders than the uninformed. Also, consistent with extant literature, aggressively priced orders (Hasbrouck and Saar ,2009 and Fong and Liu, 2010) and large orders (Liu, 2009) are more likely to be revised. We also find evidence in favor of the 'chasing' hypothesis posited by Hasbrouck and Saar (2009); order cancellations and positive order modifications are more likely when prices move away from an order, while negative modifications are less likely.

Finally, panel regression analysis of execution costs of traders' order portfolios show that institutional traders, especially those belonging to financial institutions, significantly benefit from order revisions. Specifically, controlling for market conditions, stock characteristics, and trader's skill (through trader fixed effects), we find a negative relation between the number of times an order in an institutional trader's portfolio is revised and the portfolio's execution cost — measured by a modified[13] version of the Perold (1988) implementation shortfall method. Results also show that institutional traders reduce the adverse selection costs of executed trades and the opportunity costs associated with unexecuted orders through order revisions. These results indicate that institutional traders use order revisions to 'time' the limit order book; when the mid-quote is, say, below the fundamental value, they positively modify buy orders — 'walk up' the book — to ensure executions, and/or they negatively modify or cancel sell orders — 'walk down' the book — to avoid executions. In contradistinction, these results do not hold for individual traders. Bloomfield et al. (2005) argue that informed traders have a competitive advantage in limit order trading because they can manage adverse selection risk better than other traders. The panel regression results show that order revisions are one of the strategies through which informed traders

[13]Since order revisions are prominently employed by intermediaries, who are not precommitted to orders, as suggested by Harris and Hasbrouck (1996), the modified measure accounts not only for the cost of order execution (Price Impact) and the opportunity cost of unexecuted orders (Opportunity Cost), but also for the adverse selection spread, measured by the movement in market prices subsequent to the execution of orders (Ex post performance).

actualize this competitive advantage. Further, financial institutional traders use order revisions to mitigate the incremental execution costs on earnings announcements days, when information uncertainty and the value of private information are high. Bloomfield et al. (2005) show that, in an experimental set-up, informed traders use market orders when the value of information is high. Results here show that informed traders use order revisions to mitigate the incremental costs of liquidity provision when the value of information is high.

This paper directly contributes to the small but growing literature on order revision strategies. To the best of my knowledge, this is the first study to show that informed traders and de facto market makers use order revisions the most, that changes in traders' ordinary and equivalent inventories influence their order revision strategies, and that informed traders use order revisions to reduce the execution costs of their order portfolios. These findings also contribute to our understanding of at least three more important aspects of limit order trading.

First, extant empirical studies on limit order trading have neglected the effect of inventory management on traders' limit order strategies. Current empirical papers have focused mostly on the influence of spreads (e.g., Harris,1998; Biais et al.,1995), depth (e.g., Beber and Caglio, 2002; Ranaldo, 2004), volatility (e.g., Ahn et al., 2001; Handa et al., 2003), and pre-trade transparency (e.g., Aitken et al., 2001; De Winne and D'Hondt, 2007;Bessembinder et al., 2009) on limit order strategies. Bloomfield et al (2005) find that large liquidity traders, when placed with a deadline, place market orders instead of limit orders. However, there results are based on an experimental setup, not an actual LOB market. This is the first paper to provide direct empirical evidence of the inventory effect in limit order books. Similarly, the result that limit order strategies in a stock are also dependent on traders' inventories in related stocks (equivalent inventory) is also a novel finding; this is the first study to find evidence consistent with the Ho and Stoll (1983) model of equivalent inventory management. The inventory effect documented here should be especially instructive because of the increasing role of high frequency traders (HFTs) in LOB markets. HFTs, who account for more than 50% of trading volume in the US and European markets, are generally the implicit market makers in modern LOB markets.[14] More importantly, their trading strategies invariably involve high trading volumes and low (intraday and overnight) inventories.[15] Similar to the

[14] See, for example, Jovanovic and Menkveld (2010), Hendershott and Riordan (2009), and Brogaard (2011).
[15] Kirilenko et al. (2010).

exchange members at the NSE, HFTs' order submissions will be significantly influenced by their inventory imbalances. Also, since monitoring costs are negligible for HFTs, they trade simultaneously in multiple securities and markets. Hence, the equivalent inventory effects documented in this study should be particularly profound for such traders and for the LOB markets they trade in.

Second, few papers have examined the profitability of limit order strategies. Harris and Hasbrouck (1996) find that conditional on execution, limit orders are more profitable than market orders; Griffiths et al. (2000) examine the relation between order aggressiveness and performance; Bessembinder et al. (2009) find a negative relation between the use of hidden quantity and execution costs. These papers analyze the performance of individual orders, not of a traders' portfolio of orders. Given the frequent order cancellations and resubmissions in LOB markets around the world, the net execution cost of a trader's portfolio of orders should be the more pertinent measure of performance. To that end, Handa and Schwartz (1996) analyze the profitability of placing a network of buy and sell orders. However, there examination is based on executions of hypothetical limit orders given actual price time series, not actual transactions. This paper adds to the literature on the profitability of limit order strategies by examining the relation between execution costs of a trader's portfolio of orders and an important aspect of limit order trading — order revisions.

Third, this study also adds to the literature on the role of informed traders in limit order books. The traditional models (e.g., Rock,1996; Glosten,1994; and Seppi,1997) that assumed that limit orders were submitted only by uninformed traders have been recently questioned. Kaniel and Liu (2006) posit that informed traders will prefer to submit limit orders more than market orders, especially when their information is persistent. Goetler et al. (2009) theorize that in a dynamic limit order market with asymmetric information, informed traders submit a large proportion of limit orders even when their information is short lived. Bloomfield et al. (2005) use an experimental electronic market to show that pre-identified informed traders use more limit orders than uninformed. Anand et al. (2005), similar to the current study, indentify institutional traders as informed traders. Consistent with Bloomfield et al. (2005), they find that informed traders shift from market to limit orders over the course of the trading day. However, extant empirical evidence is based either on an experimental market

(Bloomfield et al., 2005) or on the two decade old TORQ dataset[16] (Anand et al., 2005). This paper adds to the literature by providing evidence of informed limit order trading in a (relatively) modern pure LOB market. More importantly, unlike extant studies, this paper documents that informed traders significantly benefit from active limit order trading.

The findings in this paper have implications for market regulators as well. Importance of order revisions stems from the result that informed traders and voluntary market makers prominently employ them. These two, often overlapping, classes of traders dictate the evolution of prices and liquidity in LOB markets. Consequently, if the option to revise orders were to become costlier due a regulatory directive, pricing efficiency and liquidity could be adversely affected. Specifically, the de facto intermediaries use order revisions to mitigate their information and inventory risks. In the absence of order revisions, they will maintain larger limit order spreads as a compensation for the increased risks, resulting in higher transaction costs for liquidity demanders. Further, as argued by Handa and Schwartz (1996), "the viability of LOB markets depends on limit order trading being profitable for a sufficient number of public participants." The results here show that the order revisions enhance limit order profitability for informed traders. If order revisions were to become costlier, due to reduced profitability, informed traders may opt for alternative means of trading, such as trading in 'dark pools' or in upstairs markets (Bessembinder et al., 2009). Such a development could potentially impede price discovery in LOB markets.

This paper is organized as follows. Section 2 reviews the extant literature on limit order revisions, and presents the testable hypotheses. Section 3 describes the data and the institutional features of the NSE. Section 4 examines the relation between trader categories, styles, and order revisions. Results from duration analysis of order cancellations and modifications are presented in Section 5. In Section 6, we examine the relation between order revisions and performance of trader's order portfolios. Section 7 presents concluding remarks.

[16] Audit trial data on NYSE stocks between November 1990 and January 1991.

2. Literature Review and Hypotheses

2.1. Literature on Limit Order Revisions:

Literature on limit order revisions is still in its infancy, and has recently witnessed a spurt in interest. Liu (2009) theorizes and empirically tests the relation between limit order revisions, the management of 'free trading option' and non-execution risks, and monitoring costs. Empirical examination of 23 stocks from the Australian Stock Exchange finds evidence in favor of his theory that order revision activity is higher when order submissions risks are higher, when spreads are narrower, and when the concerned firm is larger. Fong and Liu (2010) also find evidence in line with that of the Liu (2009). More specifically, they document that order revision activity increases with free trading option and non-execution risks, size of the order, and decreases with costs of monitoring. They also find evidence that order revisions are succeeded by favorable mid-quote returns. Further evidence linking order cancellations and monitoring costs in found in Boehmer, Saar and Yu (2005). They document an increase in the intensity of limit order cancellations and a decrease in time-to-cancellations after the introduction of NYSE's OpenBook, which increased pre-trade transparency. Evidence on the relation between order revisions and free-option risk is also documented by Biais et al. (1995). They find that after large sales (buys), which convey negative (positive) information, rate of cancellations increases on the buy (sell) side of the book. They also find positive serial correlation in order cancellations in a sample of stocks trading on the Paris Bourse; Ellul et al. (2007) find a similar autocorrelation on the NYSE. An explanation for this autocorrelation is provided by Yeo (2005), who documents that majority of cancellations originate from split orders.

Hasbrouck and Saar (2009) study the phenomena of fleeting orders — orders that are cancelled within two seconds of submission — in a sample of 100 NASDAQ stocks traded on the INET platform. They find evidence indicating that fleeting orders are submitted by impatient traders chasing market prices and searching for latent/hidden liquidity. Further, they document that rapid order cancellations are a consequence of automation and fragmentation in markets. Theoretical explanations for fleeting orders have been put forth by Large (2004) and Rosu (2011). Large (2004) proposes a model wherein resolution of order flow uncertainty leads to fleeting orders. Rosu (2011) presents a dynamic model of limit order trading where agents are allowed to modify and cancel orders. This theory posits that when limit order books are full, traders cancel preexisting limit orders and place market order to expedite execution.

2.2. Contributions and testable hypotheses:

While the aforementioned studies have examined some important determinants of order revisions, our understanding of this recent phenomena is far from complete. This paper is distinguished from the extant literature for at least three reasons. One, we examine the characteristics of traders that employ order revision strategies. Two, we relate order revision decisions to inventory management of traders. Finally, we also analyze the relation between order revisions and performance of traders' portfolio of orders. The next section develops the hypotheses relating to the unique contributions of the paper.

2.2.1. Inventory management and order revisions:

The literature on dealer markets has extensively examined the role of inventory management in establishing a dealer's trading behavior and market liquidity. Starting from Garman(1976), inventory management models (e.g., Amihud and Mendelson, 1980; Ho and Stoll, 1981 and 1983; O'Hara and Oldfield, 1986; Madhavan and Smidt ,1993) theorize that since a dealer has access only to finite or limited capital, he must actively adjust his prices or quotes to manage inventory. As noted by Madhavan (2000), a general implication of these models is that when a dealer's inventory is above (below) its optimal level, the dealer is more (less) likely to sell rather than buy the security. Empirical studies find evidence mostly in favor of these inventory management models. Ho and Macris (1984) show that specialists quotes in the AMEX options market are significantly affected by their inventories; the specialist decreases his bid and ask quotes when his inventory is positive. Hasbrouck (1988) and Madhavan and Smidt (1991) document weak intraday effects of specialists inventory management in equity markets, and Madhavan and Smidt (1993) find that the specialist inventory adjustments are slow and have a half-life of 7.3 days. On the other hand, Lyons (1995) using intraday data on dealer positions finds a strong evidence in favor of the inventory-control effect on prices. Similarly, Manaster and Mann (1996) use data on locals' intraday inventory positions in the commodity markets and find strong support in favor of the inventory models: locals with long (short) positions are the most active sellers (buyers). Comerton-Forde et al (2010) document a positive relation between NYSE specialists' overnight inventories and market spreads.

More recently, models of dynamic limit order trading have formalized the effect of inventory imbalances on limit order submission strategies. Harris (1998), Foucault et al. (2005), and Rosu (2009) propose models wherein an inventory imbalance increases the waiting costs — costs of delayed or non-execution of orders — for a trader. Hence, the impatient trader finds it optimal to place orders aggressively so as to rebalance his portfolio, particularly when faced with a deadline. In Goettler et al. (2005 and 2009), traders with liquidity or inventory rebalancing motives have a predisposition (private value) to placing orders on one side of the book over the other. A trader with a positive inventory imbalance is more likely to be aggressive on the sell side rather than on the buy side. Although empirical studies are yet to examine inventory effects in LOMs, Bloomfield et al (2005) find evidence supporting the same in an experimental set-up. They find that large liquidity traders (traders constrained to meet a target by a deadline) place limit orders to begin with, but as the deadline approaches place market orders to ensure execution of their outstanding orders.

