Stock Market Liquidity: Role of Short-term and Long-term Traders

Mila Getmansky, Ravi Jagannathan, Loriana Pelizzon, and Ernst Schaumburg[1,2]

April 15, 2015

Abstract

Using unique trader-identified data from the National Stock Exchange of India, we examine the role of short and long term traders in liquidity provision during normal times and crashes. Short term traders who carry little or no inventory overnight provide liquidity on one side of over 2/3rd of the shares traded. During normal price fluctuations, these traders put in buy orders when prices decline and sell when prices rise, thereby providing liquidity to the market and stabilizing prices. However, during the two fast crash days in our sample, their buying was insufficient to meet the liquidity needs of selling foreign institutions. Inventories of short term traders were high preceding the two crashes, indicating limited capital of short-term liquidity providers. Buying by domestic mutual funds, which have a natural advantage in making a market in the basket of stocks they hold, and infrequent traders led to price recoveries, highlighting the stabilizing role of slow moving market making capital in fast crashes.

Keywords: Liquidity Provision; Market Fragility; Slow-Moving Capital; Hot-Potato Trading

1) Mila Getmansky: Isenberg School of Management, University of Massachusetts Amherst. Ravi Jagannathan: Kellogg School of Management, Northwestern University, and NBER, ISB and SAIF. Loriana Pelizzon: Goethe University Frankfurt - Center of Excellence SAFE and Ca' Foscari University of Venice. Ernst Schaumburg: Federal Reserve Bank of New York. We thank the Centre for Analytical Finance at the Indian School of Business and the National Stock Exchange of India for data. We thank Viral Acharya, Lawrence Glosten, Merrel Hora, Dermot Murphy, Nirmal Mohanty, Todd Pulvino, Ramabhadran Thirumalai, Ravi Varanasi, Vish Viswanathan, Pradeep Yadav, Brian Weller, and participants in the NSE-NYU Indian Capital Markets Conference 2013 for helpful comments. Isacco Baggio, Nuri Ersahin, Naveen Reddy Gondhi, Caitlin Gorback, Mrinal Mishra, and Roberto Panzica provided valuable research assistance. Special thanks to Rudresh Kunde and Tomasz Wisniewski for data support. All errors are our own.

2) The views expressed in the paper are those of the authors and do not represent the views of the Federal Reserve Bank of New York or the Federal Reserve System.

I. Introduction

A liquid and stable stock market plays a critical role in the economy. It channels savings into long term investments that are necessarily illiquid while at the same time providing liquidity to investors through access to their capital when needed by trading with others, thereby promoting economic growth.[3] Due to advances in technology, trading through anonymous open electronic order book markets, has become the preferred avenue for trading stocks.[4] The popular view is that this in turn has increased short term trading which has adversely affected the liquidity and short term volatility in the market contributing to its potential fragility. The empirical findings are mixed.[5] In this study we contribute to this debate by identifying short term and long term traders and examining their role in liquidity provision during normal and fragile market conditions in such a market.

Using a unique database, we are able to track individual traders and their transactions over time, and identify liquidity providers based on their trading behavior and classify traders into short and long term traders since traders with different investment horizons are known to have differing liquidity provision characteristics, especially during market crashes.[6] We find that short term traders (STT) who carry relatively small amounts of inventory intra-day relative to their trading volume and/or carry little inventory overnight were important providers of liquidity during normal times, and they were on one side of over 2/3rd of the shares traded. There are two fast crashes in the spot market in our sample – days when the price for the stock declined by more than 3% and then sharply recovered by more than 3% during a 15 minute time span. The unusually large liquidity shocks were due to large selling by foreign institutional investors.

[3] There is widespread agreement among academics and policy makers that a well functioning stock market, by providing permanent capital to fund socially beneficial long term projects while at the same time providing liquidity to investors, promotes economic development. See Levine (2005) for an excellent survey on finance and growth.

[4] Trading through anonymous open electronic order book markets has become the preferred avenue for securities trading, as foreseen by Glosten (1994), and now accounts for a major share of trading in securities, with automated trading replacing what was mostly manual trading. This is evidenced by the fact that 65% of the 5-day average notional trading volume in U.S. equities on April 8, 2015 of about $235 billion was due to trading in electronic limit order book markets, i.e., other than NASDAQ (DQ) and NYSE (DN). *Taken from the Market Volume Summary page of BATS Trading (http://www.batstrading.com/market_summary/).*

[5] Hasbrouck and Saar (2009) find that the increase in low latency activities, i.e., increase in immediacy, improves short term volatility, price impacts and spreads, but not necessarily during rapid crashes and recoveries. Hendershott and Moulton (2011) find that increased automation and the consequent reduced latency led to an increase in the price of immediacy but improved price efficiency.

[6] See Duffie and Strulovici (2009) and Cella, Ellul, and Giannetti (2013).

Buying by short term traders who provide liquidity during normal times was not enough. Mutual funds and other long term traders had to step in to provide price support for price recovery to take hold. That took time which is consistent with Mitchell, Pulvino, and Stafford (2007) and Duffie (2010) who characterize the role of slow moving market making capital during periods of market turmoil.

We use order book and transactions data for three months in 2006 on shares of a large firm traded on the National Stock Exchange (NSE) of India which provides a unique identifier for each broker-trader combination.[7] During this period, there were 108,542 distinct traders transacting a total of 115.6 million shares in the spot market for shares of the stock. NSE became the largest stock exchange in India by volume of trading overtaking the Bombay Stock Exchange[8] (BSE) at the end of 1995. NSE was the third largest exchange worldwide in 2006 based on the number of trades, after NYSE and NASDAQ.

The National Stock Exchange of India classifies traders in terms of their legal affiliations. We find that these legal classifications of traders, like retail, institutions, etc. are not adequate for understanding liquidity provision in the market. Liquidity provision is an action, and as such is dynamic. Under some circumstances several traders become liquidity providers, and under different scenarios, they may become liquidity demanders[9]. Several types of traders are short term liquidity providers – i.e., they tolerate deviations from their desired inventory positions for short periods of time. Some are longer term liquidity providers who can tolerate persistent deviations from their target inventory positions. We therefore go beyond legal classification of traders and identify short term and long term liquidity providers directly based on their trading behavior.

We find that during normal price fluctuations STT buy when prices decline and sell when prices rise thereby providing liquidity and stabilizing prices.[10] Order modification is an important tool they use in managing their inventory risk. When STT inventories are large and positive (large and negative), the ask-side (bid-side) becomes more liquid and the bid-side (ask-side) becomes less liquid due to order modifications.

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7 A particular trader may choose to trade through several brokerage accounts. In that case we will identify each broker-trader combination as a different trader.

[8] BSE was established in 1875, is one of Asia's oldest stock exchange.

[9] For example, those employing Pairs Trading strategies will in general be providing liquidity/immediacy on one side of their trade whereas they will be demanding liquidity/immediacy on the other side.

[10] Brogaard, Hendeshott and Riordan (2013) find that HFTs, who are essentially STTs, trade in the opposite direction of transitory pricing errors, which is consistent with our findings regarding the behavior of STTs.

While STT contribute to about 2/3rd of the total trading volume in the spot market for the stocks in our sample period, 2/3rd of their trades are amongst themselves. This pattern is similar to what has been observed in foreign exchange markets by Lyons (1995), and Hansch, Naik, and Viswanathan (1998) and Reiss and Werner (1998) in the London Stock Exchange market. This phenomenon is often referred to as the hot potato trading. As Viswanathan and Wang (2004) observe, the underlying mechanism generating hot potato trading in open limit order book markets is different than the one in dealer markets. In the former, a typical market maker covers her market making costs and protects herself against trading with those with superior information through the bid-ask spread. However, there is also the need to process information as it arrives over time requiring quote revisions, and that consumes time. Holding inventories over shorter periods of time by passing some of the inventory to other market makers while processing information that arrives in the interim helps inventory risk management. Our findings are consistent with the view that STT use hot potato trading as an inventory risk management tool.[11]

The *flash crash* of May 6, 2010 focused the attention of exchanges and regulators on the need to understand what causes market fragility[12]. The initial focus was on the role of the high frequency trading (HFT), which is a relatively recent development. However, there were no HFT during the October 19, 1987 U.S. stock market crash (Black Monday). Also, Kirilenko, Kyle, Samadi, and Tuzun (2011) studying a brief period of extreme market volatility on May 6, 2010 (Flash Crash) conclude that HFTs did not trigger the Flash Crash. This suggests that there may be other important forces that influence short term liquidity and occurrence of crashes in stock markets. Sudden influx of sell orders concurrent with bad news about the economy or about the stock[13] and slow moving market making capital may be the primary drivers of crashes. The large 900 point flash crash in the Nifty index of the National Stock Exchange (NSE) of India on October 5, 2012 lends further support for this view.[14] We add to the literature by documenting the behavior of those who provide liquidity to the market during normal price fluctuations and during fast

[11] For examle, Weller (2014) who finds that chains of intermediaries provide facilitate trade on exchanges by providing liquidity.
12 See Easley, Lopez de Prado, and O'Hara (2012) for an excellent discussion of the flash crash of May 6, 2010. The flash crash is characterized by a quick drop and recovery in securities prices that happened around 2:30 pm EST on May 6, 2010.

[13]Very large marketable sell orderscould also be due to order placement errors
[14] NSE CNX Nifty index was launched in 1996 and is composed of 50 diverse stocks traded by NSE, covering over 22 industry sectors.

crashes using data from an electronic limit order book market during a time period where HFTs (as in the US markets) were not present.[15]

During the two fast crashes in our sample order modifications played an important role.[16] We propose a new method for summarizing the role of order modifications that result in limit order book changes: we decompose the price change from one trade to the next into two orthogonal components. For convenience we attribute the price change that would have occurred if the limit order book had not changed to *private information* and the other that is due to changes in the limit order book to *public information*. During fast crashes, the public information component becomes a significant fraction of price changes, highlighting the role of order modifications in inventory risk management during such episodes, which accentuates market fragility.

The rest of the paper is organized as follows. Section II relates our work to the literature. Section III describes the data. Section IV introduces methodology we use to identify Short Term Traders (STT) and characterizes their liquidity provision. In Section V we study the behavior of STT during two specific days when the market crashes. We conclude in Section VI.

II. Relation to the Literature

The literature on electronic order book markets is vast, and therefore we discuss only a few closely related papers. Conventional wisdom based on Ho and Stoll's (1983) seminal work is that *hot potato trading* is the means by which market makers share risk. Lyons (1997) and Viswanathan and Wang (2004) develop models which generate "hot potato" trading. Viswanathan and Wang (2004) make the intuition in Ho and Stoll (1983) precise and show that sequential trading leads to risk sharing and better prices compared to one shot uniform price auctions.[17] Lyons (1995) finds that inter-dealer trading accounts for about 85% of the total volume in FX markets highlighting the importance of inter-dealer trades. Hanch, Naik, and Viswanathan (1998) and Reiss and Werner (1998) find that inter dealer trading accounts for a

[15] The high transaction cost structure in the Indian spot market, e.g. associated with the Securities Transaction Tax (STT) introduced in 2004, effectively inhibits the emergence of US style HFT-market making but not algorithmic trading more generally.
[16] Lyle, Naughton, and Weller (2015) find that market wide jumps in prices are preceded by withdrawal of liquidity through order modifications and cancellations by market makers in all securities.
[17] Hagerty and Rogerson (1987) show the robustness of posted price mechanisms (open limit order book is one such mechanism) when agents have private information about the value of a good.

large fraction of the total volume in the London Stock Exchange and provide evidence favoring the view that such trades help dealers manage their inventory risk. Hansch, Naik and Viswanathan (1998) find that market markers trade to bring large inventory positions quickly back to target level. Reiss and Werner (1998) find that inter dealer trading more than doubles to 65% of total trading volume in the subset of FTSE stocks they study when dealer inventories spike. Biais, Martimort, and Rochet (2000), characterize the limit order book when order flow is informative where no inter dealer trades are allowed. Viswanathan and Wang (2004) show that the limit order book is a robust mechanism less prone to trading break down than inter dealer trading through sequential auctions when large information events happen.

Naik and Yadav (2003) provide support for the view that market makers' inventories affect market quality. Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010) find market-maker financial conditions explain time variation in liquidity. Raman and Yadav (2013) study limit order revisions. They find that informed traders and voluntary market makers revise orders more often, and changes in market prices and inventories including inventories of other related stocks, influence order revisions. Further, active order revisions reduce execution costs. Shachar (2012) finds that order imbalances of end users cause significant price impact in CDS markets, and the effect depends on the direction of trades relative to dealer inventories and counterparty risk.

Harris (1998) studies optimal dynamic order submission strategies in a stylized environment and illustrates the role of time in the search for liquidity. Foucault, Kadan, and Kandel (2005) find that the average time until a transaction increases with the size of the spread, and other things being equal, both market resiliency and the expected duration between trades decrease with the proportion of impatient traders. Rosu (2009) develops a model of an order-driven market where traders choose between limit and market orders. An interesting insight is that a sell market order not only moves the bid price down. The ask price also falls though less than the decrease in the bid price, widening the bid-ask spread. Goettler, Parlour, and Rajan (2005) model a dynamic limit order book market and show that the midpoint of the bid-ask quote need not equal the fair value of the stock.

Recently there has been a surge in the number of articles that study Algorithimic and High Frequency Trading (HFT). Hendershott, Jones and Menkveld (2011) attribute the decline in bid-ask spreads during 2002-2007 to increased algorithmic trading. Lyle, Naughton and Weller (2015) examine specific mechanisms through which this reduction in spreads may have occurred and why spreads did not continue to fall further with increased algorithmic trading. While there is consensus regarding the effect of HFT on spreads for small trades, examining welfare implications of HFT is difficult in part due to the difficulties associated with modeling the need for liquidity and the benefits to earlier resolution of uncertainties and the lack of comprehensive data. Budish, Cramton, and Shim (2014) argue in favor of frequent batch auctions and against continuous limit order book based trading that promotes HFT by rewarding speed. The literature is vast and we refer the interested reader to Biais, Foucault and Moinas (2013) for an excellent discussion of the issues involved.[18]

The flash crash of May 6, 2010 has focused the attention of several researchers on understanding the determinants of market fragility. Easley, Lopez de Prado and O'Hara (2012) develop a method for identifying order flow toxicity that adversely affects market makers resulting in market fragility. Andersen and Bondarenko (2013) argue that realized volatility and signed order flows may also be useful as real time market stress indicators. Kirilenko, Kyle, Samadi, and Tuzun (2011) study the role of HFTs in the flash crash.

There is also a growing literature examining market liquidity during financial crises. One of the findings is that those who normally provide liquidity in the market stood on the sidelines during the times of crises. This can be a response to perceived increase in uncertainty (Di Maggio, 2013) or increase in risk aversion (Huang and Wang 2013). Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), He and Krishnamurthy (2010)) postulate that adverse shocks to the balance sheet of intermediaries, who act as liquidity providers, lowered their ability to commit capital for market making. Interestingly, in the electronic order book market for stocks that we examine

[18] In US equity markets, HFT has reached a point at which the marginal social benefit of shaving off an extra millisecond from the latency is highly dubious. At the same time, HFT firms find themselves caught in a classic prisoners' dilemma whereby they as a group would all be better off if they could credibly commit to stop the technological arms race to reduce latency. The following example illustrates the issues. Suppose there is a basket ball field that has 1,000 seats. The total social utility to watching the game is fixed in this case. Suppose those who want to see the game have to go to the field to buy the ticket before the game starts, and there are 1,010 people interested in watching the game in the field. Initially, suppose everyone walks to the field's ticket counter, and an individual specific random shock affects each person's travel time. So, 10 of those who want to watch will have to go home disappointed and watch the game on TV, since they arrived last at the ticket counter. If one can pay for a faster mode of transportation, and the speed of travel is an increasing function of the amount paid, everyone will pay for faster travel to such a level that they all become indifferent to attending the game. Most of the social benefit to watching the game will be lost in increased transportation costs to get to the basket ball field ahead of the others! The counter argument is that, speed trading improves market liquidity. In the example, it is as though faster travel to the basket ball field will increase the number seats available. That could happen, if those who arrive early could spend the time they save to build additional seats.

here, during one of the two fast crash days when there was a sharp drop in the stock index as well, trading was suspended. On that day many of those who make a market and provide liquidity on most days kept away possibly for similar reasons.