The implications of the inventory control models for order revisions are immediate. A liquidity provider should revise his preexisting limit orders in response to changes in his inventory; for example, he should respond to an increase in his inventory by cancelling or by negatively (positively) modifying his preexisting buy (sell) order. [17] Accordingly, we state my first set of hypotheses.

H1a: A trader's propensity to cancel a buy (sell) order increases (decreases) after his inventory in the same stock increases.

H1b: A trader's propensity to negatively modify a buy (sell) order increases (decreases) after his inventory in the same stock increases.

H1c: A trader's propensity to positively modify a buy (sell) order decreases (increases) after his inventory in the same stock increases.

[17] A positive modification is one where an order's price is revised aggressively.

Of particular importance to the current study is the model proposed by Ho and Stoll (1983). They solve the dealer's pricing problem by relaxing the assumption of dealer monopoly and accommodating multiple dealers, which is a primary attribute of limit order markets. They show that a dealer's reserve price depends, among other things, on his *equivalent* inventory in the stock. In other words, a dealer revises his quotes in stock '*s*' based not just on his inventories in '*s*' (ordinary inventory), but also based on his inventories in other stocks whose returns are correlated with those of stock '*s*'(equivalent inventory). However, Naik and Yadav (2003) find that trading behavior of dealer *firms* in the London Stock Exchange is governed by ordinary inventories rather than their equivalent inventories. They argue that due to limitations on real time communication between traders and complications in performance evaluation, dealer firms adopt a decentralized framework of market-making, wherein every individual trader manages his inventory in isolation without regard to firm-level equivalent inventories. Notwithstanding the Naik and Yadav (2003) study, the *dealer-level* pricing problem vis-à-vis equivalent inventories as theorized by Ho and Stoll (1983) remains untested. Unlike their study, the current one employs trader-level data that enables a direct examination of the theory.

To the extent that stocks in the same industry (2 digit SIC) are highly correlated, an implication of the Ho and Stoll proposition is that a liquidity provider's order revision behavior should also be guided by his inventory in stocks from the same industry as the concerned stock. For example, a liquidity provider will respond to an increase in his inventory in stocks from the same industry as the concerned stock by cancelling or negatively (positively) modifying his preexisting buy (sell) order in stock *s*. Accordingly, we state my next set of hypotheses.

H2a: A trader's propensity to cancel a buy (sell) order increases (decreases) after his inventory in stocks from the same industry as the concerned stock increases.

H2b: A trader's propensity to negatively modify a buy (sell) order increases (decreases) after his inventory in stocks from the same industry as the concerned stock increases.

H2c: A trader's propensity to positively modify a buy (sell) order decreases (increases) after his inventory in stocks from the same industry as the concerned stock increases.

We can also test the relation between order revisions and inventory management by examining the nature of traders who employ order revisions on a regular basis. Intermediaries are most concerned about inventory management. If order revisions are driven by inventory management (amongst other factors), we should find traders performing an intermediary function employing order revisions more than other type of traders.

H3a: Intermediaries revise a greater proportion of orders than other traders.

2.2.2. Order Revisions and Performance:

Limit orders are ex ante commitments to trade a fixed quantity of shares at a specific price. Hence, Copeland and Galai (1983) treat them as free options written by limit order traders to other market participants. The limit order trader faces the risk of being 'picked off' when the market prices move adversely after he places the limit order. To ensure that limit orders do not go 'stale', traders monitor market events after placing the order. In the model proposed by Foucault et al. (2003), NASDAQ dealers choose to monitor market events after placing their quotes in order to minimize the risk of being picked off by professional day traders. Liu (2009) extends the Foucault et al. (2003) model to incorporate non-execution risk, and also allows traders to revise posted limit orders. In his model, limit order traders weigh the benefits of monitoring against the costs of non-execution and free-option risk while placing orders. Even in Goetler et al. (2009), traders revise unexecuted limit orders so as to reflect changes in market conditions. In their model, traders choose to revise orders when the benefit from adjusting the order's specifications to reflect changes in market factors is greater than the cost incurred from losing the order's time priority due to the revision. The emergent intuition from these models is that order revisions are a consequence of traders monitoring and strategically responding to changing market conditions. Further, the objective of a revision is to ensure that the revised order reflects the trader's new expectation of market conditions and other factors that affect the order's payoff. Consequently, revised orders should contain more information and perform better than other orders. Accordingly, we state the following hypothesis:

H4a: Performance of an order is positively related to the number of times it is revised.

Extant literature has consistently found that institutional traders are more informed than individual traders. For example, Bartov et al. (2000) and Campbell et al. (2007) find that institutions take positions to arbitrage mispricing around earnings announcements; Chakravarty (2001) and Anand et al. (2005) find that institutional orders have a significantly greater price impact than orders placed by individuals; Boehmer and Kelly (2008) show that prices of stocks with greater institutional ownership are more efficiently prices and Boehmer et al. (2008) document that institutional short sales are more informed than short sales initiated by other traders. Kumar et al. (2009), who employ the same dataset as the current paper, conduct an examination of the informativeness of orders placed by different traders on the NSE. They find that the information level of institutional traders, especially financial institutional traders, is significantly greater than the information level of individual traders. Accordingly, if limit order revisions are indeed employed more by informed traders, we should expect institutional traders to revise orders more frequently than others.

H5a: Institutional traders employ order revisions more frequently than others.

Unlike other traders, informed traders can recognize mispricing in securities. There trading strategies are also a consequence of market prices straying away from fundamental values. Indeed, Bloomfield et al. (2005) show that informed traders strategically place aggressive orders to arbitrage mispricing in market prices. Since order revisions enable traders to dynamically respond to evolving market conditions, informed traders will employ them also to actualize their informational superiority. In contrast, other traders will be able to use order revisions only to manage information and inventory risks. Therefore, the relation between order revisions and order performance should be more positive for informed (institutional) traders than for other market participants.

H6a: Order performance is more positively related to the number of revisions for institutional traders than it is for other market participants.

3. Data

NSE was created in 1994 as part of major economic reforms in India. It operates as pure electronic limit order book market, and uses an automated screen based trading system called National Exchange for Automated Trading (NEAT), which enables traders from across India to trade anonymously with one another on a real-time basis using satellite communication technology. NSE was the first exchange in the world to use satellite communication technology for trading. In terms of total number of trades, NSE is the second largest pure electronic LOB market in the world, just behind Shanghai Stock Exchange (SSE), and it is the fourth largest among all markets irrespective of market structure, behind NYSE, NASDAQ and SSE.[18] NSE 's order books accommodate all the standard types of orders that exist internationally in order-driven markets, including limit orders, market orders, hidden orders, stop-loss orders, etc. Limit orders can be continuously cancelled or modified without any incremental fees. NSE operates a continuous trading session from 9:55 am until 3:30 pm local time. The tick size is INR 0.05 (less than USD 0.01). Outstanding orders are not carried over to the next day. There is no batch call auction at the beginning of the trading day. The opening price is also determined by pure order matching.

The sample consist of all the 50 stocks in Standard & Poor's CNX Nifty index, which represents about 60% of the market capitalization on the NSE and covers 21 sectors of the economy. The sample period is from April 1 through June 30, 2006, covering 56 trading days. Table 2 presents summary statistics on the trading characteristics of the sample stocks over the sample period. There are, on average, 19,121 trades per day, or 57 trades per stock per minute. There are, on average, 24,907 order submissions per stock per day, or about 75 order submissions per stock per minute.[19] More importantly, on an average, 24% of all incoming limit orders and 45% of incoming limit order volume is cancelled. The same for modifications are 16% and 26%, respectively. Larger orders are more likely to be cancelled or modified. In sum, about 36% of all incoming limit orders and 61% of all limit order volume is revised.

[18] World Federation of Exchanges, Annual Report, 2011
[19] These statistics are as reported in Kumar et al. (2009)

The dataset provides complete information of trades and orders that enables the reconstruction of the order book to obtain best quotes and depth information. Further, the data also provides identification codes and classifications of traders for all the orders and trades in the dataset. We aggregate the 14 trader classifications flagged in the dataset into 4 broad categories: *Individuals, Financial Institutions, Dealers,* and *Other Institutions*. Table 3 presents summary statistics and descriptions of the four trader categories. While *Individuals* outnumber other trader categories, institutional traders, especially *Dealers*, are more active in terms of order submissions. Although the NSE is a pure electronic limit order book market with no designated intermediaries, *Dealers*, who are registered members of the NSE, trade on behalf of their clients and also trade for their proprietary accounts. These traders generally function as voluntary intermediaries at the exchange[20]. The table also presents order revision activity by different trader groups. Clearly, traders revise a substantial proportion of their limit order volume. Dealers cancel the greatest proportion of their limit order volume; they cancel about 68% of their limit order volume. Financial institutional traders modify the greatest proportion of limit order volume; they modify about 34% of their limit order volume. Interestingly, individual traders appear to be more revising a greater proportion of limit order volume than financial institutional traders. This apparent anomaly is driven by the fact the individuals are an extremely heterogeneous group of traders. That a small portion of individual traders are influencing the revision numbers reported here is further substantiated in the next section where we examine order revision activity of an average trader in each category.

4. Trader categories, styles, and order revisions

In this section, we examine the relation between different attributes of traders — such as their category, reliance on inventory management, and trading frequency — and their use of order revisions. We next define the variables that are employed in the analysis.

The intensity of order cancellations and modifications for trader i is measured using the entire sample of 50 stocks (s) and 56 days of trading (t):

[20] See www.nseindia.com/content/press/NSEbyelaws.pdf for further details.

$$Cancellation\ Ratio_i = \frac{\sum_{t=1}^{56}\sum_{s=1}^{50} \text{Number of Cancellations}_{i,s,t}}{\sum_{t=1}^{56}\sum_{s=1}^{50} \text{Number of Order Submissions}_{i,s,t}}$$

$$Modification\ Ratio_i = \frac{\sum_{t=1}^{56}\sum_{s=1}^{50} \text{Number of Modifications}_{i,s,t}}{\sum_{t=1}^{56}\sum_{s=1}^{50} \text{Number of Order Submissions}_{i,s,t}}$$

Note that unlike the *Cancellation Ratio*, the *Modification Ratio* can be greater than 1 because each order can be modified multiple times. *Revision Ratio* is defined as the sum of the two ratios.

$$Revision\ Ratio_i = Cancellation\ Ratio_i + Modification\ Ratio_i$$

The *Revision Ratio* measures the number of times trader *i* revises (either cancels or modifies) orders for every limit order he places. We also define the following indicator variables based on trader categories as given in the dataset.

$$Dealer_i = \begin{cases} 1 & \text{if trader } i \text{ is identified as a trading member of the NSE in the dataset} \\ 0 & \text{otherwise} \end{cases}$$

$$Indiviual_i = \begin{cases} 1 & \text{if trader } i \text{ is identified as an individual in the dataset} \\ 0 & \text{otherwise} \end{cases}$$

$$Fin_i = \begin{cases} 1 & \text{if trader } i \text{ is identified as belonging to a financial institution in the dataset} \\ 0 & \text{otherwise} \end{cases}$$

$$Others_i = \begin{cases} 1 & \text{if trader } i \text{ is identified as belonging to a non-financial institution in the dataset} \\ 0 & \text{otherwise} \end{cases}$$

Table IV, Panel A presents results from the analysis of trader categories, *Revision Ratio*, *Cancellation Ratio*, and *Modification Ratio.* Exchange members (*Dealers*) and financial institutions (*Fin*) use revisions the most. The median revision ratios show that they approximately revise (modify and/or cancel) once for every two limit orders they place. Exchange members (*Dealers*) use cancellations more than any other class of traders; about 50 exchange members (p90), cancel every second limit order they place. However, financial institutions (*Fin*) modify orders most frequently; about 580 financial traders (p90), modify every orders more than once. To the extent that dealers and financial institutions are mostly likely to function as intermediaries in an electronic limit order market, these results are in line with *H3a*. Individuals (*Individual*) use order revisions least frequently. The difference between the average revision, cancellation, and modification ratios of institutional and individual trades is positive and statistically significant (at 1% level). These results are consistent with *H5a*; institutional traders, who are more likely to be the informed traders in the market, revise orders with greater intensity than individual traders.