We contribute to this literature in several ways. First, we develop a new approach to identify short term liquidity providers based on their trading behavior and find that short term traders play an important role in providing short term liquidity. Second, we find that during the two fast crashes in our sample order modifications and the resultant evaporation of liquidity from the limit order books played an important role. Buying by domestic mutual funds, which have a natural advantage in making a market in the basket of stocks they hold, and infrequent traders led to price recoveries, highlighting the stabilizing role of slow moving longer term market making capital in fast crashes. We also develop a method to summarize the role of order modifications that result in limit order book changes. Third, we find that short term traders carry little inventory overnight, presumably due to capital constraints. We find that short term traders on average sell to other long term traders at the end of the trading day and buy form them at the beginning of trading during the following day. Our findings provide one possible explanation of overnight returns being higher on average than during the trading day returns on stocks.

III. Data Description and Summary Statistics

III.A Prices, Orders, and Volume

We conduct our analysis based on a representative stock traded on the NSE. We obtain order, transaction, modification, and cancellation information for this specific asset for 53 trading days during April 3rd 2006 to June 30th 2006 for both spot and futures markets. All of our subsequent analysis is conducted for this one representative NSE stock.

We provide a brief history of trading at NSE in Appendix A.1; describe the behavior of the price of the stock we study and its futures price during our sample period in Appendix A.2; and examine the intra-day patterns in trading volume and the liquidity of the stock using commonly used measures in Appendix A.3. The patterns for the stock we examine during the sample period of our study are similar to the patterns reported in the literature for stocks traded in U.S. exchanges.

We report the number of traders, the transaction types, and traded volume inTables III.1 and III.2,. During the 53 days in our sample period there are 108,542 traders in the spot market for this stock with a total volume of 115.6 million shares, while in the futures market for this stock there were 37,046 traders transacting in 721,583 futures contracts.[19] In total, there were 139,652 traders that traded either in the spot, futures, both in spot & futures, or submitted the orders which were not executed during this time period. However, for 8.44% traders (11,792), no trades were executed during this 3-month time period; therefore, the number of effective traders whose orders resulted in at least one trade during this time period is 127,860.

(Insert Table III.1 here)

As can be seen from Table III.1, 71.44% of traders participate both as buyers and sellers for the stock and 87.35% of traders participate both as buyers and sellers in the futures market. Most of the traders are active on both buy and sell sides of the market and there are only a small number of traders who operate solely as buyers or sellers in both spot and futures markets during our sample window.

From Table III.2, it is evident that the volume on the futures market dwarfs that on the spot market for the shares of the firm; futures volume is about five times the volume on the spot market.

(Insert Table III.2 here)

Table III.3 describes the types of orders on both stock and futures markets. A trader can add, cancel, or modify an existing trade. We find that for stock (futures) market, modifications and cancellations represent 29.20% (39.75%) of all buy and sell orders on average, with modifications being less frequent than order cancellations. On NSE more than 91% of orders are limit orders, with the rest being “market”, “fill or kill”, “immediate or cancel”, or “stop-loss” orders.

(Insert Table III.3 here)

III.B Trader Classifications Based on Legal Status

The National Stock Exchange of India classifies traders in terms of their legal affiliations. There are three primary categories: individuals, corporations, and financial institutions and 13 sub-categories: individual traders, partnership firms, Hindu undivided families, public and private

[19] Each contract is for 750 shares.

companies or corporate bodies, trust or society, mutual funds, domestic financial institutions, banks, insurances, statutory bodies, Non-Resident Indians, FII Foreign Institutional Investors, and overseas corporate bodies. Table III.4 reports distribution of traders in the stock, futures, and both markets. For both markets, individual traders account for the majority of trading (87.5% of trader population in the spot market and 78.0% in the futures market). However, public and private corporate bodies or corporate bodies, Hindu undivided families, mutual funds, non-resident Indians, and overseas corporate bodies are also active on the spot market. For the futures market, the composition of trader population is similar, except for mutual funds and non-resident Indians who are rarely engaged in derivatives trading on the NSE.

(Insert Table III.4 here)

Corporations category includes partnership firms, public and private companies, corporate bodies, and trust and society. This category accounts for a mere 0.5% of the total trader population on the spot market but a larger proportion (4%) on the futures market. Corporations tend to utilize the futures market to hedge specific risks; thus, they are more likely to trade on the futures market.

During our three-month period we study trading frequency of all traders whose trades were executed. We find that most of the traders (94.9%) on the spot market are active for ten or less days during this sample period. Almost half of all traders (47.4% of 99,306 traders) are active during only one day for the entire 3-month period. Figure III.1 graphs the trading frequency for all traders. According to Figure III.1, we clearly see a large presence of low frequency traders.

(Insert Figure III.1 here)

As described earlier, in total, there are 139,652 traders that trade either in the stock, futures, both in stock & futures, or submitted the orders which were not executed during this time period.

IV. Short Term Traders

As we discussed earlier, legal classifications of traders, like retail, institutional, pension funds, etc. are not adequate for analyzing the role of traders in liquidity provision in different types of market conditions. Therefore, we classify traders based on their trading behavior and the role in the market. We focus our attention on those with a short inventory holding horizon (Short Term Traders) and examine how their inventory positions affect market liquidity, and how they manage their inventory risk.

IV.A Trader Classifications Based on Trading Behavior

On each day, we classify active traders on that day into a number of categories based on their actions as depicted in Figure IV.1. We first isolate Mutual Fund (MF) and Foreign Institutional Investors (FII) based on Table III.4 Legal Category Classifications. We further classify the remaining traders based on the frequency of trading. Infrequent traders are the ones who trade for 3 days or less during our sample. For traders who traded more than 3 days during the sample, we separate them into Other Long Term Traders who carry over-night inventory (end-of-the day inventory is greater than 1% of traded volume) and those who do not. If a trader trades more than 100 shares and routinely (more than 10% of the time is active) has limit orders of at least 100 shares on both sides of the book within 1% of the mid-point, and does not carry over-night inventory, we denote that trader a Market Maker (MM). Otherwise, we separate the traders into active or passive traders. We calculate a passive ratio as the ratio of passive volume and the total volume traded. For traders whose passive ratio is greater than 0.66, we indicate them as PDT (Passive Day Traders). For traders whose passive ratio is less or equal to 0.33, we call them ADT (Active Day Traders), and the rest of day traders are classified as MDT (Medium Day Traders). MDT are further classified as proprietary (P_MDT) and non-proprietary (NP_MDT). A trader is called proprietary if the trade member id matches the client id; otherwise, he is classified as a non-proprietary trader.

Infrequent traders are the ones who trade for 3 days or less during our sample. We call this category Unspec_Infrequent. Frequent traders can be consistent or inconsistent. Consistent traders are traders who belong to the same behavioral category more than 50% of the times in the sample. Consistent day traders are day traders who belong to the day trader category more than 50% of the times in the sample. It is possible that day traders are not consistently PDT, MDT, or ADT, but they are consistently behaving as one of the day trader categories. Therefore, we will categorize these traders as ODT (Other Day Traders). Otherwise, the rest of traders are classified as Unspec_Inconsistent.

In summary, we have 11 major categories: ADT, PDT, P_MDT, NP_MDT, MM, OLTT, ODT, Unspec_Inconsistent, Unspec_Infrequent, FII, and MF. All categories are non-overlapping by construction.

(Insert Figure IV.1 here)

For categories based on trading behavior, Table IV.1 provides transition probabilities for traders belonging to the same or different trader types on the next day that trader trades. Traders tend to change trader types across successive days. ADT tend to stay in the same category 68% of the time. The same goes for PDT (62%), P_MDT (63%), and NP_MDT (60%). However, ADT 21% of the time becomes NP_MDT, 5% PDT, and 6% OLTT. P_MDT tends to become ADT (15%), PDT (15%), and OLTT (6%). MM has 75% probability of staying MM next day; however, there the rest of 25% is equally distributed among other behavioral categories. Infrequent, FII, and MF tend to belong to the same category (100% of time) next day. ODT have 25% becoming ADT, 22% PDT, 32% NP_MDT, and 19% OLTT. Unspec-Inconsist have 22% of becoming PDT, 14% of becoming MM, and 42% of becoming OLTT. On average, all traders are more likely to be consistent in using their categories the next day. However, classifications tend to change over time. However, day traders tend to stick with being day traders. Long-term traders also tend to stick with being long-term traders. However, there is some spillover to other categories. For day traders, less than 10% move to OLTT category; however, 25% of OLTT become day traders. Also, we find that market making (MM) is a highly specialized category, and day traders or long-term traders rarely move into that category.

(Insert Table IV.1 here)

Table IV.2.A provides the number of traders in different categories on each of the trading days. Note that the number of traders in different categories varies across days. For example, there are no FII on May 17, 2006. There were 66 PDT on April 4, 2006, and 376 on June 19, 2006. The presence of mutual fund traders on May 19th (25 mutual funds) and May 22nd(16 mutual funds), two fast crash periods in the sample, is larger than in other 51 days on average (12.3 mutual funds). The presence of foreign institutions is relatively large on May 22nd. Table IV.2.B gives the trade and order volumes of different behavioral categories.

(Insert Table IV.2A and IV.2B here)

According to Table IV.2B, all day traders traded about half of the total volume. Specifically, ADT, NP_MDT, ODT, PDT, and P_MDT comprised 48.56% of all traded volume and 43.78% of all order volume. If you look at individual categories, OLTT had the highest traded volume (18.83% of all traded volume). The second largest was ODT (16.44%). However, based on the order volume, MM constituted the largest share (21.89%) with OLTT being the close second (20.79%). Tables IV.2.C and IV.2.D give the trades taking place amongst different behavioral trading categories. As can be seen short term traders (STT) consisting of ADT, MM, NP_MDT, P_MDT, PDT, and ODT were on one side of 2/3rd of the trading volume[20]; and of the total 1,764,183 shares that exchanged hands, 1,148,070 (65%) shares traded within categories belonging to STT* -- STT and Unspec.Inventory Inconsistent plus Unspec. Inventory Infrequent who were often short term traders. Further, 780,309 (44%) shares traded within STT. We also find (not reported) that ADTs are mostly (92%) individual traders.

(Insert Table IV.2.C and IV.2.D here)

IV.A.1 Intra Day Cyclical Patterns in Buys and Sells of Traders

While short term traders consisting of day traders and market makers on average handle a large part of the total trading volume, rarely carry inventories overnight. That means that they are more likely to be on the buy side of trades in the early hours of the trading day and on the sell side of trades during the closing hours of the trading day.

(Insert Figure IV.2 and IV.3 here)

Figures IV.2 and IV.3 confirm that this is indeed the case, where the total buys and sells are normalized to equal 1 and -1. Day traders are net buyers during the first half hour of trading and net sellers during the last half hour of trading. OLTT are the net sellers during the first half hour and net buyers during the last half hour.

(Insert Figure IV.4 here)

Figure IV.4 give the directed trading volume network of net buys and sells among various behavioral trader categories – during the first half hour of trading, the last half hour of trading and during the rest of the trading day. Notice that OLTT are net buyers from STT during the last half hour of trading in a day; and they are net sellers to STT during the first half hour of the day.

[20] In an earlier version of the paper we used a different method for identifying trader categories. With that scheme, we found that STT were on one side of 75% of the trading volume and 3/5th of that trading volume was due to trading among themselves.

Such cyclical patterns in buys and sells that occur at 24 hour intervals provides one possible explanation for the intra-day patterns in stock returns documented in Heston, Korajczyk, and Sadka (2010) and Murphy and Thirumalai (2013).

With this pattern in trading, overnight returns have to be sufficiently higher to induce OLTT to hold overnight inventories. Suppose prices changes (returns) over 24 hours, i.e., one day's close to the next day's close reflect information that arrive during that interval efficiently. Then if overnight returns are higher to induce carrying inventories overnight, then during the day returns will have to be lower by the same amount as the cost of providing liquidity during the trading day. If this were the case, we should expect to find that close to open price changes are on average larger than the corresponding open to close price changes that follow. As can be seen from Table IV.3, the close to open, CO (open to close, OC) price changes averaged Rs. 2.37 (Rs. -4.09) with a standard deviation of Rs. 13.77 (Rs. 28.39). The difference, CO minus OC averaged Rs. 6.98 with a standard deviation of Rs. 29.01. We can reject the hypothesis that the CO – OC has zero mean against the alternative that it is positive at the 5% (one tail).

(Insert Table IV.3 here)

IV.B Liquidity Provision

Having identified liquidity providers based on their trading behavior, in this section we provide several tests to verify that these traders actually provide liquidity in the market for the stock when needed. If short term traders were providing liquidity in the market, we should expect liquidity to improve on the ask side and liquidity to worsen on the bid side when their collective inventory holdings rise. In contrast when those who demand liquidity buy and increase their inventories, liquidity on the ask side of the market should worsen since those who are making a market will have less than desired level of inventory; and the liquidity on the bid side of the market should improve since buyers will be more anxious when inventories are lower.

In Table IV.4.A and IV.B we show that price elasticity (the number of shares required to be traded to move price by a given amount using the aggregate market limit order book) is related to the inventory level of short term liquidity providers. Specifically, for each trader, we calculate the path of his intraday inventories (starting each day at zero) and use this variable as a proxy of the inventory capacity used by each trader. We then investigate the relationship of this variable with price elasticity.

We report the estimates for the following regression specification for each of the 8 different measures of price elasticity in Table IV.4.A and IV.B.

$$\pi_{i,t} = \sum_i \alpha_i (FE_i) + \sum_b d_b \, TD_b + \beta(Inv_{i,t}) + \varepsilon_{i,t} \ ,$$

where $\pi_{i,t}$ is the price elasticity of the order book (measured as #Shares it would take to move the volume weighted average purchase price by 100, 75, 50, or 25bp from the mid-price on either the bid or the ask side) on date *i* during several time intervals *t*. To control for day effects and time of the day effects we include date fixed effect (FE_i) and half-hourly time dummies proxying for the intraday pattern in liquidity (TD_b). $Inv_{i,t}$ is the inventory of one of the six trader groups: ADT (Active Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), PDT (Passive Day Trader), and PROP (Proprietary Trader).

According to the Table IV.4, there is a significant positive relationship between the price elasticity of the market limit order book and the inventory levels of short term traders (STT and STT*) on the ask side. The volume of shares purchased required to move prices up by 25, 50, 75, or 100bp is higher, i.e., ask side is more liquid when short term traders' inventories are higher. In contrast, the relationship is negative and significant for mutual funds – i.e., when their inventories are higher, the ask side of the book in the market is less liquid – which would be the case if they were demanding liquidity. Conversely, the volume sold required to drive prices down by 25, 50, 75, or 100bp is lower, indicating lower liquidity on the offer side of the book, when inventories increase for short term traders. However the effect is less statistically significant, as is to be expected, since traders who make a market may be more willing to tolerate holding less than desired inventories, and willing to be more patient when buying to reach their target inventory levels. The sign for mutual fund inventories are positive but not significant. The signs for the other trader categories are also consistent with what we would expect.

(Insert Table IV.4 here)

To summarize, the results are consistent with the view that when inventories of short term traders who provide liquidity in the market are relatively large, the market wide ask side liquidity improves and bid side liquidity worsens, consistent with various models of market making in the literature.[21] We hypothesize that the reluctance of short term traders to hold on to inventories for long in part arises from the need to understand and process public information which consumes time. When their attention is diverted to that task, it would be rational to shed inventory risk. The importance of public information in moving prices is illustrated by the fact that during more than one third of the days in our sample (39% of the days) price changes are in the opposite direction to trade imbalance, i.e., prices declined (rose) even though there were more buy (sell) initiated volume (see Appendix figures A.3 and A.4)

Next, we study the behavior of traders during normal price fluctuations and confirm that we correctly identify short term liquidity providers. If our classification is right, we should find that during normal times when small booms (price recoveries) and busts (price declines) cycles occur, those who provide short term immediacy will be providing price support by increasing their inventories during busts and reducing their inventories during booms.

We investigate this hypothesis by first identifying price fluctuation that occur during a typical trading day – i.e., smalls booms and busts in prices using the algorithm in Lunde and Timmermann (2004). The algorithm works by identifying peaks and troughs for any given filter size. We use a filter of 1.5% window – i.e., troughs are identified by the recovery following a 1.5% or more price drop from the previous peak, and the next peak is identified by price rise following a recovery of 1.5% or more from the previous trough. The algorithm is described in more detail in Appendix A.4.

Note, that during our 3-month period, we also observe two fast crashes involving a price drop exceeding 3% within 15 minutes, much larger in magnitude than the 1.5% price decline over a possibly longer period, occurring on May 19 and May 22, 2006. We leave the analysis of these two fast crashes to Section V.

Using the Lunde and Timmermann (2004) algorithm we have identified several peaks and troughs. During our 8 weeks of data, there is at least one peak per day and at least one peak to

[21] See Amihud and Mendelsohn (1980), Ho and Stoll (1983), Viswanathan and Wang (2004), Foucault, Kadan, and Kandel (2005), and Goettler, Parlour and Rajan (2005).

trough per day and there are 300 boom and bust cycles during the sample period. We winsorised the sample by removing peaks and troughs that follow each other within a second.

(Insert Table IV.5)

The summary statistics of the winsorized sample is given in Table IV.5. Since some of the durations (|peak time-trough time|) are too short and some are too long, we also looked the following fast cycles using the following filters: we omitted peak to trough cycles with durations <10th percentile of the sample (33 seconds) and exceeding 15 minutes. We then looked at the peaks following those troughs provided the peaks occurred within 15 minutes, and otherwise looked took the price at the end of 15 minutes as the peak. This gave us 33 cycles listed in Appendix A.4. We compare the behavior of traders during these fast cycles and during the two fast crashes on 19th and 22nd May 2006 in our sample.

Tables IV.6.A and IV.6.B give the estimates for the 8 different measures of price elasticity for the boom (rolling up) and bust (bust) periods of the winsorized cycles. The patterns are generally similar to what we saw for the entire sample. We do not examine the price elasticity regressions for the 33 fast boom-bust cycles since there are not enough observations to estimate the relations sufficiently precisely.

(Insert Table IV.6.A, 6.B, 6C)

The signed volume of trade by different behavioral categories during the beginning, middle and the end of normal boom (rolling up) and bust (rolling down) cycles are given in Figures IV.5 and IV.6 respectively.

(Insert Figures IV.5 and IV.6 here)

As can be seen from Figure IV.5, MM, MDT, ODT, PDT and Unspec-Infreq consistently provide price support (net buyers) when prices are "rolling down" during normal busts, and prices hit the bottom in such busts takes place OLTD also step in and buy. However, price recovery takes hold when MM and Unspec-Infreq step up their buying as can be seen from Figure IV.6.

Figure IV.7 presents the directed volume network during the rolling down and the rolling up periods. Notice that ODT are the primary buyers during the bust (rolling down) and MM are the major buyers during the boom (rolling up) periods.

V. Behavior of Traders During Fast Crashes and Recoveries

As we noted in section IV, short term traders rarely carry inventories overnight. Further, on average they hold their positions for less than ten minutes. That suggests that while their inventory carrying capacity may be sufficient to provide liquidity during normal times, they may not be able to meet sudden surges in demand for liquidity and long term traders who provide liquidity will have to move their capital in to provide price support.

In this section we therefore examine the behavior of various trader types during price declines and price recoveries during two larger fast crash days in our sample when prices declined by more than 3% and recovered by more than 3% within a 15 minute interval as mentioned earlier; one on May 19 and another on May 22, 2006. There was a trading halt on 22nd May.

V.A Inventories

We first examine how the inventories of PDT, ADT, MM, FI, and MF changed during the fast crashes on May 19 and May 22, 2006. Figure V1.1 gives the inventory behavior on May 19 and Figure V.2 gives the inventory behavior on May 22.

First, notice that the collective inventories of ADT, MM, and PDT increased during the first crash in price on May 19 and the inventories started declining when the recovery was well under way. The crash in price was primarily due to selling by FIIs. However, prices started recovering only after MFs, whom we view as stand-by liquidity providers, started buying and increasing their inventories. The inventory behavior exhibits a very similar pattern on May 22 as well.

This is consistent with the view that ADT, MM, and PDT provide sufficient liquidity during normal price fluctuations that occur on most days, but their inventory carrying capacity is limited and when there are larger selling pressures, standby liquidity providers – mostly MFs and other financial institutions who hold large inventories of stocks in their portfolios – have to step in to provide price support for price recovery to take hold.

(Insert Figure V.1 here)

(Insert Figure V.2 here)

V.B Role of Order Modifications

As we discussed in the previous section, one of the important inventory risk management method is being on one side of the market, where order modifications and order cancellations play an important role. To understand the effect of order modifications and order cancellations i.e., changes in the limit order book that contribute to price changes in addition to price changes that take place due to market orders riding up or down existing limit orders on the book, we decompose price changes (which we denote as returns for convenience) into two orthogonal components: (a) the "private" return as the price change that would have taken place during a second if only the observed market orders and marketable limit orders had arrived without any additional limit orders or changes to limit orders arriving; (b) the "public" return as the price change due to the net effect of fresh limit orders and order changes/cancellations.

When the public component of the return is larger, it is an indication that price changes are more due to order cancellations and order modifications that change the supply and demand schedules in the limit order book. In contrast when the private component of the return is larger, it indicates that price changes are more due to market orders and marketable limit orders that demand liquidity.

The arrival of public information will in general result in a change in the stock's price with little trade taking place. In contrast, the arrival of private information, could be investor specific liquidity shocks, will in general lead to a change in the stock price only when trades take place. Consider two points in time when two trades took place in succession. We can think of the trades that took place as having taken place due to arrival of private information that triggered market (or marketable limit) orders at those two points in time. The price (the mid-point of the best bid and the best ask) immediately prior to the occurrence of the second trade would have been different from the price that prevailed immediately following the first trade, and we view this difference as being due to the arrival of public information during the time that elapsed between the two trades that took place. Part of the price change between the two trades can be attributed to arrival of public information and the rest of it can be attributed to arrival of private information that gets incorporated into the price due to the second trade taking place.

We examine what the price change would have been if the second trade took place without any change in the order book taking place after the first trade. We denote the difference between the resulting hypothetical price and the transaction price of the first trade as the price change component due to private information; and the difference between the transaction price of the second trade and the hypothetical price we computed as the component due to public information. We need the following notation to describe the decomposition in more detail.

- Let t denote the clock time in seconds on the trading day
- Let t_s denote the time at which the s'th trade occurred
- Let t_{s+1} denote the time at which the s+1'th trade occurred
- Let p_s and p_{s+1} denote the prices at which the trades occurred
- Let t_{s+} denote the time just after the s'th trade occurred but before the s+1'st trade took place
- Let $\breve{p}_{s+1}$ denote the price at which the trade s+1 would have taken place if the limit order book had not changed by the time the s+1'st trade took place following the s'th trade.
- $r_{s+1} = (p_{s+1} - p_s)$ denotes the price change from the s'th trade to the s+1'th trade
- $r_{priv,s+1} = (\breve{p}_{s+1} - p_s)$ denotes the hypothetical price change assuming that the order book remained the same and did not get refreshed. We use the subscript "priv" to indicate that price hypothetical price change that would have occurred due to riding up or down the limit order book.
- $r_{pub,s+1} = (p_{s+1} - \breve{p}_{s+1})$ denotes the price change from the hypothetical price at which the s+1'st trade would have taken place and the actual price at which the s+1'st trade took place. We use the subscript "pub" to indicate that this part of the price change. Hence the price change between two trades, $r_{s+1} = r_{priv,s+1} + r_{pub,s+1}$

The decomposition allows us to shed new light on the behavior of liquidity providers during normal busts and fast crashes. In particular, we expect the private information component to be dominant during the "rolling down" period of normal (normal) price fluctuations that occur every day and the public information component to be larger during the "rolling up" that follows. We expect the public information component to be dominant during fast crashes i.e., order cancellations and modifications to be significant, with subsequent recovery being slower with the arrival of stand by liquidity providers acting through market orders riding up the limit order book – i.e., private information component being dominant in the recovery that follows.

A typical marketable limit order is for several shares at a single price. When an order gets executed in full, we take the price at which the last of the share in the marketable limit order is executed. When a marketable limit order is partially executed, the unexecuted part will sit on the book as a limit order. All marketable limit orders were fully executed on May 19, and only two of the marketable limit orders were partially executed on May22.

(Insert Figure V.3 and V.4 here)

Figure VI.3 and Figure VI.4 depict the decomposition of the cumulative price change into the two components. On May 19 the price declined sharply and hit a bottom of Rs. 740 at 10:38:59am and then sharply recovered. The price dropped subsequently to the lowest value for the day of Rs. 715 at 2:46:23pm. It is interesting to note that during the price crash on May 19, most of the price decline was due to private information – i.e., sell orders depleting the limit order book without the book getting replenished. The public return component was positive indicating that order modifications prevented prices from falling further.

In contrast, during the crash on May 22 evaporating limit orders due to order cancellations, i.e., public return component contributed as much to the crash. Recovery on May 19 was primarily due to the private return component, i.e., buying by liquidity providers. On May 22, during the initial phase of the recovery was due to the public return component, i.e., replenishment of the limit order book, when the market opened after the stop of trading.

Figures V.5 plots the stock price (right vertical axis) and the buy and sell (negative) volume in number of shares (left vertical axis) over a 15 minute window from the price trough, with time on the horizontal axis for the May 19 crash. Figure V.6 provides the details for the May 22 crash.

The NIFTY index is normalized to have the same value as the price of the stock at the beginning of the time interval in the figures. All orders are recorded in the order book in the same order in which they arrived in calendar time, even though time is recorded in integral seconds. When a trade takes place, the order numbers associated with the buyer and the seller, the time of the trade in seconds, and the quantity of the trade are recorded in trade book. Therefore, by looking at the sequence in which the buy and the sell orders arrived, we are able to determine whether the buy or the sell order initiated the trade, i.e., the market order (or marketable limit order).

The pattern that emerges from these figures is consistent with the inventory behavior in Figures V.1 and V.2 discussed in section V.A.

(Insert Figure V.5 and V.6 here)

Finally in Figures V.7 and V.8 we validate the conclusions we reached through examining the behavior of private and public return components during the fast crash on May 19 and May 22. Figure V.7 examines order modifications and cancellations on May 19. Aggressive buy (sell) modifications are defined as those where volumes are increased or quotes are revised toward the existing mid-point and passive buy (sell) as those where volumes are decreased or quotes are revised away from the existing mid-point. As can be seen, ADTs and OLTTs contributed more through aggressive sells during the fast crash (first price decline); but no one group played a major role in order modifications during the second price decline. ADTs were aggressively modifying sells and OLTTs were aggressively modifying buys towards the end of the day when the price also increased – consistent with ADTs liquidating their inventories and unwilling to hold sizeable positions towards the end of the day. MM and PDT primarily submitted defensive order modifications/cancellations during the fast crash with aggressive modifications picking up as the market recovered. This is consistent with the private return component in the price decomposition as highlighted in Figure V.3, and specifically indicates who are the main actors that generates the pattern of private returns.

(Insert Figure V.7 here)

(Insert Figure V.8 here)

Figure V.8 provides order modifications and cancellations by trader types on May 22. The pattern is similar to that on May 19. During the recovery period, OLTTs were modifying their buy orders aggressively, consistent with them making a major contribution to the recovery. PDT, and especially MM, played a relatively minor role on May 22 relative to May 19. It should be stressed that MM were much less active on both May 19 and May 22 than typical in the rest of the sample, thus contributing to the overall market fragility on those days. Again this is consistent with the private return pattern highlighted in Figure V.4.

V.C Sellers and Buyers in Crashes and Recoveries and Slow Moving Capital

Table V.1 gives details of buyers and sellers during the two flash crash days and during 33 more severe of the price declines that occurred during the normal bust cycles where prices dropped more than 1.5% during the 15 minute interval preceding the trough that we identified using the Lunde and Timmerman in section IV – described in detail in Appendix A.4. A common pattern emerges. As can be seen from Table V.1 FII sold 50,000 shares during the crash on May 19 and 26,493 shares on May 22. MF and STT both took the other side of these trades. Since the NIFTY drop was significant, that affected the stock as well resulting in a trading halt. On May 19 FII sold another109,026 shares when prices recovered and stabilized though at a lower level, and MF took most of the other side of the trade. In contrast, on May 22 FII did not sell when the market opened. Price recovery was mostly due to recovery in NIFTY index value. STT sold over 30,000 shares following recovery and MF provided the liquidity by taking the opposite side of those trades. Note that the signed trading volume does not sum to zero – the signed trades of LTT other than FII and MF is left out.

(Insert Table V.1 here)

It is interesting to note that FII sold into the normal busts in the 33 more severe of the normal boom/bust cycles and continued buy when prices were recovering. Since FII are mostly long term traders, their selling is likely to portfolio rebalancing considerations and MF, who are also long term traders, had to enter to augment the price support provided by STT before price recovery could take place. While STT buy during price declines and sell during recoveries MF buy during price declines and continue to buy even more during price recoveries. This is consistent with the view that MF making capital is slower to move but is critical in helping price recoveries.

VI. Summary and Conclusions

We study the role of short and long term traders in liquidity provision in an electronic order book market using data for the period April – June 2006 for a particular heavily traded stock from the National Stock Exchange of India that uniquely identifies each trader. We group traders into different types -- market makers who provide two sided quotes most of the times and carry little overnight inventory, impatient and patient day traders who carry no inventory overnight, long term liquidity providers who consistently provide quotes on both sides of the market and carry inventories across days, and other long term traders -- based on their observed trading behavior. We find that short term traders (market makers and day traders) accounted for more than 2/3rd q of the total trading volume; and over 2/3rd of that trading volume is due to trading among them.

During normal intraday price fluctuations short term traders bought when prices declined and sold when prices recovered thereby stabilizing prices and providing liquidity. However their inventory capacity was limited and when their inventories were high, ask side liquidity improved and bid side liquidity worsened, consistent with slow movement of longer term market making capital.

During the fourth of the days in our sample, buy minus sell volumes and price changes had the opposite signs – prices declined (rose) even though there was excess buyer (seller) initiated trading volume, consistent with public information based price movements being dominant on some days.

There were two “fast crash” days in our sample when prices declined by more than 3% and recovered by more than 3% within a 15 minute interval. Foreign institutions, who often carry inventories overnight, sold leading to the fast crash in prices on these two days. During the period leading up to the fast crashes, the inventory position of the short term liquidity providers peaked, exhausting their inventory carrying capacity. Buying by short term traders was insufficient to provide liquidity during the two fast crashes. Mutual funds, who had a relatively longer horizon, moved in and started buying which helped prices to recover. However, it took time for mutual funds to move their market making capital, and, in the interim, short term traders who provided liquidity appeared to hold back, causing continuing drop in the stock price, highlighting the role of slow moving market making capital during crashes and subsequent sharp recoveries in prices. Since HFTs are similar to STTs, our findings suggest that while HFTs are unlikely to be the cause of crashes, they are also unlikely to be in a position to provide liquidity when it is needed most for the market to recover from crashes (when they do occur).