We next examine the relation between trader characteristics — *Closing Ratio, Network Trading Ratio, Trader Size,* and *Trader Frequency* — and order revision ratios. Following Kirilenko et al. (2010), *Closing Ratio* is calculated as the ratio of a trader's daily closing position and his daily total trading volume. The ratio is calculated for each trader *i,* initially for each of the *m* days that he traded in stock *s* and then averaged over the *n* stocks he traded during the sample period.

$$Closing\ Ratio_i = \sum_{s=1}^{n_i} \frac{\dfrac{\sum_{t=1}^{m_{i,s}} \dfrac{\left|\text{End of day position}\right|_{i,s,t}}{\text{Daily tradng volume}_{i,s,t}}}{m_{i,s}}}{n_i}$$

A low *Closing Ratio* implies that the trader liquidates most of his intraday position before the close of trading. Hence, *Closing Ratio* proxies for the frequency of inventory management related trades, and thereby the half-life of the trader's inventories. Further, traders who function as intermediaries generally carry only a small component of their daily trading volume as overnight inventory. Consequently, *Closing Ratio* also identifies de facto or voluntary intermediaries in the market. Lower the value of *Closing Ratio* for a trader, more the trader behaves as an intermediary. Similarly, we also estimate *Network Trading Ratio* to identify the implicit or de facto market makers. Market makers typically post multiple two-sided quotes (network of quotes) and in doing so create their own limit order spread. Handa and Schwartz (1996) refer to such limit order trading as 'network trading'. The *Network Trading Ratio* captures the intensity of network trading for each trader in the dataset. Snapshots of the order book are created for all the stocks at one-minute intervals. In each such interval, a trader is said to be *Network Trading* if he has multiple orders on both sides of the book.

$$Network\ Trading_{i,s,k} = \begin{cases} 1 \text{ if trader } i \text{ has a network of orders in the } k^{th} \text{ snapshot of stock } s \\ 0 \text{ otherwise} \end{cases}$$

Network Trading Ratio is calculated for each trader *i*, initially for each of the *m* snapshots of stock *s* that his orders are present in and then averaged over the *n* stocks he traded during the sample period.

$$Network\ Trading\ Ratio_i = \sum_{s=1}^{n_i} \frac{\sum_{k=1}^{m_k} \frac{Network\ Trading_{i,s,k}}{m_k}}{n_i}$$

Trader Size and *Trader Frequency* variables are defined as follows:

$$Trader\ Size_i = \frac{\sum_{s=1}^{n_i} \frac{\sum_{t=1}^{m_{i,s}} \mathrm{Trade\ Volume}_{i,s,t} * \mathrm{Average\ Price}_{i,s,t}}{m_{i,s}}}{n_i} \qquad Trader\ Frequency_i = \frac{\sum_{s=1}^{n_i} \frac{\sum_{t=1}^{m_{i,s}} \mathrm{Number\ of\ Trades}_{i,s,t}}{m_{i,s}}}{n_i}$$

Table IV, Panel B presents results from the regression analysis of trading styles and order revision ratios. As shown in Table IV, Panel B, large and active traders revise a greater proportion of orders. More importantly, we find a negative coefficient on *Closing Ratio* in both the *Cancellation Ratio* and *Modification Ratio* regressions. The coefficient is also statistically significant (at 1% level). This implies that traders who actively manage their inventory revise a greater proportion of orders. Further, *Networking Trading Ratio* is also positively related to the intensity of order cancellations, modifications, and revisions. Again, the coefficients are statistically significant (at 1% level). These results indicate that traders who function as market makers employ order reversion strategies more regularly than others; evidence is consistent with *H3a.*

In sum, large and frequent traders, exchange members/dealers, traders belonging to financial institutions, traders who most frequently manage their inventories, and network traders employ order revisions the most. These findings are consistent with the previously stated hypotheses that informed traders and intermediaries revise orders more regularly than others.

5. Duration Analysis of Order Revisions

In this section we employ hazard analysis techniques to examine the determinants of a trader's decision to revise an order.

Order revisions are dynamic strategies executed by traders at high frequencies after order submission. In order to examine the determinants of such a phenomena we need to relate traders' decisions to developments in market conditions and other factors of interest through the life of the order. In fact, the inventory hypotheses built in the previous section require an analysis of changes in a trader's inventory after order submission. For example, if a trader decided to cancel a limit order 1 minute after submission, how did changes in his inventory in the said 1 minute affect his decision to cancel the order? The question of interest here is not how a trader's inventory affects his order placement, but how a change in his inventory since order submission affects his decision to revise the previously submitted order. Hence, a standard duration analysis[21], wherein the conditioning variables are all established prior to the submission of the order, is not best suited for the purposes of this study. Instead, following Hasbrouck and Saar (2009), we employ a (Cox's) proportional hazards duration model with *time-varying* covariates[22] to analyze traders' strategic responses to the evolving market conditions and other time variant factors post order submission.

We first discuss the explanatory variables, and then present the parameter estimates from hazard analysis of cancellations, positive modifications, and negative modifications. In accordance with Hasbrouck and Saar (2009), we include *Lagged Volume*, *Lagged Volatility*, and *Spreads* to account for the general market conditions prevailing prior to the submission of the order.

$$LaggedVolume_{o,s} = \text{Log}(\text{total trading volume}) \text{ in sotck } s \text{ over the 5 mins leading to the submission of order } o$$

$$LaggedVolatility_{o,s} = |\text{Return}| \text{ in sotck } s \text{ over the 5 mins leading to the submission of order } o$$

$$Spreads_{o,s} = \frac{(Best\ \text{Ask} - Best\ Bid)}{Midquote} \text{ in sotck } s \text{ prevailing 5 secs before the submission of order } o$$

Hasbrouck and Saar (2009) also find a positive relation between price aggressiveness and intensity of cancellation, which supports their (search) hypothesis that traders cancel orders after failing to find latent liquidity within the spread. Although the NSE does not permit complete hidden orders, which limits the extent of liquidity searching, price aggressiveness remains an important factor. Liu (2009) theorizes that traders revise orders to

[21] For examples of such applications please see Lo, Mackinlay and Zhang (2002) and Boehmer, Saar and Yu (2005).

[22] See Allison (1995) for an excellent and detailed discussion of proportional hazard duration models.

manage the "free-option" risk. Since this risk is positively related to price aggressiveness, include the Hasbrouck and Saar measure of the order's price aggressiveness ($p^{Relative}$) in the analysis. The definitions of buy and sell orders are analogously defined, and the definition for a buy order is as follows:

$$p_{o,s}^{Relative} = \frac{\left(\text{Limit Price}_{o,s} - \text{Best Bid}_{s,t=0}\right)}{\text{Best Bid}_{s,t=0}}; \text{ where } \mathrm{t}=0 \text{ is the time of order } o\text{'s submission in sotck } s$$

Further, Hasbrouck and Saar (2009) find a positive (negative) relation between the intensity of order cancellation and post-submission changes in quotes on the same (opposite) side as the submitted order. They interpret the positive relation as evidence of traders "chasing" market prices by cancelling stale orders and resubmitting more aggressive ones; the negative relation as evidence of traders cancelling orders and submitting market orders to exploit cheaper opposite quotes. Accordingly, we include two time-variant variables Δq_t^{same} and $\Delta q_t^{opposite}$. The definitions of buy and sell orders are analogously defined, and the definitions for a buy order is as follows:

$$\Delta q_{s,t}^{same} = \frac{\left(\text{Best Bid}_{s,t} - \text{Best Bid}_{s,t=0^+}\right)}{\text{Best Bid}_{s,t=0^+}}; \text{ where } \mathrm{t}=0^+ \text{ is the instant after order submission in stock } s$$

$$\Delta q_{s,t}^{opposite} = \frac{\left(\text{Best Offer}_{s,t} - \text{Best Offer}_{s,t=0^+}\right)}{\text{Best Offer}_{s,t=0^+}}; \text{ where } \mathrm{t}=0^+ \text{ is the instant after order submission in stock } s$$

Fong and Liu (2010) document that large orders are more likely to be revised due to fixed costs of monitoring. Hence, we include *Order Size* as a covariate.

$$Order\ Size_{o,s} = \text{Log}(\text{Order Volume}_{o,s} \times \text{Limit Price}_{o,s})$$

Next, we define the time varying inventory related variables that are central to the hypotheses developed earlier. The following definitions are for buy orders; variables for the sell orders are defined analogously.

$$\Delta Inventory\_Stock_{s,t,i,buy} = \text{Change in trader } i\text{'s buy-side inventory in stock } s \text{ over the period } (\mathrm{t}-5, \mathrm{t}]$$

$$\Delta Inventory\_Stock_{s,t,i,sell} = \text{Change in trader } i\text{'s sell-side inventory in stock } s \text{ over the period } (\mathrm{t}-5, \mathrm{t}]$$

$$\Delta Inventory\_Stock_{s,t,i} = \text{Log}(\Delta Inventory\_Stock_{s,t,i,buy} - \Delta Inventory\_Stock_{s,t,i,sell})$$

Change in trader i's inventory in stock s over the period (t - 5, t]

Similarly,

$$\Delta Inventory\_Related_{s,t,i} = \text{Log}(\Delta Inventory\_Related_{s,t,i,buy} - \Delta Inventory\_Related_{s,t,i,sell})$$

Change in trader i's inventory in all stocks that belong to the same industry (2 digit SIC) as stock s over the period (t - 5, t]

$$\Delta Inventory\_Industry_{s,t,i} = \Delta Inventory\_Stock_{s,t,i} + \Delta Inventory\_Related_{s,t,i}$$

$$\Delta Inventory\_Unrelated_{s,t,i} = \text{Log}(\Delta Inventory\_Unrelated_{s,t,i,buy} - \Delta Inventory\_Unrelated_{s,t,i,sell})$$

Change in trader i's inventory in all stocks that don't belong to the same industry (2 digit SIC) as stock s over the period (t - 5, t]

Further, we also employ trader classification dummy variables that were defined earlier. Finally, following Lo et al. (2002), we also include the logarithm of average stock prices as a covariate to capture the differences across stocks.

$$LPR_S = \text{Log}(\text{AveragePrice}_S)$$

5.1. Order Cancellations

The data creation and the following analysis are similar to that of Hasbrouck and Saar (2009).Using all the orders in 50 stocks for duration analysis is computationally costly and unwarranted. Hence, we randomly sample 10,000 limit orders from each of the 50 stocks. Since there are only 50 stocks in the cross section, following Lo et al (2002), we pool all the orders for the analysis. In order to address dependence among orders from the same stock, we cluster standard errors by stock. The data is organized in a "counting process" format[23]; at each 5 second interval from the time of order submission, it is recorded whether the interested event — order cancellation — occurred, and the corresponding values of all covariates are also recorded. As seen in Figure 1, more than 50% of order cancellations and more than 60% of order modifications happen within 2 minutes of

[23] See Hosmer et. al. (2008) and http://www.ats.ucla.edu/stat/sas/faq/survival_repeated_events.htm for a detailed explanation.

order submission. Hence, we track all orders only through the first 2 minutes. Execution is viewed as a competing process.[24] All the stock specific variables are standardized.

5.1.1. Results

Results of the proportional hazard duration model are presented in Table V. The estimates are generally consistent with the extant literature. The positive sign on the estimated coefficients on *Lagged Volume* and *Lagged Volatility* indicate that traders cancel orders to eliminate the 'free-option risk' in volatile periods. This finding is consistent with the model developed by Liu (2009). The coefficient on the *Spreads* variable is always positive, but never statistically significant. The pricing aggressive variable ($p^{Relative}$) is always positive and statistically significant. This result is consistent with the 'search' hypothesis of Hasbrouck and Saar (2009) and the free-option risk hypothesis of Liu (2009) and Fong and Liu (2009). However, the NSE does not permit completely hidden orders, which reduces the potency of the 'search' hypothesis in this market. Hence, we infer that traders are more likely to cancel aggressive orders to manage their free-option risk. The statistically significant coefficients on the time varying same-side quote change variable (Δq_t^{same}) are consistent with the 'chasing' hypothesis posited by Hasbrouck and Saar (2009). Traders appear to be cancelling orders to post more aggressive ones when the markets prices move away from the posted limit prices. However, unlike Hasbrouck and Saar (2009), we do not find evidence in favor of the 'cost-of-immediacy' hypothesis — when ask (bid) quotes increase, traders cancel preexisting buy(sell) orders and submit market orders to execute against favorable ask (bid) quotes — that predicts a negative coefficient on the $\Delta q_t^{opposite}$ variable.

The coefficient relating to the indicator variable *Dealer* is positive and statistically significant (at 1% level) in all the specifications. Clearly, dealers have a greater propensity to cancel orders than the rest of the market. The hazard or intensity of cancellation for dealers is about 185% of the hazard for other traders. Since dealers are most likely to make markets, these results add further credence to the inventory hypotheses. The hazard for individuals is only about 47% of the hazard for other traders. To place the results in a better perspective, we restate the relevant results in terms of probabilities. Probability estimates are obtained through the

[24] Chakrabarty et al. (2006) also analyze order executions and cancellations as competing events.

survivor function that is non-parametrically estimated from the fitted hazard model[25]. When the order is submitted by a dealer (*Dealer* = 1 and *Individual* = 0), and all the other variables in specification 3 are held at the respective sample means, the probability of order cancellation(within 2 minutes of submission) is 33.74%; the same when the order is placed by an individual trader is 9.96%. The category of the trader has a non-trivial impact on the probability of order cancellation. This finding is consistent with the inventory hypotheses (*H3a*): de facto intermediaries such as the trading members/dealers, who manage inventory on a regular basis, utilize order cancellations more frequently than other traders. These results are also consistent with the descriptive analysis and the results from the OLS regressions, which showed that dealers use order cancellations the most and individuals the least. Further, the result that individual traders employ order cancellations with a lower intensity than institutional traders supports the hypothesis that informed traders employ more order revisions.

More important to this study are the coefficients on the inventory variables. The coefficient relating to the change in a trader's same-stock inventory ($\Delta Inventory\_Stock_t$) is always positive and statistically significant (at 1% level). These results imply that, after controlling for the category of the trader, price aggressiveness, order size, market volatility and volume and changes in quotes, an increase in a trader's inventory increases (decreases) his propensity to cancel preexisting buy (sell) orders; this evidence strongly supports *H1a*. The same-stock inventory effect is also economically significant. The estimated percentage change in hazard for each unit increase in covariate *x1* is given by $(e^{\beta_{x1}} - 1)$. Therefore, a unit increase in $\Delta Inventory\_Stock_t$, increases the intensity of cancellation by 1.3%. Or, the intensity of cancellation for a preexisting buy (sell) order in stock '*s*' increases (decreases) by 1.3% after the corresponding trader, in the previous 5 seconds, has bought 2.72 more units of '*s*' than he has sold. As before, we restate the results in terms of probabilities: when a trader increases his inventory in the stock by 1000 units (approximately 1 standard deviation in trade size), and all other variables are held at their respective sample means, the probability of a buy (sell) order cancellation increases (decreases) by 1.7 percentage points or 8.2%.

[25] See Allison (1995) for an excellent and detailed discussion of proportional hazard duration models.

The coefficient on $\Delta Inventory\_Related_t$ (change in a trader's inventory in related or correlated stocks) is also significantly positive (at 1% level). This implies that traders' order cancellation decisions are not driven only by their inventory of the corresponding stock, but also by their inventory in stocks of the same industry as the said stock. Traders appear to be managing their *equivalent* inventory; this evidence is consistent with *H2a*. Although the coefficient on $\Delta Inventory\_Related_t$ is smaller than it is for $\Delta Inventory\_Stock_t$, the related-stock inventory effect is not trivial. A unit increase in $\Delta Inventory\_Related_t$, increases the intensity of order cancellation by 0.80%. Or, the intensity of cancellation for a preexisting buy (sell) order in stock '*s*' increases (decreases) by 0.80% after the corresponding trader, in the previous 5 seconds, has bought 2.72 more units of stocks in the same industry (2 digit SIC) as '*s*' than he has sold. Or, a 1 standard deviation increase in a trader's inventory in related stocks, increases (decreases) the probability of cancellation for a buy (sell) order by 1.00 percentage point or 4.8%. Not surprisingly, the coefficient on $\Delta Inventory\_Industry_t$ is also positive and statistically significant (at 1% level).

To further examine the validity of the inventory results, we introduce $\Delta Inventory\_Unrelated_t$ — trader's inventory in unrelated stocks or stocks that don't belong to the same industry as the concerned stock — in place of $\Delta Inventory\_Related_t$. The results are shown in the fifth column of Table V. In accordance with the *equivalent* inventory hypothesis (*H2a*), the coefficient, although positive, is statistically insignificant from zero. Lower the (absolute)correlation between two stocks, lower the impact inventory in one has on order cancellation decisions in the other.

5.2. Order Modifications

The empirical design is identical to the one employed for analyzing order cancellations, except for the following differences. One, the events of interest are positive and negative modifications, not order cancellations. Two, while analyzing modifications we consider order cancellations and executions as competing events. Finally, since modifications are repetitive events, we cluster standard error by order to mitigate the effects of dependency amongst repeated events.[26]

[26] See Hosmer, Stanleu and May (2008) and http://www.ats.ucla.edu/stat/sas/faq/survival_repeated_events.htm for a detailed explanation.

5.2.1. Results

The results of the analysis are presented in Tables VI and Tables VII. Wider *Spreads* increase the intensity of positive modifications; the effect on negative modifications, although negative, is statistically insignificant. This implies that, ceteris paribus, traders positively modify their orders when the returns for providing liquidity are higher. The coefficients on *Lagged Volatility* is again consistent with the free-option risk hypothesis of Liu (2009). It appears that active markets (*Lagged Volume)* discourage negative revisions and encourage positive revisions. The coefficient on price aggressiveness ($p^{Relative}$) is positive for both positive and negative modifications in all specifications; similar to order cancellations, traders employ order modifications to manage their 'free-option' risk. Intensity of order modifications is again positively related to *Order Size*; evidence supports the monitoring hypothesis of Liu (2009).

The coefficients on quote changes (Δq_t^{same} and $\Delta q_t^{opposite}$) provide strong support to the 'search' hypothesis of Hasbrouck and Saar (2009). Further the best quotes get from the limit order price, higher (lower) the intensity of positive (negative) order modifications. A one standard deviation increase in the Δq_t^{same} increases (decreases) the intensity of positive (negative) modifications by 5.5% (8.0%). Similarly, a one standard deviation increase in $\Delta q_t^{opposite}$ increases (decreases) the intensity of positive (negative) modifications by 10.4% (8.5%).

Similar to the order cancellation results, the coefficient relating to the indicator variable *Dealer* is positive and significant , while the coefficient relating to the variable *Individual* is negative and significant for both positive and negative modifications. That individuals modify orders with a lower intensity than institutional traders is consistent with the hypothesis that informed traders revise a greater proportion of their limit orders than the uninformed. That dealers most actively modify orders is consistent with the hypotheses that de facto intermediaries, who are most concerned about inventory levels, employ order revisions the most.

Results also show that an increase in same-stock inventory ($\Delta Inventory\_Stock_t$), increases the hazard of negative modifications and decreases the hazard of a positive modification. These results support inventory hypotheses *H1b* and *H1c*. When a trader increases his inventory in stock '*s'* by 2.72 units, his propensity to positively (negatively) modify a buy order reduces by 6.1% (2.5%). In terms of probabilities: 1 standard deviation increase in a trader's inventory in the stock, while all other variables are held at their respective sample means, increases the probability of a buy order positive (negative) modification by 4.41 (0.41)percentage points. Once again, after controlling for all the other factors, changes in inventory have a substantial impact on traders' order revision strategies. These results strongly support the inventory hypotheses.

The coefficient on $\Delta Inventory\_Related_t$ is statistically insignificant in both positive and negative modifications regressions. This evidence does not support hypotheses *H2b and H2c*. However, change in the total industry inventory ($\Delta Inventory\_Industry_t$) still affects order modification decisions. A 2.72 units increase in same-industry inventory, increases (decreases) the intensity of negative (positive) modifications by 4% (1.9%). The results indicate that traders employ order modifications to manage their ordinary inventory, not their equivalent inventory.

5.3. Summary

We find that limit order revisions (cancellations and modifications) are a function of various market and trader related factors. The results are consistent with extant literature that has documented that traders revise their orders to manage their free-option and non-execution risk. More important to this study is the finding that even after controlling for price aggressiveness, order size, market volatility and volume, and changes in best quotes, order revision decisions in a stock are governed by changes in traders' inventory in the same stock and ,to a lesser extent, in correlated stocks. Also, the category of the trader surfaces as an important determinant of the probability of order revisions: institutional traders employ order revisions strategies more regularly than individual traders do.

6. Order Revisions and Performance

Having shown that traders use order revisions to dynamically respond to changes in market prices/conditions and their own inventories, and that, even after controlling for all relevant factors, certain type of trades have a greater propensity to revise orders, We now try to answer the natural follow-up question: what is the net effect of such rampant and frenetic order management on the performance of traders' order portfolios?

Typically, the implementation shortfall measure (Perold,1988), which incorporates the cost of order execution (Price Impact) and the opportunity cost of unexecuted orders (Opportunity Cost) is used to evaluate the performance of orders.[27] However, as noted by Harris and Hasbrouck (1996), this method is better suited to analyze the performance of precommitted orders as it imputes a (substantial) penalty for non-execution. Evidence in the previous section implies that traders behaving as market intermediaries or middlemen use order revisions the most. Such traders are not precommitted to orders, but execute them opportunistically. Therefore, their performance evaluation should also incorporate the movement in market prices subsequent to the execution of their orders to account for the adverse selection component of the trade. Accordingly, we also employ the 'ex post' measure proposed by Harris and Hasbrouck (1996) to examine the relation between order revisions and performance. The ex post performance measure is as follows:

$$Ex\ post_o = \begin{cases} bid\ price_{t+60\min} - fill\ price & \text{for a buy order } o \text{ executed at time } t \\ fill\ price - offer\ price_{t+60\min} & \text{for a sell order } o \text{ executed at time } t \\ 0 & \text{if the order is unexecuted} \end{cases}$$

Further, to facilitate a trader-level aggregation of performance measures, the ex post measure is standardized by the price of the stock an instant before order submission ($Price_{t^-}$). $Ex\ post\_Ratio_o = \dfrac{Ex\ post_o}{Price_{t^-}}$

The price impact and opportunity cost variables are defined as in Bessembinder et al (2009):

$$Price\ Impact_o = \begin{cases} midquote_t - fill\ price & \text{for a buy order } o \text{ submitted at time } t \\ fill\ price - midquote_t & \text{for a sell order } o \text{ submitted at time } t \\ 0 & \text{if the order is unexecuted} \end{cases}$$

$$Opportunity\ Cost_o = \begin{cases} closing\ price - midquote_t & \text{for a buy order } o \text{ submitted at time } t \\ midquote_t - closing\ price & \text{for a sell order } o \text{ submitted at time } t \\ 0 & \text{if the order is completly executed} \end{cases}$$

Price Impact and *Opportunity Cost* variables are also standardized by the price of the stock an instant before order submission ($Price_{t^-}$).

[27] See, for example, Griffith et al. (2000) and Bessembinder et al. (2008).

$$Price\ Impact\_Ratio_o = \frac{Price\ Impact_o}{Price_{t^-}}$$

$$Opportunity\ Cost\_Ratio_o = \frac{Opportunity\ Cost_o}{Price_{t^-}}$$

Finally *Total Cost* of implementation for an order *o* is obtained as the weighted sum of *Ex Post* performance, *Price Impact*, and *Opportunity Cost*.

$$Total\ Cost_o = \frac{Volume\ Executed_o * (Price\ Impact_o - Ex\ Post) + Volume\ Unexecuted_o * (Opportunity\ Cost_o)}{Total\ Volume_o}$$

$$Total\ Cost\_Ratio_o = \frac{Total\ Cost_o}{Price_{t^-}}$$

Variable *Total Revisions*$_O$, which measures the total number times order *o* has been revised, is used to measure revision activity. Other order related and stock related control variables, following Bessembinder et al. (2009), are defined as follows:

$$Hidden_o = \begin{cases} 1 & \text{if a proportion of order } o\text{'s quantity is hidden} \\ 0 & \text{if no proportion of order } o\text{'s quantity is hidden} \end{cases}$$

$$Buy_o = \begin{cases} 1 & \text{if order } o \text{ is a buy order} \\ 0 & \text{if order } o \text{ is a sell order} \end{cases}$$

$$Log\ Quantity_o = \text{Logarithm of order } o\text{'s total quantity}$$

$$Past\ Volatility_{o,s} = \text{Volatility of stock } s\text{' returns during the hour prior to the submission of order } o$$

$$Past\ Trading\ Frequency_{o,s} = \text{Number of trades in stock } s \text{ during the hour prior to the submission of order } o$$

We have seen in the previous section that traders' order revision strategies are driven, amongst other variables, by changes in their total inventory in the stock; traders use order revisions to manage their portfolio of orders in a stock. Consequently, a trader's performance for the analysis of order revisions should focus on his entire portfolio of orders in a stock rather than on the performance of individual orders. Further, unexecuted limit orders at the NSE are terminated at the end of the trading day. Hence, the analysis is conducted at a daily frequency. In lieu of these issues, the previously defined variables of interest are aggregated to the trader level in each stock and on each day of the sample. The aggregation is done on a value weighted basis, where value is calculated as the product of the order's quoted quantity and limit price. Next, we illustrate the aggregation procedure for the variable *Total Revisions*$_{O.}$

$$Total\ Revisions^{p}_{i,s,t} = \frac{\sum_{j=1}^{n}(value_j * Total\ Revisions_j)}{\sum_{j=1}^{n} value_j}$$

$$\text{Where,}\ value_j = \text{Order quantity}_j * \text{Order Price}_j$$
$$n = \text{total number of orders placed by trader } i \text{ in stock } s \text{ on day } t$$

$Total\ Revisions^{P}_{i,s,t}$ is the portfolio (*P*) value weighted average of the number of times trader *i* revised each order he placed in stock *s* on day *t*. Similarly, other variables are also aggregated. Such an aggregation results in a panel dataset of variables for approximately 1.2 million traders and 50 stocks over 56 days. Consequently, we employ panel (OLS) regressions with trader and stock fixed effects. Trader fixed effects are included to ensure that the regression coefficients depicting the relation between order revisions and order performance are not corrupted by the generic relation between a trader's skill level and the performance of his orders. To the best of my knowledge, this is the first study on limit order strategies to control for trader fixed effects. Similarly, stock fixed effects control for latent stock specific factors. Further, the standard errors of the regression coefficients are clustered by time (day) to control for the contemporaneous cross-correlation in residuals.[28]

[28]See Peterson (2010) for an excellent discussion.