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APPENDIX

Appendix A1: Description of the National Stock Exchange (NSE) and Market Dynamics

National Stock Exchange (NSE) of India Ltd. was incorporated in November, 1992 following the liberalization of Indian financial market and the official establishment of Securities and Exchange Board of India in 1992. The process of financial liberalization has supported the development of a large group of stock exchanges in India. National Stock Exchange (NSE) and Bombay Stock Exchange (BSE) are the largest stock exchanges in the country based on the market capitalization and traded volume, though there are a total of 21 bourses that actively operate in India. 97.71% (55.99%) of stocks are traded daily on NSE (BSE). In 2011 the market capitalization of stocks traded on NSE was Rs. 67 trillion ($1.5 trillion) while the total market capitalization of stocks traded on BSE was Rs. 68 trillion ($1.5 trillion). In 2012 the NSE was the largest stock exchange in the world based on the number of equity trades.

NSE is a fully automated screen based platform, that works through an electronic limit order book in which orders are time-stamped and numbered and then matched on price and time priority.[22] The NSE requires all traders to submit their orders through certified brokers who are solely entitled to trade on the platform. These brokers are trading members with exclusive rights to trade and they can trade on their own account (proprietary trades) or on behalf of clients. Brokers can trade in equities, derivatives, and debt segments of the market. The number of active trading members has greatly grown from 940 members in 2005 to 1,373 members in 2012. Most of them trade in all segments of the market. Every day more than two million traders actively trade on the platform through several trading terminals located throughout India. While there are no designated market makers on the NSE, a small group of de-facto market makers typically control a large portion of trading.

Futures contracts have been trading on the National Stock Exchange of India since November 2001. These futures contracts have a three month trading cycle, with each contract trading for three months until expiration. Every month a new contract is issued. So, at any point of time for a given underlying stock, there are three futures contracts being traded.

[22] For example, quotes with most favorable submitted prices will get priority and quick execution, even if there are other outstanding orders. Examples of other order driven markets like NSE are NYSE Euronext, Hong Kong Stock Exchange, and Toronto Stock Exchange.

In 2006 trading sessions for both stock and futures markets were between 9:55 am and 15:30 pm with a closing session of 20 minutes from 15:40 pm till 16:00 pm only for the spot market.[23]

Appendix A.2: Additional Statistics for the Spot Market

Figure A.1 reports price and volume for the stock from April 3rd 2006 to June 30th 2006. A similar behavior is seen in the futures market.[24] There are three trends that emerge for both stock and futures markets. From April 3rd to May 2nd 2006 there is a positive price trend with a price increase of 25% from the starting price. During this period, the volume increased reaching a local maximum value of 5 million of stocks traded on April 13th.

On April 13th a dramatic price rise during the first minutes of trading caused a slow correction of the market. Subsequently the stock price continued rising through April, reaching a peak on May 2nd, before declining steadily through May 22nd, and then stayed relatively flat through the end of June. Circuit breakers suspend trading if there is a relevant drop or rise of quotes on the NSE CNX Nifty Index[25]. The mechanism works for three scenarios of price movements (10%, 15% and 20%) and it sets the closure of the trading session for a period of time that depends on the time of the shock and its size. On May 22nd 2006 the Nifty Index recorded a drop of -340.6 points at 11:56:38 that activated the filter breach of 10%. Considering that the time of the shock was earlier than 13:00, the circuit breaker stopped trading on both stock and futures markets for one hour.

Figure A.2 reports the variability of stock prices during our sample from April 3rd 2006 to June 30th 2006. Open prices are identifiable by blue circles while closure prices by red circles. As Figure A.2 shows, the variability of the prices on certain days is quite large, in particular on May 19th and May 22nd, 2006.

Figure A.3 depicts the range of open and close prices, intra-day max and min prices, and the active trading imbalance. As can be seen, on several days stock prices drop, i.e., the price at the open is higher than the price at close, even though there were more active buys than sells. However, it is clear that during the steadily rising market in April, active buyers consistently

[23] Further information about the rules and the management of the NSE can be found in http://www.nseindia.com
[24] The figure is not included but is available upon request.
[25] NSE CNX Nifty index is the benchmark of the Indian economy. The index was launched in 1996 and is composed of 50 diverse assets traded by NSE, covering over 22 industry sectors.

outnumbered active sellers, while this pattern partially reversed during the market decline through May.

Figure A.4 plots the daily return against the order imbalance, i.e., whether there were more buying or selling during the day. We measure the order imbalance by the buyer initiated volume minus the seller initiated volume during the day normalized by the total volume during that day. On 13 of the 53 trading days in our sample prices and order imbalance moved opposite to each other.

Appendix A.3: Liquidity Measures

We calculate bid-ask spreads for the stock during the time period in our sample as follows. The spread refers to the difference between the lowest sell (ask) and highest buy (bid) quotes at each time. Bid-ask spreads are calculated for limit orders during the normal trading session from 9:55 am to 15:30 pm, excluding the post-closing session from 15:40 pm to 16:00 pm. The top left panel of Figure A.5 presents results for median spreads measured during 5 minute intervals during the trading days in April, May, and June 2006. As clearly seen, we observe a strong U-shaped behavior of the bid-ask spreads during a day, similar to what is observed in the NYSE. Specifically, we observe a lower liquidity, measured by the bid-ask spreads during the opening minutes of trading with a quick reduction of the spread after 10:00am. The spread subsequently starts to increase rapidly during the closing minutes of the trading day.

In Figure A.5 we also present median trading volume and intraday depth-of-book liquidity measures for these time periods. Specifically, we graph median intraday volume, and median bid and ask depths for the spot market. Similar to the spread measure, we observe a U-share curve for the median intraday volume, consistent with the literature. We also depict price impact for both ask and bid orders. Specifically, we graph the number of shares it takes to move ask and bid prices by 100 basis points. The ask depths exhibit an inverse U-shape behavior during the day confirming the low liquidity at the beginning of the trading session and at the end of the trading session. The bid depths measure instead shows a “smirk” pattern with a low liquidity level at the beginning of the trading session and an increase of the liquidity at the end of the trading day session. The bifurcation of this liquidity measure indicates the presence of a significant fraction of sellers versus buyers. In sum, all results in Figure A.5 regarding bid-ask spread, volume, and market impact point to lower liquidity in the first and last half-an-hour of trading, and relatively large and constant liquidity during the rest of the day.

The depth of book measures further allow us to depict the differential liquidity observed on the bid and ask side of the book during our sample, as shown in Figure A.6. In the left column, the median number of shares required to be traded (shown on the y-axis) in order to move the market by a given number of basis points (shown on the x-axis) for the spot market is depicted. Points to the left of zero correspond to the bid side of the book and points to the right of zero correspond to the ask side. As can clearly be seen, the ask side is deeper on average compared to the bid side of the book. We further depict the depth of the book measured at 10 am, 12:30 pm, and 15:00 pm. The book is deeper at the end of the day compared to the morning, and is the deepest during the middle of a day. A similar pattern holds true in the futures market, as shown in the right hand column of Figure A.6, and is consistent across April, May, and June months.

We further investigate the presence of fast crashes in our data. We define a fast crash as having occurred if during any 15 minute interval, price declined by more than 3% and recovered by more than 3% within any 15 minute interval. We exclude the intervals in the first and last half-an-hour of trading for stock and futures markets. During our 3-month period, there are only two days: May 19 and May 22, 2006 when both spot and futures market experienced fast crashes. Specifically, on May 19th 2006 for the spot market during the 10:29:34-10:44:33 interval, the spot market experienced a 5.27% drop followed by a 4.72% rise, while the futures market experienced a 5.27% drop followed by a 4.06% rise during the 10:29:07-10:44:06 period. On May 22th, for the spot market during 11:39:46 – 11:54:45 period, the spot market experienced a 13.90% drop and a 5.81% rise, and during the 11:41:21-11:56:20 period, the futures market experienced a 13.17% drop followed by a 5.75% rise.

Appendix A.4: Lunde and Timmermann (2004) algorithm

Financial analysts and market commentators frequently classify market phases into bull and bear periods. However, Lunde and Timmermann (LT) deploy a technique to statistically verify the prevalence of bull and bear phases in a market. To characterize these phases, LT use the following definitions from Sperandeo (1999):

”Bull market: A long-term ... upward price movement characterized by a series of higher intermediate ... highs interrupted by a series of higher intermediate lows.

Bear market: A long-term downtrend characterized by lower intermediate lows interrupted by lower intermediate highs".

The algorithm used by LT is as follows:

I – Bull market indicator taking the value 1 if the market is in a bull phase at time t, and zero otherwise

P_t *- The stock price at the end of period t*

λ_1 *- Scalar defining the threshold of the movements in stock prices that trigger a switch from a bear to a bull market*

λ_2 *- Scalar defining the threshold of the movements in stock prices that trigger a switch from a bear to a bull market*

We start at t_0 *with the market at local maximum* $I_{t0} = 1$ *and* $P_{t0}^{max} = P_{t0}$ *where* P_{t0} *is the stock price at the starting time. Let* τ_{max} *and* τ_{min} *be the stopping time variables defined by:*

$$\tau_{max}(P_{t0}^{max}, t_0 | I_{t0} = 1) = \inf\{t_0 + \tau\colon\ P_{t0+\tau} \geq\ P_{t0}^{max}\}$$

$$\tau_{min}(P_{t0}^{max}, t_0, \lambda_2 | I_{t0} = 1) = \inf\{t_0 + \tau\colon\ P_{t0+\tau}\ < (1 - \lambda_2)\ P_{t0}^{max}\}$$

where $\tau \geq 1$*. Then min* (τ_{max}, τ_{min}) *is the first time the price crosses one of the two barriers* $\{P_{t0}^{max}, (1 - \lambda_2)P_{t0}^{max}\}$*. If* $\tau_{max} < \tau_{min}$*, we update the local maximum in the current bull state:*

$$P_{t0+\tau_{max}}^{max} =\ P_{t0+\tau_{max}}$$

and the bull market continued between $t_0 + 1$ *and* $t_0 + \tau_{max}$: $I_{t0+1} = \cdots \ldots \ldots .. =\ I_{t0+\tau_{max}} = 1$.

Conversely if $\tau_{min} < \tau_{max}$ *such that the stock price at* $t_0 + \tau_{min}$*has declined by a fraction* λ_2 *since its local peak*

$$P_{t0+\tau_{min}} < (1 - \lambda_2)P_{t0}^{max}$$

Then the bull market has switched to a bear market that prevailed from $t_0 + 1$ *and*

$t_0 + \tau_{min}$: $I_{t0+1} = \cdots \ldots \ldots .. =\ I_{t0+\tau_{min}} = 0$*. We then set* $P_{t0+\tau_{min}}^{min} =\ P_{t0+\tau_{min}}$.

With t_0 *as the starting point in the bear market state, the stopping times get defined as:*

$\tau_{min}\left(P_{t0}^{min}, t_0 \middle| I_{t0} = 1\right) = \inf\{t_0 + \tau\colon\ P_{t0+\tau} \leq\ P_{t0}^{min}\}$

$\tau_{max}\left(P_{t0}^{min}, t_0, \lambda_1 \middle| I_{t0} = 1\right) = \inf\{t_0 + \tau\colon\ P_{t0+\tau}\ < (1 + \lambda_1)\ P_{t0}^{min}\}$.

Thus, the definition of bull and bear states partitions the given data set into stock prices that mutually exhaustive and exclusive bull and bear market subsets based on the passage of time. The resulting indicator function I_t gives us a random variable T which measures the duration of bull and bear markets which is nothing but the time between the successive switches in I_t.

The smaller the values of λ_1 and λ_2, the higher the frequency of bull and bear market spells one can observe. We use a value of 1.5% for λ_1 and λ_2 in our analysis. – i.e., troughs are identified by the recovery following a 1.5% or more price drop from the previous peak, and the next peak is identified by price rise following a recovery of 1.5% or more from the previous trough.

Using the above scalars, we obtain 300 Timmermann cycles. Subsequently, the following filters have been applied to these 300 micro cycles to create a list of 33 microcycles:

- Filter 1: Duration >0
- Filter 2: Duration>10th percentile i.e., duration >33 sec
- Filter 3: Look for fast boom and bust cycles with duration <15 minutes including May 19th and May 22nd.

In the above tables, the red entries in italics are the ones that coincide with the mini cycle on May 22nd. Since we are treating the mini cycle on May 22nd separately, we remove these entries from our list. After removing the same, we are left with 33 cycles. We also remove the micro cycle for May 23rd 2006 as it coincides with a special trading session which we do not consider for our computations. Hence, we are left with a list of 32 cycles for our computation.

The mean and median duration for the above fast boom and bust cycles is 6.5 mins and 4.5 mins

- For the recovery phase, we use Timmermann cycle data from final_time to final_time + 15 mins. So, we take each fast bust in the above 33 cycles and use final_time to final_time +15 mins as the recovery period (when the subsequent peak does not occur within 15 minutes from reaching the trough)..

The list of 37 Timmermann cycles remaining after this exercise are:

Date	Initial_time	Mediumtime	Final_time	Duration
13-Apr-06	9:55:54	9:57:34	9:59:15	201
13-Apr-06	13:54:24	14:01:42	14:09:00	876
28-Apr-06	10:00:15	10:01:04	10:01:54	99
3-May-06	9:55:33	9:57:30	9:59:27	234
9-May-06	9:55:39	10:01:13	10:06:48	669
11-May-06	9:58:36	9:59:55	10:01:15	159
16-May-06	9:55:51	9:56:37	9:57:24	93
16-May-06	14:21:15	14:27:18	14:33:21	726
19-May-06	10:57:54	11:00:09	11:02:24	270
19-May-06	11:27:06	11:29:13	11:31:21	255
19-May-06	11:51:51	11:57:22	12:02:54	663
19-May-06	14:35:21	14:40:46	14:46:12	651
22-May-06	9:56:00	9:56:49	9:57:39	99
22-May-06	11:26:21	11:31:40	11:37:00	639
22-May-06	*11:55:06*	*11:55:22*	*11:55:39*	*33*
22-May-06	*13:01:21*	*13:02:22*	*13:03:24*	*123*
22-May-06	*13:05:39*	*13:07:16*	*13:08:54*	*195*
22-May-06	*13:10:39*	*13:11:24*	*13:12:09*	*90*
22-May-06	13:37:33	13:43:24	13:49:15	702
22-May-06	13:56:03	14:00:01	14:04:00	477
22-May-06	14:54:39	15:01:39	15:08:39	840
23-May-06	*9:55:51*	*9:57:34*	*9:59:18*	*207*
24-May-06	9:55:36	9:56:51	9:58:06	150
30-May-06	9:55:39	9:57:12	9:58:45	186
31-May-06	9:55:33	9:55:49	9:56:06	33
31-May-06	14:16:36	14:22:24	14:28:12	696
1-Jun-06	10:50:48	10:56:55	11:03:03	735
2-Jun-06	9:56:03	9:57:13	9:58:24	141
6-Jun-06	9:55:36	9:56:16	9:56:57	81
7-Jun-06	14:01:18	14:04:16	14:07:15	357
8-Jun-06	9:57:39	10:00:24	10:03:09	330
9-Jun-06	9:58:33	10:00:10	10:01:48	195
13-Jun-06	9:55:54	9:56:10	9:56:27	33
13-Jun-06	12:47:30	12:54:42	13:01:54	864
16-Jun-06	9:55:51	10:02:01	10:08:12	741
19-Jun-06	9:55:48	9:56:49	9:57:51	123
27-Jun-06	10:37:12	10:40:33	10:43:54	402

May 19th

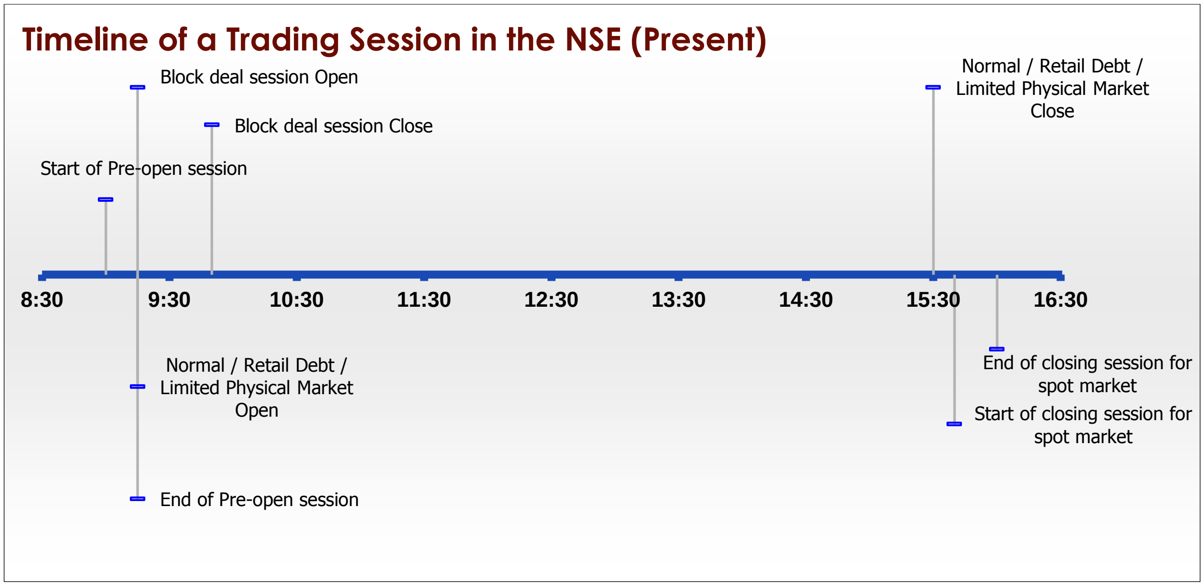
- For May 19th, the trough for the fast crash is identified as '10:39:14'.
- We use trough_time-15 mins to trough_time as crash period and trough_time to 'trough_time+15' mins as recovery period.