6.1. Results

Table VIII presents results obtained from panel regressions of ex post performance ratio, price impact ratio, opportunity cost ratio, and total cost ratio on revision intensity, other order characteristics, and market conditions. Panels A, B, C and D report results relating to financial institutions, other institutions, dealers, and individuals, respectively. In all panels, columns 1a-3a include all trader portfolios; columns 1b and 2b consider only trader portfolios with either partial or complete execution; coefficients in column 3b are obtained by including only trader portfolios with zero or partial executions.

Ex post performance of trader portfolios is positively related to the number of order revisions. As seen in column 1a in all panels, *Total Revisions* is positively and significantly related to ex post performance.[29] When we discard trader portfolios with no executions, the story changes. The relation between ex post performance and order revisions is positive and significant (at 10% levels) only for institutions, and is strongest for financial institutions; it is not statistically significant for individual traders. To the extent that institutional traders are more informed than other market participants, we can infer that order revisions are beneficial to ex post performance only when traders are informed. This evidence is in line with hypothesis *H6a*: order revisions are one of the strategies through which informed traders capitalize their informational advantage. Interestingly, price aggressiveness ($p^{Relative}$) is negatively related with ex post performance. This result is in accordance with the theory and evidence provided by Kaniel and Liu (2006) that limit orders perform better than market and marketable limit orders.

Price impact ratio of a trader's portfolio of orders is positively related to the average number times an order in the same portfolio is revised. The result is statistically significant (at 10%) for all classes of traders, except for dealers (*dealer*). The relation is even stronger for trader portfolios with at least partial execution (column 2b). This finding is consistent with positively revised orders walking up the limit order book and incurring higher price impact costs. However, for institutional traders, this increase in price impact cost is compensated by superior ex post performance; they incur higher price impact costs to ensure execution of

[29] Results are robust to the duration over which ex post performance is measured. Analyses of ex post performance measured over 5 minute, 15 minute, and 30 minute durations provide qualitatively similar results.

informed orders. Consistent with Bessembinder et al (2009), trader portfolios with a greater proportion of hidden orders (*Hidden*) incur lower price impact costs. Price impact costs are positively related to the average price aggressiveness ($p^{Relative}$) and size of portfolios ($Log\ Quantity$) . Further, price impact costs increase with market volatility ($Past\ Volatility$) and decrease with market activity ($Past\ Trading\ Frequency$).

Order revision activity is negatively and significantly (at 10%) related to opportunity costs in all panels. This relation is not merely because positively revised orders are less likely to remain unexecuted. Even when we consider trader portfolios with only partial or zero executions (column 3b), the relation between order revisions and opportunity cost ratio is negative and significant (at 5%). This result is consistent with negatively revised orders facing less adverse movements till close of day; even negatively revised orders appear to be informed. Opportunity costs are also significantly higher in volatile markets. Amongst other findings, the hidden order results are especially noteworthy. Portfolios with a greater proportion of hidden orders incur higher opportunity costs. This result implies that hidden orders are informed traders, and hence incur higher opportunity costs when they go unexecuted. On the contrary, Bessembinder et al. (2009) find that hidden orders are negatively related to opportunity costs, and hence infer that they are posted by uninformed traders. However, the current finding supports the theory posited by Moinas (2006). She argues that informed liquidity providers use hidden orders to "camouflage" their orders as uninformed orders to increase the probability of execution. Further, Kumar et al. (2009) find that an overwhelming proportion of hidden orders at the NSE are posted by institutional (informed) traders wanting to mask the information content of their orders.

The net effect of order revisions is presented in columns 4 and 5. The results in column 4 greatly depend on the category of the trader. While financial and other institutional traders (*Fin* and *Others*) significantly (at 10%) benefit from order revisions, the relation, although negative, is not significantly different from zero for dealers (*Dealer*) and individual (*Indi*) traders. Also, the coefficient on *Total Revisions* in Panel A (financial institutions) is significantly greater (at 5% level) than same coefficient in the remaining three panels. To the extent that financial institutions are more informed than other market participants, we can infer that the more informed a trader, the greater is the benefit of order revisions. This result supports hypothesis *H6a*. For traders belonging to financial and other institutions, the relation between order revisions and performance is also economically significant. When the average number of total revisions (*Total Revisions*) of a financial trader's portfolio increases by one unit (approximately 1 standard deviation), the portfolio's total execution cost (*Total Cost Ratio*) reduces by 8.23% of its mean value; the same for a trader belonging to other institutions is 8.49%.

Furthermore, financial institutions benefit more from order revisions on days with earnings announcements. As shown in column 5 of Panel A, the interaction between *Total Revisions* and *Earnings Day* is negative and statistically significant (at 10% level).The interaction is statistically insignificant for the other class of traders. Understandably, total cost ratio is significantly (at 10% level) higher on day with earnings announcements. But financial institutional traders employ order revisions to mitigate the increased execution costs around earnings announcements. This result indicates that informed traders (financial institutions) benefit more from order revisions, especially when the value of information is high. The evidence obtained here strongly supports hypothesis *H6a*. Total cost ratio is generally higher for portfolios that are more aggressively priced, larger in size and number, and for those that include a greater proportion of hidden orders. The results on hidden orders appear to be mainly driven by opportunity costs. Also, total cost ratio increases with market volatility and decreases with market activity.

7. Conclusion

While numerous studies have analyzed order submission strategies, few have focused on order revisions, which are post-submission strategies involving decisions on when and how to cancel or modify preexisting limit orders. We know relatively little about the type of traders who revise orders, the factors that govern their order revision strategies, and the profitability of actively managing order portfolios through order revisions. This is especially surprising given the predominance of order revisions in limit order book markets around the world. The current study fills this void in literature.

Analysis of order revision activity in the sample of 50 stocks, which constitute 60% of NSE's market capitalization, between April 1 and June 30, 2006, shows that about 36% of all incoming limit orders or 61% of all limit order volume is revised. More importantly, analysis of different trader categories and trading styles shows that large and frequent traders, financial institutional traders, exchange members (voluntary dealers at the NSE),traders who most frequently manage their inventories, and traders who regularly post a network of two-sided quotes employ order revisions the most. In general, results indicate that informed traders and traders who function as voluntary market makers employ order revisions most prominently.

We employ a (Cox's) proportional hazards duration model with time-varying covariates to analyze traders' strategic responses to changing in market conditions, inventories, and other time variant factors after the orders are submitted. Results show that traders revise orders not only in response to changes in market prices, but to manage their inventories as well. We find that, after controlling for price aggressiveness of the order, order size, market volatility and volume, and changes in best quotes, a trader's decision to revise a preexisting order is substantially driven by changes in his inventory in the stock and ,to a lesser extent, in correlated stocks. Further, consistent with the hypothesis that informed traders dominate revision activity, We find that an order is more likely to be revised if it is submitted by an institutional trader rather than by an individual trader.

We also investigate the relation between order revisions and performance of traders' order portfolios. Results from panel regressions indicate that institutional traders, especially financial institutional traders, significantly reduce the execution costs of their order portfolios through order revisions. Institutional traders reduce the adverse selection costs of executed trades (i.e. obtain favorable price changes for executed orders) and the opportunity costs associated with unexecuted orders(i.e. obtain favorable price changes for unexecuted and/or cancelled orders) through order revisions; they seem to be using order revisions to 'time' the limit order book. In contrast, these results do not hold for individual traders. Results also show that financial institutional traders benefit the most from order revisions on earnings announcement days, when the value of private information is high.

These findings are of interest to market regulators as well. The proliferation of automated trading has heightened regulatory concern that traders manipulate order flow and market prices through nefarious order cancellations. Consequently, market regulators in Europe and the US are debating regulatory measures to curtail order revisions, especially order cancellations. The results presented in this paper should be especially instructive in this regulatory context. That traders, especially informed traders and implicit market makers, revise orders to manage information and inventory risks implies that order revisions are a valuable feature of modern limit order trading. A regulatory intervention that constrains order revisions could have an adverse effect on market liquidity and pricing efficiency.

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Table I – Variable Definitions

Variable	Description
	Trader Analysis
Modification Ratio	Ratio of total number of order modifications (positive and negative) and order submissions. It is calculated for each trader, across all stocks, and through all the trading days in the sample.
Cancellation Ratio	Ratio of total number of order cancellations and order submissions. It is calculated for each trader *i*, across all stocks, and through all the trading days in the sample.
Revision Ratio	Sum of *Cancellation Ratio* and *Modification Ratio*.
Closing Ratio	Average of the ratio of a trader's daily closing position and his daily total trading volume. It is calculated for each trader, first for all trading days in each stock, and then averaged across all stocks.
Trader Frequency	Average number of times a trader trades in a day through the sample. It is calculated for each trader, first by stock, and then averaged across all stocks in the sample.
Trader Size	Average size of trades placed by a trader through the sample. It is calculated for each trader, first by stock, and then averaged across all stocks in the sample.
Network Trading Ratio	Percentage number of times a trader has multiple orders on both sides of the book in one minute snapshots of a stock's order book. It is calculated for each trader, first by stock, and then averaged across all stocks in the sample.
	Hazard Analysis
Order Size	Natural logarithm of the product of the total quantity and price of the order.
Spreads	Ratio of the difference between the best buy and sell prices and the midquote prevailing 5 seconds before order submission.
Lagged Volatility	Absolute value of returns over the five minutes leading to order submission.
$P^{Relative}$	For a buy order, it is the difference between the limit price and best bid prevailing at the time of order submission, expressed as a percentage of the latter; it is analogously defined for a sell order.
Lagged Volume	Natural logarithm of the total trading volume over the five minutes leading to order submission.
LPR	Natural logarithm of the average price of the stock over the entire sample period.
Dealer	Binary variable equal to 1 when the trader is identified as a member of the exchange in the dataset.
Individual	Binary variable equal to 1 when the trader is identified as an individual trader in the dataset.
Δq_t^{same}	For a buy order, it is the change in the best bid between time t and an instant after order submission, expressed as a percentage of the latter; it analogously defined for a sell order.
$\Delta q_t^{Opposite}$	For a buy order, it is the change in the best ask between time t and an instant after order submission, expressed as a percentage of the latter; it analogously defined for a sell order.