May 20th

- On May 22nd, there was a trading halt in between. We define two troughs on this date: trough1= '11:54:37'; trough2= '12:56:25'. There were no trades between these times.

- The fast crash period is defined as the time period between 'trough1-15 mins' to trough1
- Subsequently, the recovery period is defined as the time between trough2 to 'trough2+15mins'

Appendix A.6: Trading Day Timeline



Time	Event
9:00	Start of Pre-open session
9:15	End of Pre-open session
9:15	Normal / Retail Debt / Limited Physical Market Open
9:15	Block deal session Open
9:50	Block deal session Close
15:30	Normal / Retail Debt / Limited Physical Market Close
15:40	Start of closing session for spot market
16:00	End of closing session for spot market

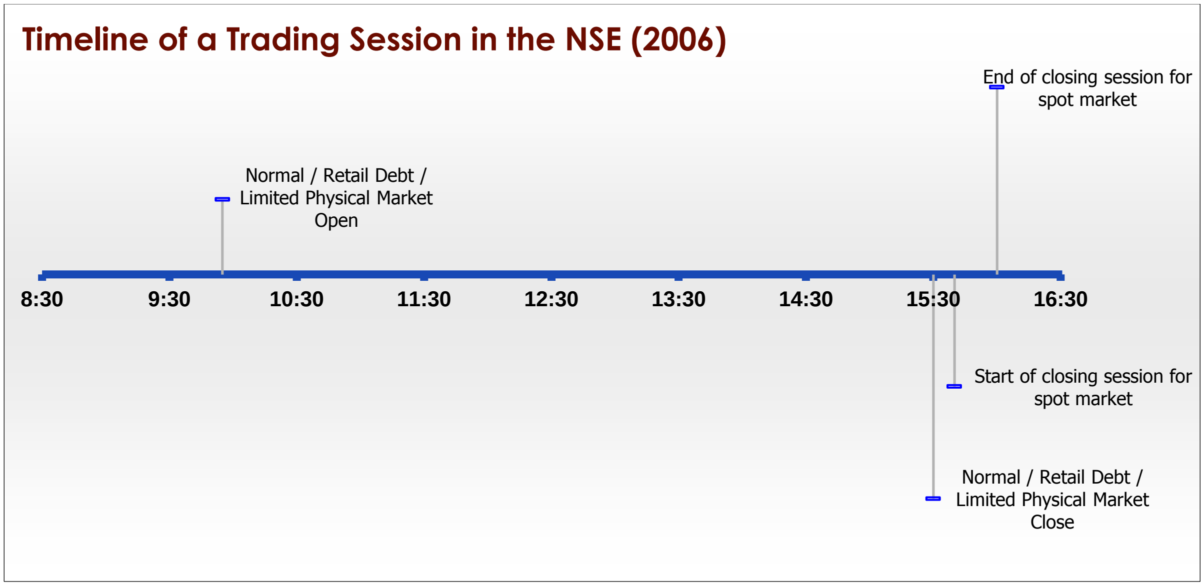
As of today, a typical trading day on the NSE lasts from 9:00 am to 4:00 pm with a pre-open, block deal and a closing session in between. However, the pre-open session was launched in 2010 to reduce the opening session volatility.

The opening session consists of 3 main slots:

1) 9.00 AM to 9.08 AM-Order collection period-Placing, modification and cancellation of orders occurs during this period.

2) 9.08 AM to 9.12 AM-Order matching period and trade confirmation period-During this period placed orders are confirmed.

3) 9.12 AM to 9.15 AM-A buffer period which facilitates the transition from pre-open to normal market session.



Time	Event
9:55	Normal / Retail Debt / Limited Physical Market Open
15:30	Normal / Retail Debt / Limited Physical Market Close
15:40	Start of closing session for spot market
16:00	End of closing session for spot market

Our analysis focuses on the period from Apr, 2006 – Jun, 2006 thus making the above timeline more apt for our analysis. The NSE changed its trade timings in December 2009 by advancing the market opening time from 9:55 am to 9:00 am. The closing hours remained unaltered at 3:30 pm.

The closing session was started by the NSE in Jun, 2003 subsequent to the reduction in the settlement cycle to T+2. Some remote centres in India were not adequately equipped to transfer funds and securities seamlessly. The 20 minute closing session accords investors the opportunity to close their trading positions before the trading ends and prevent fund shortages.

For the purpose of calculating peaks and troughs using the Timmermann algorithm, we partition the trading day into intervals of 3 minutes each. However, for the elasticity regressions we use a time period of 15 seconds to aggregate inventory level data. We also employ 30 minute time dummies to account for any intra-day

TABLES

Table III.1: Number of traders and transaction types

	Spot Market		Futures Market		Spot and Futures Market		
Buy & Sell	77,539	71.44%	32,361	87.35%	Spot& Futures	5,513	3.95%
Only Buy	14,951	13.77%	778	2.10%	Only Spot	93,793	67.16%
Only Sell	6,816	6.28%	928	2.50%	Only Futures	28,554	20.45%
No Execution*	9,236	8.51%	2,979	8.04%	No Execution*	11,792	8.44%
Total	108,542	100.00%	37,046	100.00%	Total	139,652	100.00%

*No Execution: number of traders whose orders never got executed during the entire period

This table depicts the no. of traders active in the spot market, futures market and both the markets. We also calculate the no. of traders who carry out buy and sell transactions in the spot and futures markets in the NSE.

Table III.2: Traded volume

	Total volume	Lots*	Days
Futures	541,187,250	721,583	62
Spot	115,628,537	-	53

* One lot is for 750 futures contracts.

We provide a comparison of volume traded in the futures and spot markets in the above table.

Table III.3: Types of Orders on Spot and Futures Markets

	Spot Market				Futures Market			
	Buy	%	Sell	%	Buy	%	Sell	%
Add	1,188,208	70.90%	1,202,683	70.70%	756,148	60.10%	753,234	60.40%
Cancel	277,634	16.60%	259,008	15.20%	309,808	24.60%	274,607	22.00%
Modify	209,207	12.50%	240,148	14.10%	191,981	15.30%	219,544	17.60%
Total	1,675,049		1,701,839		1,257,937		1,247,385	

The table above provides a description of the types of orders placed in the futures and spot market.

Table III.4: Traders' Legal Categories

	Legal Category	Both Markets	Spot Market		Futures Market	
			traders	no exe	traders	no exe
1	Individual traders	4,534	86,900	7,940	26,609	2,363
2	Partnership firm	44	138	7	207	11
3	Hindu undivided family	95	753	67	852	56
4	Public & private companies/corporate bodies	357	1,002	67	1,282	64
5	Trust/society	1	11		4	1
6	Mutual fund	7	318	23	22	3
7	Domestic financial institution	1	20	1	7	2
8	Bank		192	40	0	
9	Insurance		122	7	0	
10	Statutory bodies	2	7		9	
11	Non-resident Indians	1	423	69	1	
12	FII Foreign Institutional Investors	21	135	1	62	4
13	Overseas corporate bodies	129	400	38	444	21
99	Missing	321	8,885	976	4,568	454
	Total	5,513	99,306	9,236	34,067	2,979

Note: Both markets: traders active on both markets; traders: number of traders by each category; no exe: number of traders whose orders never got executed during April 3rd 2006 - June 30th 2006 time period.

Legal classification of the traders active on the National Stock Exchange (NSE). We depict the no. of traders for spot, futures and both markets taken together.

Table IV.1: Transition probabilities for categories based on trader behavior

	ADT	P_MDT	PDT	MM	NP_MDT	OLTT	Infreq	FII	Mutual fund
ADT	68%	0%	5%	0%	21%	6%	0%	0%	0%
P_MDT	15%	63%	15%	0%	0%	6%	0%	0%	0%
PDT	8%	0%	62%	1%	22%	7%	0%	0%	0%
MM	3%	3%	7%	75%	6%	8%	0%	0%	0%
NP_MDT	18%	0%	17%	0%	60%	5%	0%	0%	0%
OLTT	7%	0%	7%	0%	9%	76%	0%	0%	0%
ODT	25%	1%	22%	1%	32%	19%	0%	0%	0%
unspec-Inconsist	3%	6%	22%	14%	12%	42%	0%	0%	0%
unspec-Infreq	0%	0%	0%	0%	0%	0%	100%	0%	0%
FII	0%	0%	0%	0%	0%	0%	0%	100%	0%
Mutual Fund	0%	0%	0%	0%	0%	0%	0%	0%	100%

Note: Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions.

The table above depicts transition probabilities among various behavioural trading categories. Specifically, it shows the tendency of a given trader to switch to a different category on the subsequent trading day.

Table IV.2.A: Number of Traders by Trader Classification

Date	ADT	FII	MM	Mutual Fund	NP_MDT	ODT	OLTT	PDT	P_MDT	unspec-Inconsist	unspec-Infreq
3-Apr-06	283	4	2	13	312	428	451	103	24	3	1,436
4-Apr-06	230	4	1	5	204	318	398	66	16	3	1,027
5-Apr-06	495	3	1	8	439	600	744	139	22	1	2,248
13-Apr-06	949	9	3	11	857	1,076	995	270	31	4	3,661
17-Apr-06	792	4	4	10	816	990	938	273	33	3	2,907
18-Apr-06	801	6	3	13	708	976	965	236	33	3	2,484
19-Apr-06	1,023	6	3	13	1,007	1,226	1,166	335	34	2	3,183
20-Apr-06	791	5	4	18	685	937	831	239	23	2	2,232
21-Apr-06	748	3	1	13	676	944	850	222	32	5	1,731
24-Apr-06	443	5	1	12	391	618	526	138	22	1	1,113
25-Apr-06	413	5	1	11	384	600	774	142	17	2	999
27-Apr-06	543	3	1	13	493	756	977	192	25	3	1,475
28-Apr-06	623	5	2	20	561	832	830	192	24	3	1,529
2-May-06	663	8	1	22	605	937	1,399	212	27	6	2,221
3-May-06	1,023	9	2	11	973	1,303	1,238	324	31	6	3,018
4-May-06	769	13	2	9	788	1,043	1,028	286	32	5	1,812
5-May-06	742	7	2	9	709	930	755	283	30	3	1,476
8-May-06	566	5	1	8	587	864	1,035	232	27	6	1,432
9-May-06	636	8	2	13	552	873	869	216	24	5	1,458
10-May-06	636	11	3	11	599	879	1,165	232	26	4	1,808
11-May-06	503	9	2	10	447	712	807	154	18	3	1,065
12-May-06	891	3	2	26	948	1,388	2,090	349	34	5	4,824
15-May-06	868	4	2	20	851	1,145	1,562	293	32	7	3,878
16-May-06	832	7	3	12	763	1,038	1,369	266	30	7	3,069
17-May-06	722		2	7	632	909	1,010	236	32	6	2,341
19-May-06	698	3	1	25	601	949	1,415	238	34	10	4,375
22-May-06	594	7	2	16	527	831	1,351	197	31	5	3,396
24-May-06	665	4	3	19	604	893	984	218	29	4	2,108
25-May-06	735	3	2	13	675	997	1,046	262	38	9	2,041
26-May-06	781	1	2	10	793	1,185	1,152	315	31	8	2,412
29-May-06	742	2	2	8	758	1,062	945	305	31	6	1,855
30-May-06	732	1	1	6	736	1,061	970	292	29	6	1,870
31-May-06	869	15	1	9	883	1,247	1,334	349	37	4	2,637
1-Jun-06	784	10	2	11	742	1,018	909	278	28	3	1,444
2-Jun-06	814	5	1	9	796	1,160	1,569	313	36	4	2,088
5-Jun-06	704	8	1	8	594	893	1,019	265	24	5	1,645
6-Jun-06	767	5	2	10	717	1,003	978	292	26	6	1,508
7-Jun-06	801	7	3	14	766	1,037	1,018	327	28	4	1,737
8-Jun-06	902	11	3	13	865	1,116	1,143	333	33	8	2,478
9-Jun-06	739	5	1	9	732	1,044	1,385	299	28	6	1,983
12-Jun-06	657	3	1	9	578	868	876	258	25	7	1,246
13-Jun-06	812	15	3	10	774	999	852	300	36	5	1,782
14-Jun-06	896	5	2	24	830	1,112	975	344	32	5	2,080
15-Jun-06	751	6	2	14	786	1,040	1,155	359	32	5	2,139
16-Jun-06	778	5	2	14	746	1,022	1,176	303	26	7	2,793
19-Jun-06	794	5	2	12	864	1,102	1,071	376	28	6	2,652
22-Jun-06	595	5	3	8	584	852	961	262	26	7	2,306
23-Jun-06	597	4	2	16	593	842	778	253	19	6	1,925
26-Jun-06	503	7	2	12	490	730	711	241	23	6	1,378
27-Jun-06	580	9	1	18	601	752	632	250	20	7	1,496
28-Jun-06	562	6	3	11	621	757	559	238	30	4	1,638
29-Jun-06	375	4	1	11	407	526	485	186	19	4	1,024
30-Jun-06	473	5	2	11	501	769	1,070	241	29	7	2,098
Average	**692**	**6**	**2**	**13**	**663**	**928**	**1005**	**255**	**28**	**5**	**2124**

Note: Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions.

Behavioural classifications for traders for each trading day in our sample from April, 2006 – June, 2006.

Table IV.2B: Volume by Trader Classification

Main	Freq.	Percent	Avg. daily traded vol	% traded vol	Avg. daily order vol	% order vol
ADT	4,604	4.63	274261.96	6.63	383076.20	4.48
FII	135	0.14	302074.45	6.92	338777.60	3.75
MM	10	0.01	385688.24	9.16	1904624.62	21.89
Mutual Fund	319	0.32	147112.55	3.56	163786.23	1.92
NP_MDT	4,375	4.4	456578.80	11.04	681052.71	7.97
ODT	4,401	4.43	679686.86	16.44	1280280.50	14.98
OLTT	7,600	7.65	778294.95	18.83	1776740.32	20.79
PDT	1,681	1.69	181608.82	4.39	299723.91	3.51
P_MDT	61	0.06	415519.89	10.05	1097608.77	12.84
unspec-Inconsist	20	0.02	12855.21	0.31	25306.43	0.30
unspec-Infreq	76,190	76.65	523441.50	12.66	647000.23	7.57
Total	99,396	100	4,157,123	100	8,597,978	100

Note: Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions.