Variable	Description
	<u>Hazard Analysis</u>
ΔInventory_Stock$_t$	Natural logarithm of the change in a trader's net inventory over the period (*t*-5secs, *t*]. Net inventory is defined as the difference in buy side and sell side inventories.
ΔInventory_Related$_t$	Natural logarithm of the change in a trader's net inventory in stocks belonging to the same industry (2 digit SIC) as the concerned stock, over the period (*t*-5secs, *t*]. Net inventory is defined as the difference in buy side and sell side inventories.
ΔInventory_Industry$_t$	Sum of *ΔInventory_Stock*$_t$ and *ΔInventory_Related*$_t$.
ΔInventory_Unrelated $_t$	Natural logarithm of the change in a trader's net inventory in stocks not belonging to the same industry (2 digit SIC) as the concerned stock, over the period (*t*-5secs, *t*]. Net inventory is defined as the difference in buy side and sell side inventories.
	<u>Panel Regressions</u>
Total Revisions^P	Value weighted average of the number of revisions trader *i* employed on the orders he placed in stock *s* on day *t*.
Price Agg^P	Value weighted average of the price aggressiveness of the orders trader *i* placed in stock *s* on day *t*. Price aggressiveness, for a buy order, is the difference between the limit price and best bid prevailing at the time of order submission, expressed as a percentage of the latter; it is analogously defined for a sell order.
Past Volatility^P	Value weighted average of the volatility of returns prevailing 1 hour prior to the submission of trader *i*'s orders in stock *s* on day *t*.
Log Quantity^P	Natural logarithm of the value weighted average of the total quoted quantity of the orders submitted by trader *i* in stock *s* on day *t*.
Buy^P	Value weighted proportion of buy orders submitted by trader *i* in stock *s* on day *t*.
Hidden^P	Value weighted proportion of hidden orders submitted by trader *i* in stock *s* on day *t*.
Past Trading Frequency^P	Value weighted average of the number of trades prevailing 1 hour prior to the submission of trader *i*'s orders in stock *s* on day *t*.
Number of Orders^P	Natural logarithm of the number of orders submitted by trader *i* in stock *s* on day *t*.
Ex post Ratio^P	Value weighted ex post performance of all orders submitted by trader *i* in stock *s* on day *t*. Ex post performance, for a buy order, is calculated as the ratio of the difference between the best bid 60 mins after execution and the execution price of the order, and the price of the stock an instant before order submission; it is zero for unexecuted orders.
Price Impact Ratio^P	Value weighted price impact ratio of all orders submitted by trader *i* in stock *s* on day *t*. Price impact ratio, for a buy order, is calculated as the ratio of the difference between the midquote at the time of order submission and the execution price of the order, and the price of the stock an instant before order submission; it is zero for unexecuted orders.
Opportunity Cost Ratio^P	Value weighted opportunity cost ratio of all orders submitted by trader *i* in stock *s* on day *t*. Opportunity cost ratio, for a buy order, is calculated as the ratio of the difference between the closing price of the stock and the midquote at the time of order submission, and the price of the stock an instant before order submission; it is zero for fully executed orders.
Total Cost Ratio^P	Value weighted total cost ratio of all orders submitted by trader *i* in stock *s* on day *t*. Total cost for each order is calculated as weighted sum of the difference between price impact and ex post performance , and opportunity cost, where the weights are volume of the order executed and unexecuted, respectively. Total cost ratio is the ratio of Total Cost and the price of the stock an instant before order submission.
Earnings Day	Binary variable equal to 1 when stock *s* has an earnings announcement on day *t*.

Table II –Characteristics of Sample Stocks

This table presents trading characteristics of the 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India. The various characteristics are calculated for each of the 50 stocks using the entire sample data of 56 trading days — April to June, 2006. These Nifty constituent stocks cover 21 sectors of the economy including, and represent about 60% of market capitalization on the NSE.

	Mean	Median	Max	Min	Q1	Q3
Market Capitalization (USD Billions)	7	4	38	1	3	7
Daily Turnover per stock (USD Millions)	21	13	159	1	6	25
Effective Spread in basis points	3	3	8	2	3	4
Daily Number of Trades per stock	19,121	12,710	70,129	2,870	6,597	24,390
Daily Order Submissions per stock	24,907	18,334	94,355	4,210	9,142	35,345
Number of Order Cancellations (% of Total Number of Limit Orders)	24.24%	25.04%	30.17%	17.10%	21.61%	27.10%
Volume of Order Cancellations (% of Total Volume of Limit Orders)	44.83%	46.35%	58.93%	22.05%	41.91%	50.12%
Number of Order Modifications (% of Total Number of Limit Orders)	15.51%	15.28%	20.62%	12.73%	14.37%	16.37%
Volume of Order Modifications (% of Total Volume of Limit Orders)	26.29%	27.19%	35.48%	18.26%	22.72%	29.65%
Number of Order Revisions (% of Total Number of Limit Orders)	35.71%	36.13%	41.49%	30.18%	32.79%	37.84%
Volume of Order Revisions (% of Total Volume of Limit Orders)	61.30%	62.62%	69.47%	42.97%	58.99%	65.10%

Table III –Trader Categories

This table describes the different trader categories identified in the data. Their share of total limit order volume submitted in the sample, and the proportions of their limit order volume that are cancelled, modified and revised (cancelled or modified) are also presented. The proprietary data from the NSE identifies 14 different trader clienteles, which are further classified into 4 broader categories: Individuals, Financial Institutions, Dealers and Other Institutions.

Trader Category	Description	Number of Traders	Percentage of Total Limit Order Volume Submitted	Percentage of Limit Order Volume		
				Cancelled	Modified	Revised
Individuals	Individual Non-Residential Indians HUF (Families)	1,070,125	32.18%	32.33%	22.68%	49.12%
Financial Institutions	Mutual Fund Bank Insurance Other Domestic Financial Institutions Foreign Financial Institutions	5,771	16.45%	10.00%	34.06%	41.96%
Dealers	Exchange Members	509	40.68%	67.94%	16.32%	73.84%
Others Institutions	Public and Private companies Partnership Firms Trusts and Societies Other Corporate Bodies Statutory Bodies	153,894	10.69%	38.23%	23.94%	54.67%

Table IV –Order Revisions and Trader Attributes

These tables present results from the analysis of trader categories, trader styles and intensity of order revisions. Panel A reports results relating to trader categories and Panel B reports the same for trader styles. Measures of order revision activity and trader styles are calculated for each trader *i* using the entire sample of 50 stocks and 56 trading days — April to June, 2006. Please refer to Table 1 for variable definitions. Two tailed *p-values* are reported (within parentheses).

Panel A: Order Revisions and Trader Categories

		Individual Traders	Institutional Traders			Institutional - Individual	*p*- value
			Financial Institutions	Dealers	Other Institutions		
Revision Ratio	Median	0.167	0.552	0.480	0.106		
	Mean	0.257	0.705	0.534	0.242	0.237	*(<0.001)*
	P90	0.667	1.375	0.916	0.667		
Cancellation Ratio	Median	0.000	0.006	0.196	0.000		
	Mean	0.061	0.065	0.222	0.055	0.053	*(<0.001)*
	P90	0.208	0.198	0.462	0.200		
Modification Ratio	Median	0.083	0.498	0.224	0.000		
	Mean	0.196	0.640	0.312	0.187	0.184	*(<0.001)*
	P90	0.500	1.267	0.634	0.500		
N		1,070,125	5,771	509	153,894		

Panel B: Order Revisions and Trader Styles

$$Revision\ Ratio_i = \alpha + \beta_1 Closing\ Ratio_i + \beta_2 Trader\ Frequency_i + \beta_3 Trader\ Size_i + \beta_4 Network\ Trading\ Ratio_i + \varepsilon_i$$
$$Cancellation\ Ratio_i = \alpha + \beta_1 Closing\ Ratio_i + \beta_2 Trader\ Frequency_i + \beta_3 Trader\ Size_i + \beta_4 Network\ Trading\ Ratio_i + \varepsilon_i$$
$$Modification\ Ratio_i = \alpha + \beta_1 Closing\ Ratio_i + \beta_2 Trader\ Frequency_i + \beta_3 Trader\ Size_i + \beta_4 Network\ Trading\ Ratio_i + \varepsilon_i$$

Variable	Revision Ratio	Cancellation Ratio	Modification Ratio
Intercept	14.292%	12.091%	2.201%
	(<0.001)	*(<0.001)*	*(<0.001)*
Closing Ratio	-16.399%	-10.265%	-6.134%
	(<0.001)	*(<0.001)*	*(<0.001)*
Trader Frequency	7.414%	0.840%	6.574%
	(<0.001)	*(<0.001)*	*(<0.001)*
Trader Size	1.903%	0.080%	1.823%
	(<0.001)	*(0.001)*	*(<0.001)*
Network Trading Ratio	11.593%	10.434%	1.159%
	(<0.001)	*(<0.001)*	*(<0.001)*
N	1,170,355	1,170,355	1,170,355

Table V –Order Cancellations and Trader Inventories: Duration Analysis

This table presents results from the analysis of limit order cancellations using Cox's proportional hazard duration models. The cancellation hazard is modeled as follows:

Specification 1:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p^{Relative}_{o,s} + \beta_5 LaggedVolume_{o,s} \\ \beta_6 LPR_s + +\beta_7 Dealer_i + \beta_8 Individual_i \end{matrix}\right\}$$

Specification 2:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p^{Relative}_{o,s} + \beta_5 LaggedVolume_{o,s} \\ \beta_5 LPR_s + \beta_6 \Delta q^{same}_{o,s,t} + \beta_7 \Delta q^{opposite}_{o,s,t} + \beta_8 Dealer_i + \beta_9 Individual_i + \beta_{10} \Delta Inventory\_Stock_{s,t,i} \end{matrix}\right\}$$

Specification 3:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p^{Relative}_{o,s} + \beta_5 LaggedVolume_{o,s} \\ \beta_6 LPR_s + \beta_7 \Delta q^{same}_{o,s,t} + \beta_8 \Delta q^{opposite}_{o,s,t} + \beta_9 Dealer_i + \beta_{10} Individual_i + \beta_{11} \Delta Inventory\_Stock_{s,t,i} + \\ \beta_{12} \Delta Inventory\_Related_{s,t,i} \end{matrix}\right\}$$

Specification 4:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p^{Relative}_{o,s} + \beta_5 LaggedVolume_{o,s} \\ \beta_6 LPR_s + \beta_7 \Delta q^{same}_{o,s,t} + \beta_8 \Delta q^{opposite}_{o,s,t} + \beta_9 Dealer_i + \beta_{10} Individual_i + \beta_{11} \Delta Inventory\_Industry_{s,t,i} \end{matrix}\right\}$$

Specification 5:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p^{Relative}_{o,s} + \beta_5 LaggedVolume_{o,s} \\ \beta_6 LPR_s + \beta_7 \Delta q^{same}_{o,s,t} + \beta_8 \Delta q^{opposite}_{o,s,t} + \beta_9 Dealer_i + \beta_{10} Individual_i + \beta_{11} \Delta Inventory\_Stock_{s,t,i} + \\ \beta_{12} \Delta Inventory\_Unrelated_{s,t,i} \end{matrix}\right\}$$

Where $h_{o,s,i}$ is the estimated hazard of cancellation for order *o* of stock *s*, submitted by trader *i*, at time *t*. λ_0 is the unspecified baseline hazard rate and time *t* is measured from the moment of order *o*'s submission. Please refer to Table 1 for variable definitions. A random sample of 10,000 orders are selected from each stock. Orders are tracked through their first 2 minutes. Order executions are treated as competing events. Orders from all the stocks are stacked, and a pooled analysis is conducted. The standard errors are clustered by stock. Two tailed p-values are reported (within parentheses) below the parameter estimates.