The table above provides a break-up of the daily average traded volume and the daily average order volume by trader behavioural categories.

Table IV.2C: Buys and Sells across Trader Classification

Buy Category	Sell Category											
	ADT	FII	MF	MM	NP_MDT	ODT	OLTT	PDT	P_MDT	Un_Inco	Un_Infr	Total
ADT	10,206	3,303	1,969	12,240	21,224	34,831	25,426	11,504	17,975	544	20,618	159,840
FII	3,014	1,156	479	3,527	5,297	9,000	6,531	2,269	4,270	150	5,870	41,563
MF	1,656	434	202	1,395	2,538	3,846	2,741	1,235	1,718	50	3,088	18,903
MM	12,532	3,978	1,830	18,395	17,246	27,217	19,077	6,995	11,422	298	19,642	138,632
NP_MDT	21,119	5,461	2,681	17,247	27,873	43,833	33,681	11,639	22,761	560	30,190	217,045
ODT	34,746	10,195	4,554	28,627	44,136	67,984	54,233	17,461	38,103	850	46,901	347,790
OLTT	26,634	8,129	4,485	20,353	36,158	57,935	43,329	15,159	28,503	749	40,236	281,670
PDT	12,471	3,388	1,037	8,206	12,241	17,805	14,884	4,759	9,626	193	13,867	98,477
P_MDT	18,868	5,833	2,333	11,777	24,146	39,689	27,733	9,954	33,451	464	26,265	200,513
Un_Inco	676	184	53	317	593	834	665	205	436	11	720	4,694
Un_Infr	22,425	7,085	3,370	22,689	32,516	49,110	41,024	13,899	27,927	785	34,226	255,056
Total	164,347	49,146	22,993	144,773	223,968	352,084	269,324	95,079	196,192	4,654	241,623	1,764,183

Frequency Missing = 42559

Note: Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions.

We depict the total shares bought and sold by each category across various behavioural categories.

Table IV.2D: Buys and Sells across Trader Classification (Condensed)

Buy Category	Sell Category FII	MF	OLTT	STT*
FII	1,156	479	6,531	33,397
MF	434	202	2,741	15,526
OLTT	8,129	4,485	43,329	225,727
STT*	39,427	17,827	216,723	1,148,070

Frequency Missing = 42559

Note: Trader categories are based on trader behavior. Categories are OLTT (Other Long Term Trader) and STT* {STT* = ADT (Active Day Trader) + P_MDT (Proprietary Medium Day Trader) + PDT (Passive Day Trader) + MM (Market Maker) + NP_MDT (Non-Proprietary Medium Day Trader) + ODT (Other Day Trader) + Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders) + Unspec_Infreq (infrequent traders with no specified category)}. MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions.

The above table is a condensed version of Table IV.2 C which depicts the volume for each category specifically.

Table IV.3: Open to Close and Subsequent Close to Open Price Changes

	Mean	Std Dev	t-Stat of Mean	N
Close to Open Price Change (CO)	2.37	13.77	1.25	53
Open to Close Price Change (OC)	-4.09	28.39	-1.05	53
CO - OC	6.98	29.01	-1.73	52

Table IV.4: Price elasticity and trader behavior based categories inventory relationships

	ask 100bps	bid 100bps	ask 75bps	bid 75bps	ask 50bps	bid 50bps	ask 25bps	bid 25bps	spread
ADT Inventory	0.947	0.199	2.159**	-0.657	2.695***	-0.918	1.666***	-0.0780	-0.000334***
	(0.80)	(0.23)	(2.38)	(-0.79)	(4.00)	(-1.22)	(3.73)	(-0.17)	(-2.79)
MM Inventory	0.241	-0.444**	0.281*	-0.425***	0.281***	-0.368***	0.143***	-0.263***	0.0000148
	(1.42)	(-2.34)	(2.00)	(-2.92)	(2.91)	(-3.21)	(3.10)	(-3.31)	(1.21)
NP_MDT Inventory	-0.144	-0.546	0.157	-0.726**	0.356	-0.683**	0.346**	-0.374**	-0.0000981**
	(-0.40)	(-1.64)	(0.51)	(-2.58)	(1.53)	(-2.59)	(2.61)	(-2.18)	(-2.42)
P_MDT Inventory	0.619***	-0.0909	0.604***	-0.215	0.481***	-0.131	0.265***	0.00813	-0.0000184
	(3.60)	(-0.21)	(3.92)	(-0.51)	(4.06)	(-0.52)	(3.78)	(0.10)	(-1.23)
PDT Inventory	-0.509	-0.671	-0.166	-0.600	0.0400	-0.491	0.156	-0.266	-0.0000675
	(-0.75)	(-0.93)	(-0.28)	(-0.88)	(0.09)	(-0.93)	(0.71)	(-0.77)	(-0.54)
FII Inventory	-0.0115	-0.00323	-0.0111	-0.00140	-0.0139*	0.00483	-0.0183***	0.0117	0.000000452
	(-1.12)	(-0.24)	(-1.19)	(-0.11)	(-1.73)	(0.50)	(-2.81)	(1.59)	(0.75)
M. Fund Inventory	-0.0788***	0.0501	-0.0747***	0.0386	-0.0635***	0.0274	-0.0448***	0.0314	0.00000109
	(-5.72)	(0.86)	(-4.93)	(0.90)	(-5.94)	(0.79)	(-6.56)	(1.13)	(0.34)
STT Inventory	0.352**	-0.334	0.391***	-0.368*	0.363***	-0.308**	0.203***	-0.187**	0.000000802
	(2.59)	(-1.54)	(3.46)	(-1.85)	(4.75)	(-2.17)	(5.42)	(-2.48)	(0.09)
OLTT Inventory	0.0171	0.144***	0.0202	0.157***	0.0105	0.162***	0.00772	0.144***	-0.00000207*
	(1.03)	(7.41)	(1.43)	(7.39)	(0.89)	(7.00)	(1.17)	(7.48)	(-1.92)
Unspec. Inventory Inconsistent	1.932	0.894	4.050	2.582	6.399	2.328	6.523**	0.522	0.000915
	(0.28)	(0.17)	(0.60)	(0.69)	(1.32)	(0.82)	(2.18)	(0.23)	(0.86)
Unspec. Inventory Infrequent	0.0330	0.327**	0.0319	0.344**	0.0347	0.338*	0.0189	0.331*	-0.00000584
	(0.60)	(2.65)	(0.61)	(2.23)	(0.76)	(1.91)	(0.64)	(1.81)	(-0.80)
Prop. Inventory	0.248***	-0.145	0.250***	-0.162*	0.220***	-0.138*	0.127***	-0.0837*	-0.00000195
	(3.28)	(-1.39)	(3.76)	(-1.73)	(4.59)	(-1.92)	(4.78)	(-1.91)	(-0.49)
STT* Inventory	0.183***	-0.0615	0.200***	-0.0659	0.190***	-0.0345	0.109***	0.0183	-0.000000583
	(2.67)	(-0.53)	(3.39)	(-0.57)	(4.25)	(-0.35)	(4.10)	(0.23)	(-0.11)
Observations	68935	68877	69000	68994	69000	69000	69000	69000	69000

Note: The table reports results of the panel regressions using all days in the sample, for each of the 8 different left hand side variables and six different right hand side variables of the form $\pi_{i,t} = \sum_i \alpha_i (FE_i) + \sum_b d_b \, TD_b + \beta(Inv_{i,t}) + \varepsilon_{i,t}$,, where $\pi_{i,t}$ is the price elasticity of the order book (measured as number of shares it would take to move prices by 100, 75 ,50, or 25bp on either the bid or ask side) on date i during time interval t (15 seconds intervals during 10:00-15:30), FE_i is a date fixed effect, TD_b is $b = 1, \ldots, 9$ half-hourly time dummies (proxying for the intraday pattern in liquidity), and $Inv_{i,t}$ is the inventory of one of six trader categories. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions. For brevity, only the coefficients on the trader inventories are reported from each of the 36 panel regressions. T-stats are reported in parentheses based on robust standard errors clustered by date. Half-hour time dummies and date fixed effects are included. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$. STT* - Includes ADT + MM + NP_MDT + P_MDT + PDT + ODT + Unspec. Inventory Inconsistent + Unspec. Inventory Infrequent

Table IV.4b: Price elasticity and legal categories inventory relationships

	ask 100bps	bid 100bps	ask 75bps	bid 75bps	ask 50bps	bid 50bps	ask 25bps	bid 25bps	spread
Individual Inventory	0.114	-0.0245	0.138*	-0.0629	0.155**	-0.0558	0.118***	-0.00142	-0.00000102
	(1.33)	(-0.27)	(1.95)	(-0.70)	(2.56)	(-0.77)	(2.99)	(-0.03)	(-0.15)
Partnership Firm Inventory	0.273	-0.195	0.250	-0.224*	0.144	-0.229**	0.0945	-0.168*	0.00000168
	(1.46)	(-1.49)	(1.52)	(-1.81)	(1.33)	(-2.13)	(1.57)	(-1.98)	(0.08)
Hindu Undivided Family Inventory	6.581	0.640	5.807	-3.105	4.939*	-6.855*	2.549	-5.595**	-0.000610
	(1.33)	(0.09)	(1.44)	(-0.58)	(1.84)	(-1.68)	(1.55)	(-2.31)	(-0.77)
Public & Private Companies / Bodies Corporate Inventory	0.0375	0.124***	0.0427*	0.138***	0.0310*	0.147***	0.0185*	0.135***	-0.00000217**
	(1.64)	(5.69)	(1.98)	(6.88)	(1.69)	(6.99)	(1.80)	(7.18)	(-2.05)
Mutual Fund Inventory	-0.0788***	0.0501	-0.0747***	0.0386	-0.0635***	0.0274	-0.0448***	0.0314	0.00000109
	(-5.72)	(0.86)	(-4.93)	(0.90)	(-5.94)	(0.79)	(-6.56)	(1.13)	(0.34)
Domestic Financial Institution Inventory	-1.183	1.501	-1.011	1.303	-0.716	1.288	-0.273	1.381**	0.0000441
	(-1.20)	(1.09)	(-1.14)	(1.06)	(-1.05)	(1.30)	(-0.58)	(2.07)	(0.26)
Insurance Inventory	-1.789**	1.482	-1.610**	1.593	-1.143*	1.578	-0.904**	1.828	0.0000813
	(-2.15)	(1.33)	(-2.12)	(1.23)	(-1.84)	(1.10)	(-2.08)	(1.25)	(1.66)
Foreign Institutional Investor Inventory	-0.0115	-0.00323	-0.0111	-0.00140	-0.0139*	0.00483	-0.0183***	0.0117	0.000000452
	(-1.12)	(-0.24)	(-1.19)	(-0.11)	(-1.73)	(0.50)	(-2.81)	(1.59)	(0.75)
Overseas Corporate Bodies Inventory	0.413	0.0535	0.330	0.0132	0.274	0.0831	0.144	0.0706	-0.0000365*
	(1.48)	(0.26)	(1.34)	(0.07)	(1.62)	(0.61)	(1.43)	(0.82)	(-1.91)
Missing Category Inventory	22.36	16.46	33.67	9.615	38.87**	4.720	25.88*	0.610	0.00109
	(0.95)	(1.01)	(1.57)	(0.78)	(2.27)	(0.39)	(1.81)	(0.04)	(0.22)
Observations	68935	68877	69000	68994	69000	69000	69000	69000	69000

Note: This table reports results of eight panel regressions of the form: $\pi_{i,t} = FE_i + TD_b + Inv^{cat\ 1}{}_{i,t} + \cdots + Inv^{cat\ 99}{}_{i,t} + \varepsilon_{i,t}$, where $\pi_{i,t}$ is the price elasticity of the order book (measured as #Shares it would take to move prices by 100, 75, 50, or 25bps on either the bid or the ask side) on date i during time interval t (15 second intervals during 10:00-15:30), FE is a date fixed effect, TD_b is b=1,…,9 half-hourly time dummies (proxying for the intraday pattern in liquidity), and $Inv^{cat}_{i,t}$ is the inventory of one of the legal trader categories defined above (categories 5, 7, 10, 11 are omitted due to lack of sufficient observations). T-stats are reported in parenthesis based on robust standard errors clustered by date. Half-hour time dummies and date fixed effects are included. * $p < 0.05$, ** $p < 0.05$, *** $p < 0.01$.

Table IV.5a: Characteristics of Normal Booms/Busts in the entire sample

Weeks	Median # of peaks per day	Total # of peaks per day	Median Duration of Trough to Peak (seconds)	Median # of Peaks to Troughs	Total # of Peaks to Troughs	Median Duration of Peak to Trough (seconds)
1	2	15	3,063	1	10	3,126
2	2	13	1,605	1	9	5,505
3	2	14	1,245	1	12	11,298
4	4	46	524	4	43	726
5	2	19	2,406	2	16	2,697
6	3	21	1,995	3	19	2,691
7	4	23	3,162	3	19	2,304
8	1	12	1,766	1	9	1,920

Note: Median number of peaks per day, median duration (in seconds) of through to peak, median number of peaks to troughs, and median duration (in seconds) of peak to trough. Peaks and troughs are identified using Lunde and Timmermann (2004) algorithm. We use a filter of 1.5% window – i.e., troughs are identified by the recovery following a 1.5% or more price drop from the previous peak, and the next peak is identified by price drop following a recovery of 1.5% or more from the previous trough. Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis.

The above table shows the characteristics of the boom-bust cycles each week using the algorithm developed by Lunde and Timmermann (2004).

Table IV.5b: Characteristics of Winsorized Normal Booms/Busts

Peak/Trough	N	Duration Mean (In seconds)	Duration Median (In seconds)
Full Sample	255	4779.06	2289
“Rolling Down”	126	5167.10	2247
“Rolling Up”	129	4400.05	2319

Note: Summary statistics of duration (mean and median) after truncation (winsorization). Observations with durations less than the 10th percentile (33 seconds) are truncated. Small peaks and troughs in stock prices within each trading day (other than the two fast crash days – May 19th and May 22nd and considered). Duration is calculated using the Lunde and Timmerman (2004) algorithm.

We depict the summary statistics for the peaks/troughs calculated using the Lunde and Timmermann (2004) algorithm.