Variable	(1)	(2)	(3)	(4)	(5)
Order Size	0.287	0.286	0.286	0.286	0.286
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*
Spreads	0.003	0.003	0.003	0.003	0.003
	(0.708)	*(0.726)*	*(0.725)*	*(0.726)*	*(0.726)*
Lagged Volatility	0.088	0.059	0.059	0.059	0.059
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*
$p^{Relative}$	0.185	0.185	0.185	0.185	0.185
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*
Lagged Volume	0.027	0.029	0.029	0.029	0.029
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*
LPR	-0.036	-0.035	-0.035	-0.035	-0.035
	(0.162)	*(0.175)*	*(0.172)*	*(0.170)*	*(0.170)*
Dealer	0.615	0.616	0.616	0.615	0.616
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*	*(<.001)*
Individual	-0.757	-0.751	-0.751	-0.752	-0.751
	(<.001)	*(<.001)*	*<.0001*	*(<.001)*	*(<.001)*
Δq_t^{same}		0.037	0.037	0.037	0.037
		(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
$\Delta q_t^{opposite}$		0.005	0.005	0.005	0.005
		(0.688)	*(0.689)*	*(0.690)*	*(0.690)*
$\Delta Inventory\_Stock_t$		0.013	0.013		0.013
		(<.001)	*(<.001)*		*(<.001)*
$\Delta Inventory\_Related_t$			0.008		
			(0.008)		
$\Delta Inventory\_Industry_t$				0.011	
				(<.001)	
$\Delta Inventory\_Unrelated_t$					0.002
					(<.463)

Table VI –Positive Order Modifications and Trader Inventories: Duration Analysis

This tables presents results from the analysis of positive order modifications using Cox's proportional hazard duration models. The hazard of positive modifications is modeled as follows:

Specification 1:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p_{o,s}^{Relative} + \beta_5 LaggedVolume_{o,s} \\ \beta_5 LPR_s \end{matrix}\right\}$$

Specification 2:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p_{o,s}^{Relative} + \beta_5 LaggedVolume_{o,s} \\ \beta_5 LPR_s + \beta_6 \Delta q_{o,s,t}^{same} + \beta_7 \Delta q_{o,s,t}^{opposite} + \beta_8 Dealer_i + \beta_9 Individual_i + \beta_{10} \Delta Inventory\_Stock_{s,t,i} \end{matrix}\right\}$$

Specification 3:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p_{o,s}^{Relative} + \beta_5 LaggedVolume_{o,s} \\ \beta_5 LPR_s + \beta_6 \Delta q_{o,s,t}^{same} + \beta_7 \Delta q_{o,s,t}^{opposite} + \beta_8 Dealer_i + \beta_9 Individual_i + \beta_{10} \Delta Inventory\_Stock_{s,t,i} + \\ \beta_{10} \Delta Inventory\_Related_{s,i,t} \end{matrix}\right\}$$

Specification 4:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p_{o,s}^{Relative} + \beta_5 LaggedVolume_{o,s} \\ \beta_5 LPR_s + \beta_6 \Delta q_{o,s,t}^{same} + \beta_7 \Delta q_{o,s,t}^{opposite} + \beta_8 Dealer_i + \beta_9 Individual_i + \beta_{10} \Delta Inventory\_Industry_{s,t,i} \end{matrix}\right\}$$

Where $h_{o,s,i}$ is the estimated hazard of positive order modifications for order *o* of stock *s*, submitted by trader *i*, at time *t*. λ_0 is the unspecified baseline hazard rate and time *t* is measured from the moment of order *o*'s submission. Please refer to Table 1 for variable definitions. A random sample of 10,000 orders are selected from each stock. Orders are tracked through their first 2 minutes. Order executions and cancellations are treated as competing events. Orders from all the stocks are stacked, and a pooled analysis is conducted. The standard errors are clustered by order (Lee, Wei, and Amato, 1992). Two tailed *p-values* are reported (within parentheses) below the parameter estimates.

Variable	(1)	(2)	(3)	(4)
Order Size	0.372	0.376	0.376	0.375
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Spreads	0.082	0.112	0.112	0.112
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Lagged Volatility	0.082	-0.021	-0.021	-0.021
	(<.001)	*(0.060)*	*(0.061)*	*(0.060)*
$p^{Relative}$	0.188	0.188	0.188	0.188
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Lagged Volume	0.028	0.035	0.035	0.035
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
LPR	0.066	0.064	0.064	0.064
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Dealer	0.460	0.446	0.446	0.449
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Individual	-0.152	-0.155	-0.155	-0.151
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Δq_t^{same}		0.054	0.054	0.054
		(<.001)	*(<.001)*	*(<.001)*
$\Delta q_t^{opposite}$		0.099	0.099	0.099
		(<.001)	*(<.001)*	*(<.001)*
$\Delta Inventory\_Stock_t$		-0.063	-0.063	
		(<.001)	*(<.001)*	
$\Delta Inventory\_Related_t$			~0.000	
			(0.995)	
$\Delta Inventory\_Industry_t$				-0.041
				(<.001)

Table VII –Negative Order Modifications and Trader Inventories: Duration Analysis

This tables presents results from the analysis of negative order modifications using Cox's proportional hazard duration models. The hazard of negative modifications is modeled as follows:

Specification 1:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p^{Relative}_{o,s} + \beta_5 LaggedVolume_{o,s} \\ \beta_5 LPR_s \end{matrix}\right\}$$

Specification 2:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p^{Relative}_{o,s} + \beta_5 LaggedVolume_{o,s} \\ \beta_5 LPR_s + \beta_6 \Delta q^{same}_{o,s,t} + \beta_7 \Delta q^{opposite}_{o,s,t} + \beta_8 Dealer_i + \beta_9 Individual_i + \beta_{10} \Delta Inventory\_Stock_{s,t,i} \end{matrix}\right\}$$

Specification 3:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p^{Relative}_{o,s} + \beta_5 LaggedVolume_{o,s} \\ \beta_5 LPR_s + \beta_6 \Delta q^{same}_{o,s,t} + \beta_7 \Delta q^{opposite}_{o,s,t} + \beta_8 Dealer_i + \beta_9 Individual_i + \beta_{10} \Delta Inventory\_Stock_{s,t,i} + \\ \beta_{10} \Delta Inventory\_Related_{s,i,t} \end{matrix}\right\}$$

Specification 4:

$$h_{o,s,i}(t) = \lambda_0(t)\exp\left\{\begin{matrix} \beta_1 Order\ Size_{o,s} + \beta_2 Spreads_{o,s} + \beta_3 LaggedVolatility_{o,s} + \beta_4 p^{Relative}_{o,s} + \beta_5 LaggedVolume_{o,s} \\ \beta_5 LPR_s + \beta_6 \Delta q^{same}_{o,s,t} + \beta_7 \Delta q^{opposite}_{o,s,t} + \beta_8 Dealer_i + \beta_9 Individual_i + \beta_{10} \Delta Inventory\_Industry_{s,t,i} \end{matrix}\right\}$$

Where $h_{o,s,i}$ is the estimated hazard of negative order modifications for order *o* of stock *s*, submitted by trader *i*, at time *t*. λ_0 is the unspecified baseline hazard rate and time *t* is measured from the moment of order *o*'s submission. Please refer to Table 1 for variable definitions. A random sample of 10,000 orders are selected from each stock. Orders are tracked through their first 2 minutes. Order executions and cancellations are treated as competing events. Orders from all the stocks are stacked, and a pooled analysis is conducted. The standard errors are clustered by order (Lee, Wei and Amato, 1992). Two tailed *p-values* are reported (within parentheses) below the parameter estimates.

Variable	(1)	(2)	(3)	(4)
Order Size	0.317	0.316	0.316	0.317
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Spreads	~ -0.001	-0.002	-0.002	-0.002
	(0.987)	*(0.856)*	*(0.857)*	*(0.726)*
Lagged Volatility	0.019	0.004	0.004	0.004
	(0.167)	*(0.768)*	*(0.769)*	*(0.773)*
$p^{Relative}$	0.173	0.172	0.172	0.172
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Lagged Volume	-0.085	-0.081	-0.081	-0.081
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
LPR	-0.047	-0.046	-0.046	-0.047
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Dealer	0.412	0.417	0.417	0.416
	(<.001)	*(<.001)*	*(<.001)*	*(<.001)*
Individual	-0.248	-0.256	-0.256	-0.257
	(<.001)	*(<.001)*	*<.0001*	*(<.001)*
Δq_t^{same}		-0.083	-0.083	-0.083
		(<.001)	*(<.001)*	*(<.001)*
$\Delta q_t^{opposite}$		-0.089	-0.089	-0.089
		(<.001)	*(<.001)*	*(<.001)*
$\Delta Inventory\_Stock_t$		0.024	0.024	
		(<.001)	*(<.001)*	
$\Delta Inventory\_Related_t$			0.009	
			(0.2821)	
$\Delta Inventory\_Industry_t$				0.019
				(<.001)

Table VIII – Order Revisions and Performance: Panel Regressions

This tables presents results from panel regressions of different measures of performance on order revisions, other order characteristics and market variables. The different specifications employed in the analysis are as follows:

Specifications 1a and 1b:

$$
\begin{aligned}
Ex\ Post\ Ratio^{P}_{i,s,t} &= \alpha_i + \gamma_s + \beta_1 Total\ Revisions^{P}_{i,s,t} + \beta_2 Price\ Agg^{P}_{i,s,t} + \beta_3 Log\ Quantity^{P}_{i,s,t} + \beta_4 Buy^{P}_{i,s,t} \\
&+ \beta_5 Hidden^{P}_{i,s,t} + \beta_6 Past\ Volatility^{P}_{i,s,t} + \beta_7 Past\ Trading\ Frequency^{P}_{i,s,t} + \beta_8 NumberOf\ Orders^{P}_{i,s,t} + \varepsilon_{i,s,t}
\end{aligned}
$$

Specifications 2a and 2b:

$$
\begin{aligned}
Price\ Impact\ Ratio^{P}_{i,s,t} &= \alpha_i + \gamma_s + \beta_1 Total\ Revisions^{P}_{i,s,t} + \beta_2 Price\ Agg^{P}_{i,s,t} + \beta_3 Log\ Quantity^{P}_{i,s,t} + \beta_4 Buy^{P}_{i,s,t} \\
&+ \beta_5 Hidden^{P}_{i,s,t} + \beta_6 Past\ Volatility^{P}_{i,s,t} + \beta_7 Past\ Trading\ Frequency^{P}_{i,s,t} + \beta_8 NumberOf\ Orders^{P}_{i,s,t} + \varepsilon_{i,s,t}
\end{aligned}
$$

Specifications 3a and 3b:

$$
\begin{aligned}
Opportunity\ Cost\ Ratio^{P}_{i,s,t} &= \alpha_i + \gamma_s + \beta_1 Total\ Revisions^{P}_{i,s,t} + \beta_2 Price\ Agg^{P}_{i,s,t} + \beta_3 Log\ Quantity^{P}_{i,s,t} + \beta_4 Buy^{P}_{i,s,t} \\
&+ \beta_5 Hidden^{P}_{i,s,t} + \beta_6 Past\ Volatility^{P}_{i,s,t} + \beta_7 Past\ Trading\ Frequency^{P}_{i,s,t} + \beta_8 NumberOf\ Orders^{P}_{i,s,t} + \varepsilon_{i,s,t}
\end{aligned}
$$

Specifications 4:

$$
\begin{aligned}
Total\ Cost\ Ratio^{P}_{i,s,t} &= \alpha_i + \gamma_s + \beta_1 Total\ Revisions^{P}_{i,s,t} + \beta_2 Price\ Agg^{P}_{i,s,t} + \beta_3 Log\ Quantity^{P}_{i,s,t} + \beta_4 Buy^{P}_{i,s,t} \\
&+ \beta_5 Hidden^{P}_{i,s,t} + \beta_6 Past\ Volatility^{P}_{i,s,t} + \beta_7 Past\ Trading\ Frequency^{P}_{i,s,t} + \beta_8 NumberOf\ Orders^{P}_{i,s,t} + \varepsilon_{i,s,t}
\end{aligned}
$$

Specification 5:

$$
\begin{aligned}
Total\ Cost\ Ratio^{P}_{i,s,t} &= \alpha_i + \gamma_s + \beta_1 Total\ Revisions^{P}_{i,s,t} + \beta_9 Total\ Revisions^{P}_{i,s,t} * Earnings\ Day_{S,t} + \beta_{10} Earnings\ Day_{s,t} \\
&+ \beta_2 Price\ Agg^{P}_{i,s,t} + \beta_3 Log\ Quantity^{P}_{i,s,t} + \beta_4 Buy^{P}_{i,s,t} + \beta_5 Hidden^{P}_{i,s,t} + \beta_6 Past\ Volatility^{P}_{i,s,t} \\
&+ \beta_7 Past\ Trading\ Frequency^{P}_{i,s,t} + \beta_8 NumberOf\ Orders^{P}_{i,s,t} + \varepsilon_{i,s,t}
\end{aligned}
$$

All the variables with superscript *P* are value weighted averages of trader *i*'s portfolio (*P*) of orders in stock *s* on day *t*. Please refer to Table 1 for variable definitions. The panel regressions are conducted with trader and stock fixed effects — α_i and γ_s, respectively. Further, to control for contemporaneous cross-sectional correlation in residuals, the standard errors are cluster by day (*t*). Panels A, B, C and D report results relating to financial institutions (FIN), other institutions (Others), dealers (Dealer) and individuals (Individuals). In all panels, columns 1a-3a include all trader portfolios; columns 1b and 2b consider only trader portfolios with either partial or complete execution; coefficients in column 3b are obtained by including only trader portfolios with zero or partial executions. Two tailed *p-values* are reported (within parentheses) below the parameter estimates.

Table VIII, Panel A – Order Revisions and Performance: Financial Institutions

Variable	Ex post ratio		Price impact ratio		Opportunity cost ratio		Total cost ratio	
	All Orders	If fill rate > 0%	All Orders	If fill rate > 0%	All Orders	If fill rate < 100%	All Orders	All Orders
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4)	(5)
Total Revisions^P	0.057%	0.057%	0.069%	0.080%	-0.012%	-0.059%	-0.010%	-0.009%
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.009)*	*(<0.001)*	*(0.097)*	*(0.141)*
Total Revisions^P * *Earnings Day*								-0.050%
								(0.068)
Earnings Day								0.090%
								(0.082)
Price Agg^P	-1.791%	-4.824%	4.114%	12.544%	-3.703%	2.044%	1.721%	1.725%
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.054)*	*(0.087)*	*(0.086)*
Log Quantity^P	0.006%	0.006%	-0.009%	-0.007%	0.025%	0.052%	0.016%	0.016%
	(0.400)	*(0.472)*	*(<0.001)*	*(0.002)*	*(<0.001)*	*(0.001)*	*(0.022)*	*(0.022)*
Buy^P	-0.072%	-0.078%	-0.025%	-0.023%	-0.061%	-0.156%	-0.006%	-0.005%
	(0.328)	*(0.330)*	*(0.197)*	*(0.241)*	*(0.216)*	*(0.332)*	*(0.927)*	*(0.935)*
Hidden^P	-0.012%	-0.014%	-0.019%	-0.025%	0.039%	0.128%	0.042%	0.042%
	(0.568)	*(0.566)*	*(0.021)*	*(0.009)*	*(0.017)*	*(0.009)*	*(0.066)*	*(0.066)*
Past Volatility^P	18.421%	20.956%	4.654%	7.680%	27.128%	91.517%	14.949%	14.681%
	(0.048)	*(0.047)*	*(0.143)*	*(0.048)*	*(<0.001)*	*(<0.001)*	*(0.164)*	*(0.174)*
Past Trading Frequency^P	0.019%	0.021%	-0.003%	-0.002%	-0.007%	-0.004%	-0.025%	-0.026%
	(0.080)	*(0.095)*	*(0.249)*	*(0.460)*	*(0.297)*	*(0.860)*	*(0.017)*	*(0.014)*
Number of Orders^P	-0.004%	-0.005%	-0.002%	0.001%	-0.009%	-0.095%	-0.009%	-0.009%
	(0.402)	*(0.405)*	*(0.228)*	*(0.537)*	*(0.001)*	*(<0.001)*	*(0.112)*	*(0.113)*
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trader Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	92,083	84,100	92,083	84,100	92,083	25,689	92,083	92,083

Table VIII, Panel B – Order Revisions and Performance: Other Institutions

Variable	Ex post ratio		Price impact ratio		Opportunity cost ratio		Total cost ratio	
	All Orders	If fill rate > 0%	All Orders	If fill rate > 0%	All Orders	If fill rate < 100%	All Orders	All Orders
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4)	(5)
Total Revisions^P	0.007%	0.008%	0.012%	0.024%	-0.016%	-0.025%	-0.008%	-0.008%
	(<0.001)	*(0.022)*	*(<0.001)*	*(<0.001)*	*(0.001)*	*(0.001)*	*(0.025)*	*(0.023)*
*Total Revisions^P * Earnings Day*								~0.000%
								(0.991)
Earnings Day								0.113%
								(0.051)
Price Agg^P	-0.944%	-2.316%	2.102%	11.828%	-3.073%	0.636%	-0.153%	-0.155%
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.005)*	*(0.565)*	*(0.904)*	*(0.902)*
Log Quantity^P	-0.002%	-0.004%	0.009%	0.021%	-0.005%	-0.024%	0.008%	0.008%
	(0.495)	*(0.501)*	*(<0.001)*	*(<0.001)*	*(0.060)*	*(<0.001)*	*(0.065)*	*(0.068)*
Buy^P	-0.115%	-0.158%	-0.045%	-0.054%	-0.146%	-0.312%	-0.073%	-0.073%
	(0.072)	*(0.080)*	*(0.170)*	*(0.205)*	*(0.260*	*(0.301)*	*(0.592)*	*(0.592)*
Hidden^P	-0.006%	-0.008%	-0.035%	-0.049%	0.059%	0.114%	0.038%	0.039%
	(0.701)	*(0.677)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.073)*	*(0.071)*
Past Volatility^P	-0.108%	0.279%	-21.244%	-19.870%	41.120%	98.183%	21.738%	21.188%
	(0.988)	*(0.978)*	*(<0.001)*	*(<0.001)*	*(0.002)*	*(<0.001)*	*(0.033)*	*(0.038)*
Past Trading Frequency^P	0.002%	0.003%	-0.010%	-0.016%	-0.003%	0.015%	-0.013%	-0.014%
	(0.798)	*(0.741)*	*(0.002)*	*(<0.001)*	*(0.748)*	*(0.463)*	*(0.117)*	*(0.084)*
Number of Orders^P	0.001%	0.001%	-0.005%	0.002%	0.001%	-0.037%	-0.005%	-0.005%
	(0.767)	*(0.865)*	*(0.002)*	*(0.347)*	*(0.788)*	*(0.006)*	*(0.254)*	*(0.271)*
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trader Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	480,806	384,244	480,806	384,244	480,806	203,470	480,806	480,806

Table VIII, Panel C – Order Revisions and Performance: Dealers

Variable	Ex post ratio		Price impact ratio		Opportunity cost ratio		Total cost ratio	
	All Orders	If fill rate > 0%	All Orders	If fill rate > 0%	All Orders	If fill rate < 100%	All Orders	All Orders
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4)	(5)
Total Revisions^P	0.003%	0.004%	0.004%	0.006%	-0.004%	-0.006%	-0.001%	-0.001%
	(0.083)	*(0.117)*	*(0.201)*	*(0.298)*	*(0.088)*	*(0.012)*	*(0.656)*	*(0.591)*
*Total Revisions^P * Earnings Day*								0.018%
								(0.186)
Earnings Day								-0.006%
								(0.849)
Price Agg^P	-0.860%	-2.035%	1.899%	6.179%	-1.868%	-1.238%	0.506%	0.506%
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.013)*	*(0.123)*	*(0.570)*	*(0.570)*
Log Quantity^P	0.002%	0.002%	0.008%	0.013%	-0.014%	-0.021%	-0.008%	-0.008%
	(0.002)	*(0.038)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.002)*	*(0.002)*
Buy^P	-0.077%	-0.108%	-0.023%	-0.037%	-0.313%	-0.459%	-0.256%	-0.256%
	(0.116)	*(0.117)*	*(0.367)*	*(0.308)*	*(0.105)*	*(0.101)*	*(0.154)*	*(0.154)*
Hidden^P	0.005%	0.002%	-0.026%	-0.029%	0.043%	0.042%	0.023%	0.024%
	(0.538)	*(0.843)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.010)*	*(0.092)*	*(0.090)*
Past Volatility^P	2.033%	2.154%	-0.547%	2.068%	29.897%	47.054%	28.506%	28.465%
	(0.605)	*(0.659)*	*(0.800)*	*(0.460)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*
Past Trading Frequency^P	-0.005%	-0.005%	-0.001%	-0.002%	0.006%	0.014%	0.013%	0.012%
	(0.194)	*(0.251)*	*(0.764)*	*(0.478)*	*(0.352)*	*(0.147)*	*(0.033)*	*(0.036)*
Number of Orders^P	0.002%	0.001%	~0.000%	0.003%	0.002%	-0.007%	-0.001%	-0.001%
	(0.122)	*(0.224)*	*(0.748)*	*(<0.001)*	*(0.209)*	*(0.023)*	*(0.781)*	*(0.783)*
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trader Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	163,160	147,048	163,160	147,048	163,160	109,647	147,048	147,048

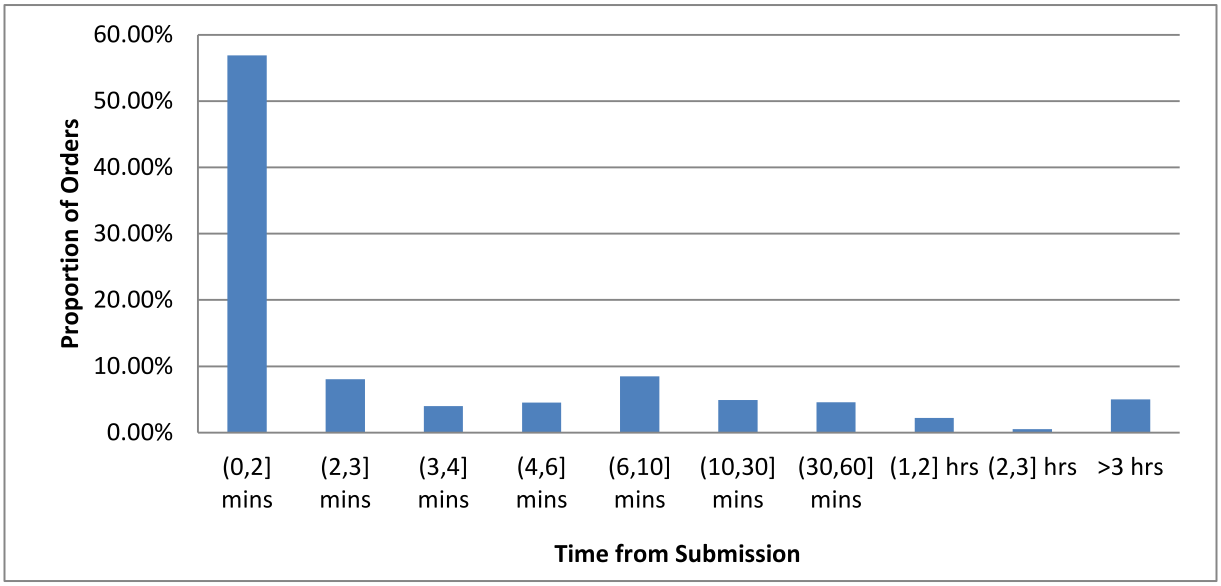
Table VIII, Panel D – Order Revisions and Performance: Individuals

Variable	Ex post ratio		Price impact ratio		Opportunity cost ratio		Total cost ratio	
	All Orders	If fill rate > 0%	All Orders	If fill rate > 0%	All Orders	If fill rate < 100%	All Orders	All Orders
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4)	(5)
Total Revisions^P	0.007%	-0.002%	0.062%	0.105%	-0.079%	-0.220%	-0.014%	-0.013%
	(0.070)	*(0.505)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.327)*	*(0.353)*
*Total Revisions^P * Earnings Day*								-0.046%
								(0.354)
Earnings Day								0.183%
								(0.026)
Price Agg^P	-0.777%	-1.712%	2.149%	11.965%	-3.058%	2.113%	-0.257%	-0.260%
	(<0.001)	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.007)*	*(0.695)*	*(0.695)*
Log Quantity^P	-0.011%	-0.013%	0.007%	0.015%	0.005%	-0.020%	0.024%	0.024%
	(0.005)	*(0.009)*	*(<0.001)*	*(<0.001)*	*(0.253)*	*(0.062)*	*(<0.001)*	*(<0.001)*
Buy^P	-0.140%	-0.202%	-0.041%	-0.041%	-0.172%	-0.358%	-0.071%	-0.072%
	(0.013)	*(0.013)*	*(0.215)*	*(0.341)*	*(0.214)*	*(0.283)*	*(0.613)*	*(0.609)*
Hidden^P	0.014%	0.019%	-0.045%	-0.050%	0.059%	0.071%	0.008%	0.008%
	(0.067)	*(0.042)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(<0.001)*	*(0.576)*	*(0.566)*
Past Volatility^P	-4.986%	-6.424%	-20.373%	-20.362%	32.379%	90.750%	17.653%	16.583%
	(0.402)	*(0.441)*	*(<0.001)*	*(<0.001)*	*(0.002)*	*(0.001)*	*(0.017)*	*(0.024)*
Past Trading Frequency^P	-0.003%	-0.004%	-0.009%	-0.017%	-0.006%	0.006%	-0.011%	-0.014%
	(0.563)	*(0.625)*	*(0.004)*	*(<0.001)*	*(0.458)*	*(0.753)*	*(0.193)*	*(0.105)*
Number of Orders^P	0.005%	0.008%	-0.004%	-0.007%	-0.005%	-0.052%	-0.013%	-0.013%
	(0.256)	*(0.134)*	*(0.075)*	*(0.015)*	*(0.436)*	*(0.004)*	*(0.049)*	*(0.057)*
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trader Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,962,603	11,206,706	13,962,603	11,206,706	13,962,603	5,182,729	13,962,603	13,962,603

Figure 1: Order Revisions and Time from submission

The following graphs show the distribution of order cancellations (Panel A) and order modifications (Panel B) over time from order submission.

Panel A: Order Cancellations



Panel B: Order Modifications