Table IV.6.A: Price elasticity and trader behavior based categories inventory (signed) relationships during the rolling up period (for winsorized cycles)

	ask 100bps	bid 100pbs	ask 75bps	bid 75bps	ask 50bps	bid 50bps	ask 25bps	bid 25bps	Spread
ADT Inventory	-0.549*	-0.362	0.301	-0.383	0.858***	-0.311	0.675***	0.0646	-0.0000749
	(-1.77)	(-0.88)	(0.96)	(-1.05)	(3.02)	(-1.03)	(3.78)	(0.27)	(-0.78)
MM Inventory	0.160	-0.706***	0.199**	-0.638***	0.202**	-0.509***	0.112**	-0.341***	-0.0000107*
	(1.36)	(-14.82)	(2.05)	(-14.18)	(2.57)	(-12.43)	(2.45)	(-10.33)	(-1.69)
NP_MDT Inventory	-0.0133	-0.521***	0.0589	-0.503***	0.139	-0.409***	0.229***	-0.100	-0.0000813***
	(-0.06)	(-3.15)	(0.30)	(-3.35)	(0.83)	(-3.20)	(2.75)	(-1.01)	(-2.79)
P_MDT Inventory	0.212**	-2.151***	0.366***	-1.901***	0.408***	-1.190***	0.313**	-0.381***	-0.0000791***
	(2.07)	(-13.95)	(2.83)	(-13.70)	(2.91)	(-11.62)	(2.29)	(-6.48)	(-7.93)
PDT Inventory	0.392	-0.138	0.389	-0.200	0.436*	-0.214	0.446***	-0.0285	0.000118
	(0.91)	(-0.53)	(1.08)	(-0.86)	(1.93)	(-1.17)	(3.86)	(-0.24)	(1.33)
inv_ODT	-0.183	-0.671***	-0.125	-0.508***	0.00144	-0.250***	0.0531	-0.0336	-0.0000265**
	(-1.46)	(-5.22)	(-1.23)	(-4.34)	(0.02)	(-2.74)	(1.13)	(-0.54)	(-2.33)
FII Inventory	-0.0128	0.00266	-0.0165*	0.00374	-0.0191***	0.0103*	-0.0205***	0.0173***	-0.000000847
	(-1.13)	(0.42)	(-1.76)	(0.62)	(-2.94)	(1.93)	(-3.65)	(4.04)	(-1.03)
M. Fund Inventory	-0.0144	-0.00731	-0.0129	-0.00867	-0.0117	0.00187	-0.00636	0.0161*	0.000000226
	(-0.89)	(-0.41)	(-0.89)	(-0.53)	(-1.18)	(0.13)	(-0.85)	(1.76)	(0.09)
STT Inventory	0.162**	-1.081***	0.242***	-0.969***	0.262***	-0.674***	0.180***	-0.319***	-0.0000319***
	(2.05)	(-20.33)	(3.27)	(-19.58)	(4.00)	(-16.58)	(3.10)	(-11.23)	(-6.18)
OLTT Inventory	-0.00441	0.128***	-0.00130	0.136***	-0.00160	0.129***	0.0000141	0.104***	0.00000127
	(-0.93)	(10.54)	(-0.39)	(10.60)	(-0.47)	(10.05)	(0.00)	(8.93)	(1.24)
Unspec. Inventory Inconsistent	1.636**	-0.404	1.451**	-0.475	0.965**	-0.587	0.418	-0.629**	0.000322*
	(2.08)	(-0.67)	(2.19)	(-0.89)	(1.96)	(-1.41)	(1.45)	(-2.01)	(1.74)
Unspec. Inventory Infrequent	-0.0159	0.0371	-0.0110	0.0433*	-0.00237	0.0562***	-0.000354	0.0777***	0.0000126**
	(-0.65)	(1.33)	(-0.51)	(1.82)	(-0.14)	(2.80)	(-0.03)	(4.55)	(2.30)
Prop. Inventory	0.0654	-0.707***	0.118***	-0.610***	0.148***	-0.423***	0.102***	-0.190***	-0.0000204***
	(1.50)	(-19.67)	(3.19)	(-18.35)	(4.27)	(-15.41)	(3.33)	(-10.42)	(-6.98)
STT* Inventory	0.0215	-0.362***	0.0516	-0.313***	0.0718*	-0.195***	0.0537*	-0.0558**	-0.00000422
	(0.66)	(-6.63)	(1.40)	(-6.44)	(1.95)	(-5.34)	(1.91)	(-2.44)	(-1.23)
Observations	31052	31050	31116	31112	31116	31116	31116	31116	31116

Note: The table reports results of the panel regressions using all days in the sample, for each of the 8 different left hand side variables and six different right hand side variables of the form $\pi_{i,t} = \sum_i \alpha_i(FE_i) + \sum_b d_b\, TD_b + \beta(Inv_{i,t}) + \varepsilon_{i,t}$,, where $\pi_{i,t}$ is the price elasticity of the order book (measured as number of shares it would take to move prices by 100, 75 ,50, or 25bp on either the bid or ask side) on date i during time interval t (15 seconds intervals during 10:00-15:30), FE_i is a date fixed effect, TD_b is $b = 1, ..., 9$ half-hourly time dummies (proxying for the intraday pattern in liquidity), and $Inv_{i,t}$ is the inventory of one of six trader categories. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions. For brevity, only the coefficients on the trader inventories are reported from each of the 36 panel regressions. T-stats are reported in parentheses based on robust standard errors clustered by date. Half-hour time dummies and date fixed effects are included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. STT* - Includes ADT + MM + NP_MDT + P_MDT + PDT + ODT + Unspec. Inventory Inconsistent + Unspec. Inventory Infrequent.

Table IV.6.B: Price elasticity and trader behavior based categories inventory (signed) relationships during the rolling down period (for winsorized cycles)

	ask 100bps	bid 100pbs	ask 75bps	bid 75bps	ask 50bps	bid 50bps	ask 25bps	bid 25bps	Spread
ADT Inventory	1.160	-0.309	0.924*	-0.726*	0.697**	-0.886***	0.248	-0.389*	-0.000199*
	(1.44)	(-0.66)	(1.71)	(-1.66)	(2.10)	(-2.60)	(1.55)	(-1.70)	(-1.82)
MM Inventory	0.313*	-0.628***	0.327**	-0.447***	0.277**	-0.314***	0.115**	-0.175***	0.00000406
	(1.68)	(-13.04)	(2.10)	(-13.35)	(2.57)	(-12.34)	(2.01)	(-10.12)	(0.69)
NP_MDT Inventory	-0.309	-0.00200	-0.145	-0.0931	-0.0304	-0.0963	-0.0179	-0.0442	-0.0000187
	(-1.11)	(-0.01)	(-0.61)	(-0.40)	(-0.18)	(-0.43)	(-0.18)	(-0.23)	(-0.69)
P_MDT Inventory	0.613**	0.0954**	0.543**	0.0940**	0.373**	0.0349	0.177**	-0.00911	-0.0000179
	(2.31)	(2.00)	(2.38)	(2.26)	(2.36)	(1.02)	(2.08)	(-0.39)	(-1.60)
PDT Inventory	-0.0949	0.185	0.202	0.177	0.265	0.135	0.315	0.00684	-0.000156**
	(-0.23)	(0.47)	(0.56)	(0.51)	(0.93)	(0.50)	(1.47)	(0.04)	(-2.21)
inv_ODT	0.506**	-0.410***	0.422**	-0.309***	0.312**	-0.221***	0.192**	-0.0940**	-0.0000299**
	(2.26)	(-4.00)	(2.09)	(-3.58)	(2.06)	(-3.30)	(2.36)	(-2.15)	(-2.16)
FII Inventory	-0.00279	-0.0212***	-0.00244	-0.0187***	-0.00579	-0.0102***	-0.0116*	-0.000205	-0.00000139***
	(-0.30)	(-4.27)	(-0.26)	(-4.08)	(-0.67)	(-2.69)	(-1.70)	(-0.09)	(-3.09)
M. Fund Inventory	-0.0680***	0.00976	-0.0646***	0.00254	-0.0528***	-0.00388	-0.0437***	0.000948	0.00000196***
	(-9.21)	(1.59)	(-9.52)	(0.47)	(-9.34)	(-0.86)	(-9.36)	(0.32)	(2.87)
STT Inventory	0.358**	-0.342***	0.352***	-0.240***	0.276***	-0.179***	0.122***	-0.107***	-0.00000431
	(2.38)	(-10.09)	(2.82)	(-9.56)	(3.27)	(-9.04)	(3.02)	(-7.78)	(-0.85)
OLTT Inventory	0.00487	0.0729***	0.00552	0.0612***	0.00436	0.0505***	0.00304	0.0402***	0.00000332***
	(0.47)	(8.53)	(0.65)	(9.09)	(0.81)	(8.83)	(1.03)	(7.98)	(3.11)
Unspec. Inventory Inconsistent	1.536***	-0.231	1.250***	0.0283	0.762***	0.0383	0.293	-0.00102	0.00000976
	(3.55)	(-0.48)	(3.75)	(0.07)	(3.43)	(0.11)	(1.61)	(-0.01)	(0.16)
Unspec. Inventory Infrequent	0.0181	0.235***	0.00754	0.224***	-0.00212	0.218***	-0.00384	0.202***	0.00000533**
	(0.98)	(5.65)	(0.53)	(5.56)	(-0.19)	(5.74)	(-0.70)	(5.64)	(1.96)
Prop. Inventory	0.320**	-0.199***	0.288***	-0.138***	0.213***	-0.0966***	0.111***	-0.0561***	-0.00000536**
	(2.55)	(-10.50)	(2.63)	(-9.23)	(2.70)	(-8.59)	(2.58)	(-7.90)	(-2.11)
STT* Inventory	0.0928	0.0950***	0.0809	0.110***	0.0565	0.121***	0.0243	0.127***	0.00000222
	(1.37)	(3.21)	(1.30)	(3.97)	(1.16)	(4.65)	(1.05)	(5.24)	(0.97)
Observations	37815	37759	37816	37814	37816	37816	37816	37816	37816

Note: The table reports results of the panel regressions using all days in the sample, for each of the 8 different left hand side variables and six different right hand side variables of the form $\pi_{i,t} = \sum_i \alpha_i(FE_i) + \sum_b d_b\, TD_b + \beta(Inv_{i,t}) + \varepsilon_{i,t}$,, where $\pi_{i,t}$ is the price elasticity of the order book (measured as number of shares it would take to move prices by 100, 75 ,50, or 25bp on either the bid or ask side) on date i during time interval t (15 seconds intervals during 10:00-15:30), FE_i is a date fixed effect, TD_b is $b = 1, ..., 9$ half-hourly time dummies (proxying for the intraday pattern in liquidity), and $Inv_{i,t}$ is the inventory of one of six trader categories. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions. For brevity, only the coefficients on the trader inventories are reported from each of the 36 panel regressions. T-stats are reported in parentheses based on robust standard errors clustered by date. Half-hour time dummies and date fixed effects are included. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$. STT* - Includes ADT + MM + NP_MDT + P_MDT + PDT + ODT + Unspec. Inventory Inconsistent + Unspec. Inventory Infrequent.

Table V.1: Signed Trading Volume by FII, MF, and STT during Fast Crashes/Normal Cycles

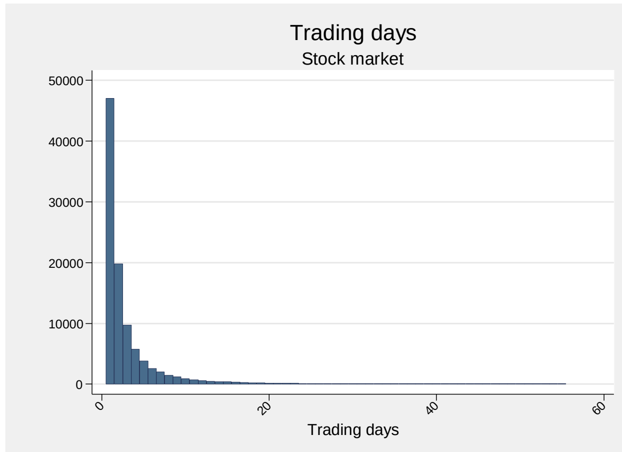
	vol_FII	vol_MF	vol_STT	vol_STT*
19-May				
Price Crash	-50,000	13,979	28,312	37,374
Price Recovery	-109,026	128,673	16,323	22,207
22-May				
	vol_FII	vol_MF	vol_STT	vol_STT*
Price Crash	-26,493	12,428	-2,736	1,425
Price Recovery	-457	33,772	-26,812	-37,534
33 Normal Boom – Bust Cycles				
	vol_FII	vol_MF	vol_STT	vol_STT*
Price Crash	-5,885.12	1,423.3	1,168.42	6,032.94
Price Recovery	-8,562.27	3,737.9	1,537.58	2,278.00

STT - as per new classification and includes ADT + MM + NP_MDT + P_MDT + PDT
STT* - Includes ADT + MM + NP_MDT + P_MDT + PDT + ODT + Unspec. Inventory Inconsistent + Unspec. Inventory Infrequent

The above table depicts the net signed volume for FIIs, MFs and STTs during price crashes and price recoveries. We depict this volume for the 2 minor crashes on May 19th and May 22nd apart from 33 micro crashes throughout our sample period from Apr' 2006 – Jun' 2006. The values for the 33 micro-cycles, the 1st quartile and the cycles in the entire sample period are averages for the cycles.

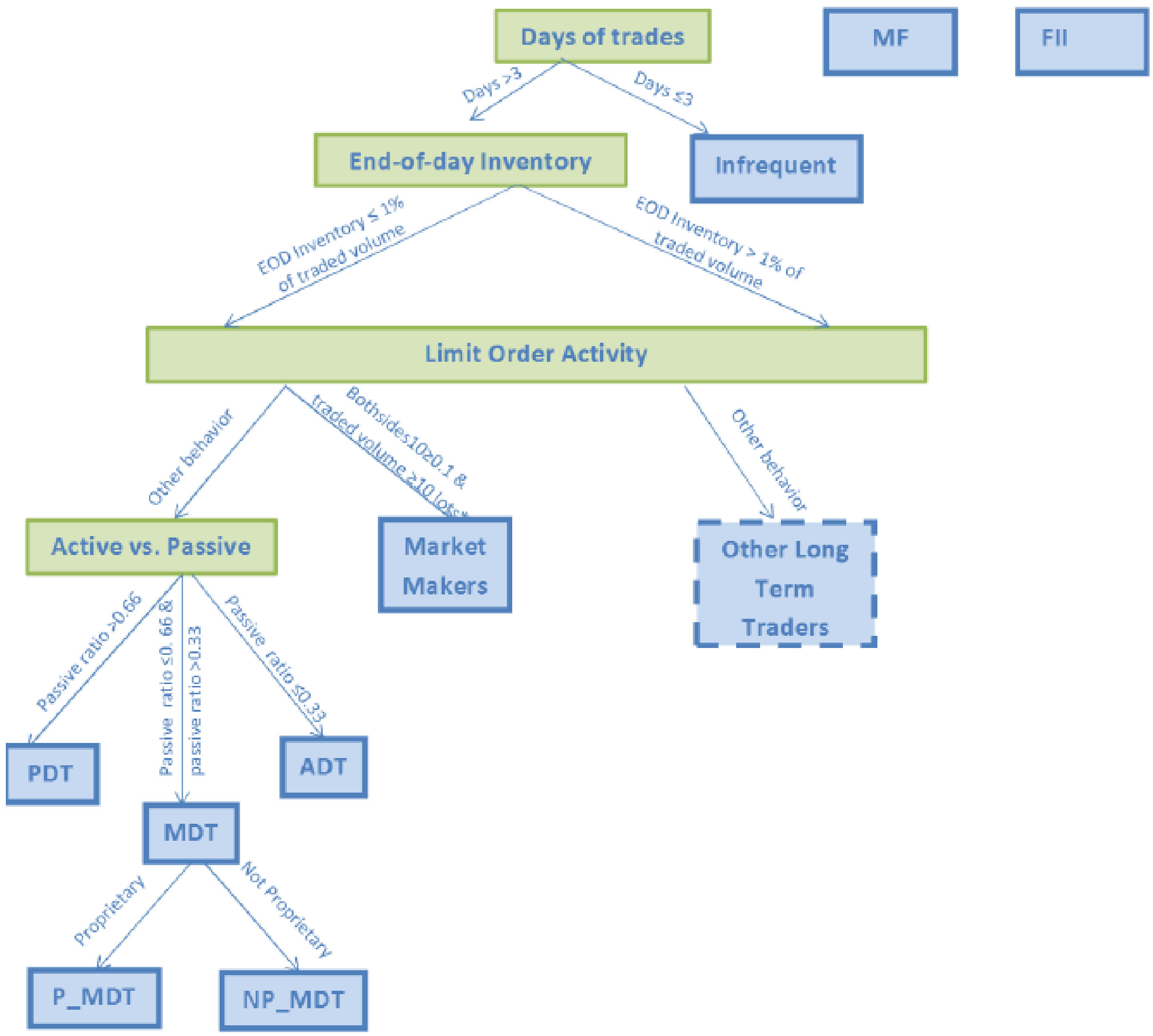
FIGURES

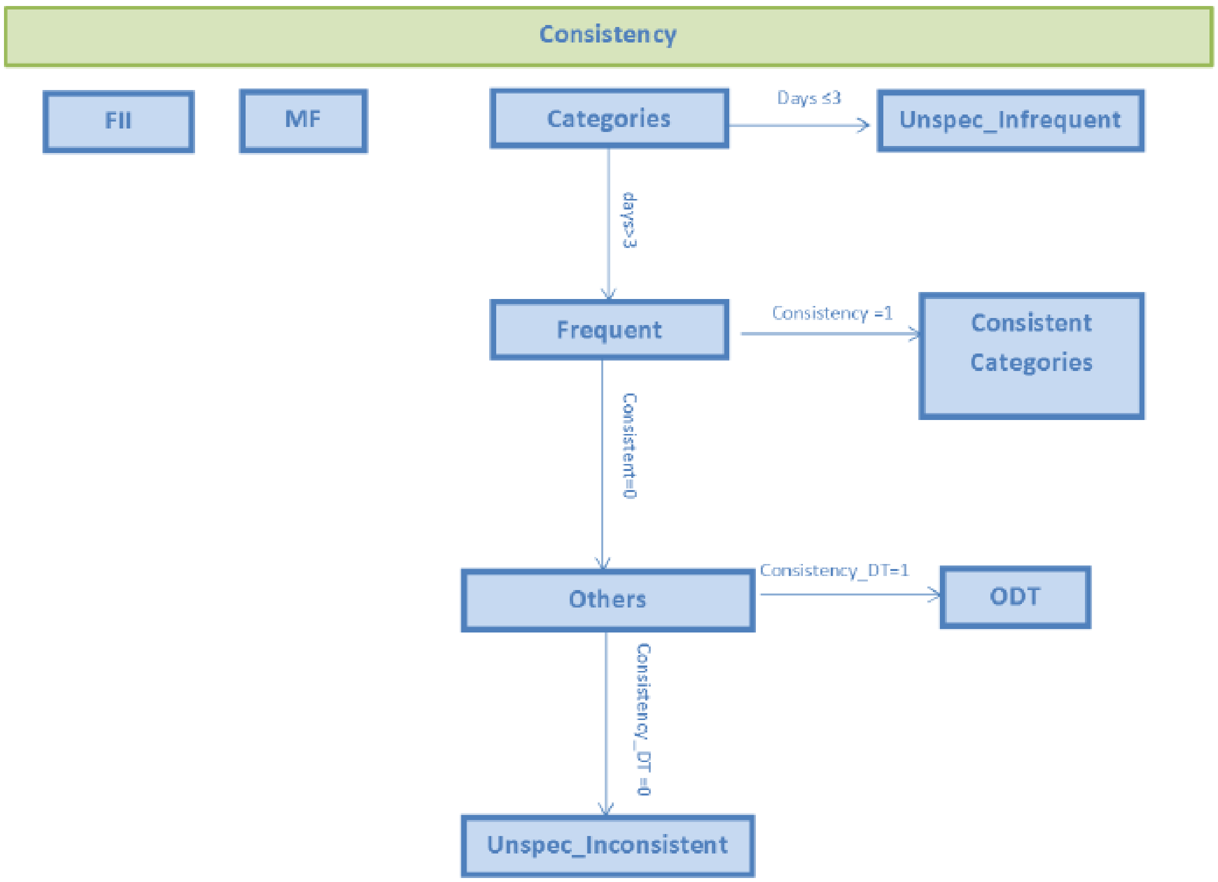
Figure III.I: Trading Frequency for Spot Market



Note: Trading frequency for all spot market traders during April 3rd 2006 to June 30th 2006 time period; X axis: Trading days; Y axis: Frequency

Figure IV.1: Hierarchy for Trader Categories

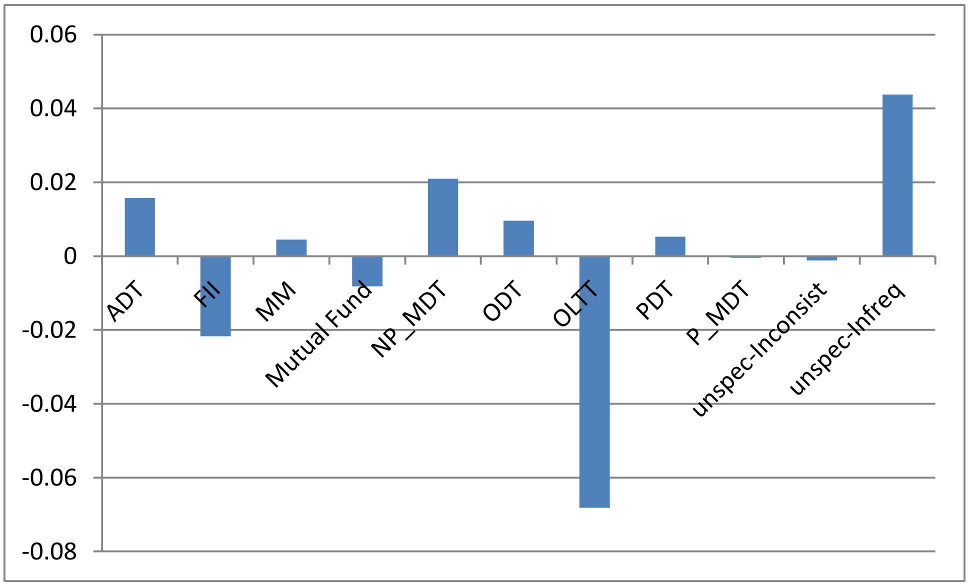




Notes: A trading lot is defined as 10 shares in the stock market, and 750 shares in the futures market. Consistency=1 when a trader belongs to the same behavioral category more than 50% of the times in the sample. Consistency_DT=1 when a trader belongs to the day trader category more than 50% of the times in the sample

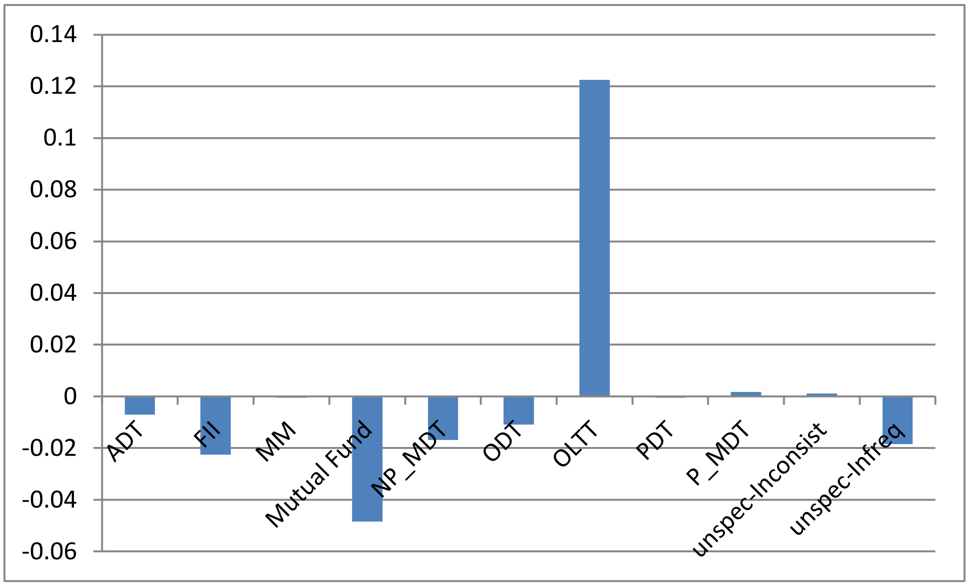
The first of the above figures demonstrates the algorithm used to classify traders into various behavioral classifications. The second figure depicts the algorithm we use to determine whether the traders are consistent or not.

Figure IV.2: Net buys and sells during the first 30 minutes of the trading day by trader type



Note: Net buys and sells during the first 30 minutes of the trading day for different trader categories. Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions.

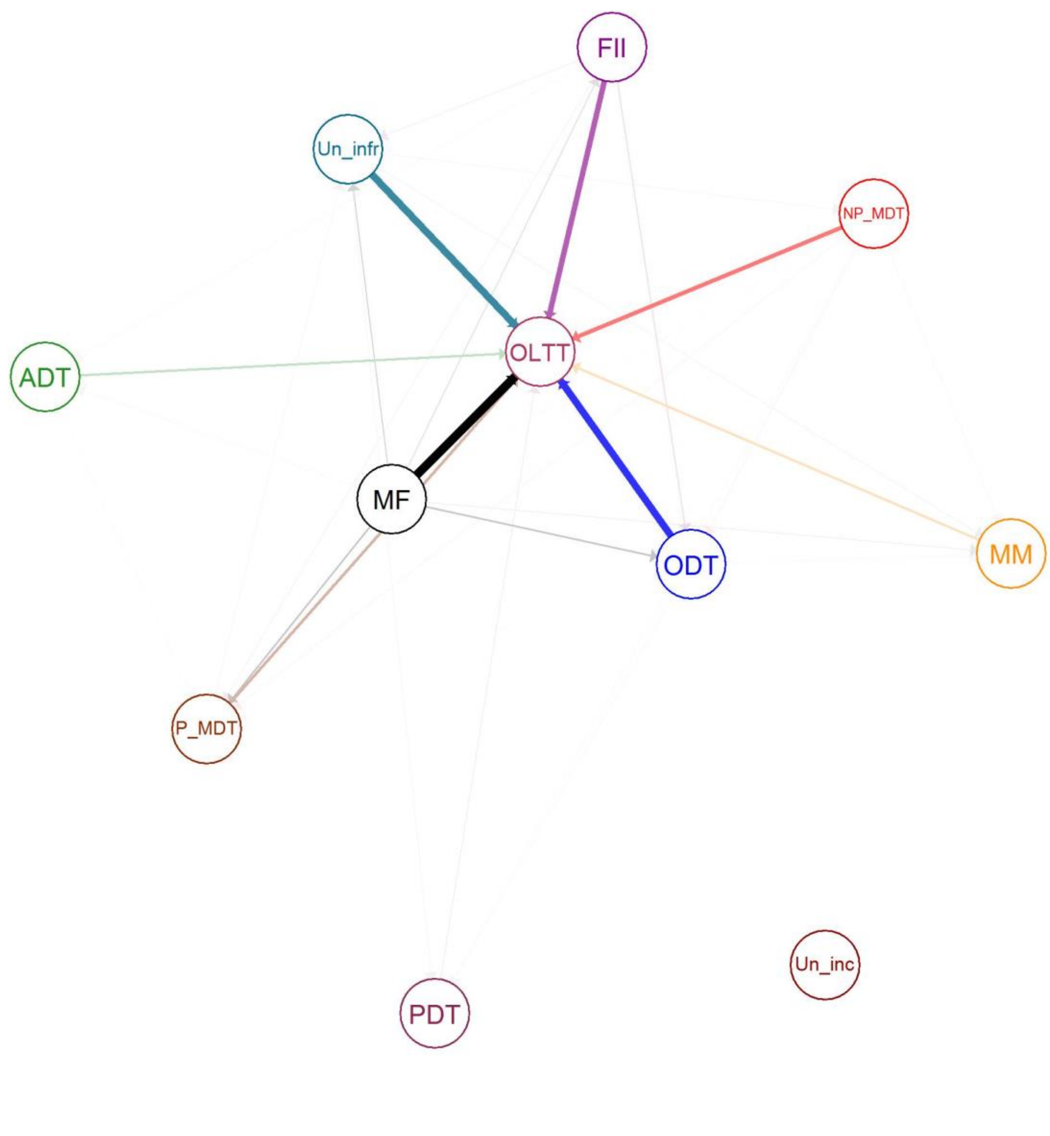
Figure IV.3: Net buys and sells during the last 30 minutes of the trading day by trader type



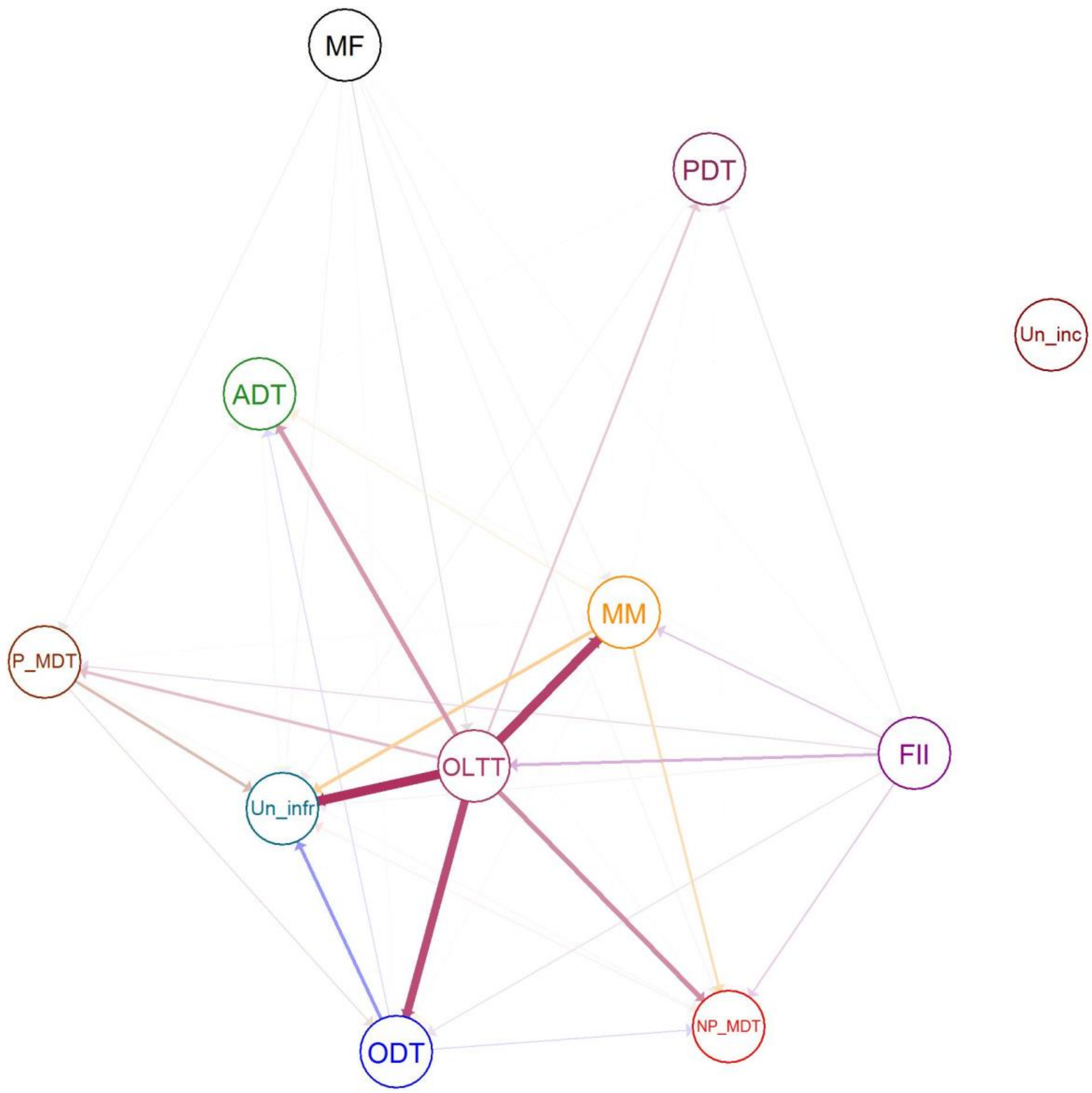
Note: Net buys and sells during the last 30 minutes of the trading day for different trader categories. Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions.

Figure IV.4: Directed Trading Volume Network

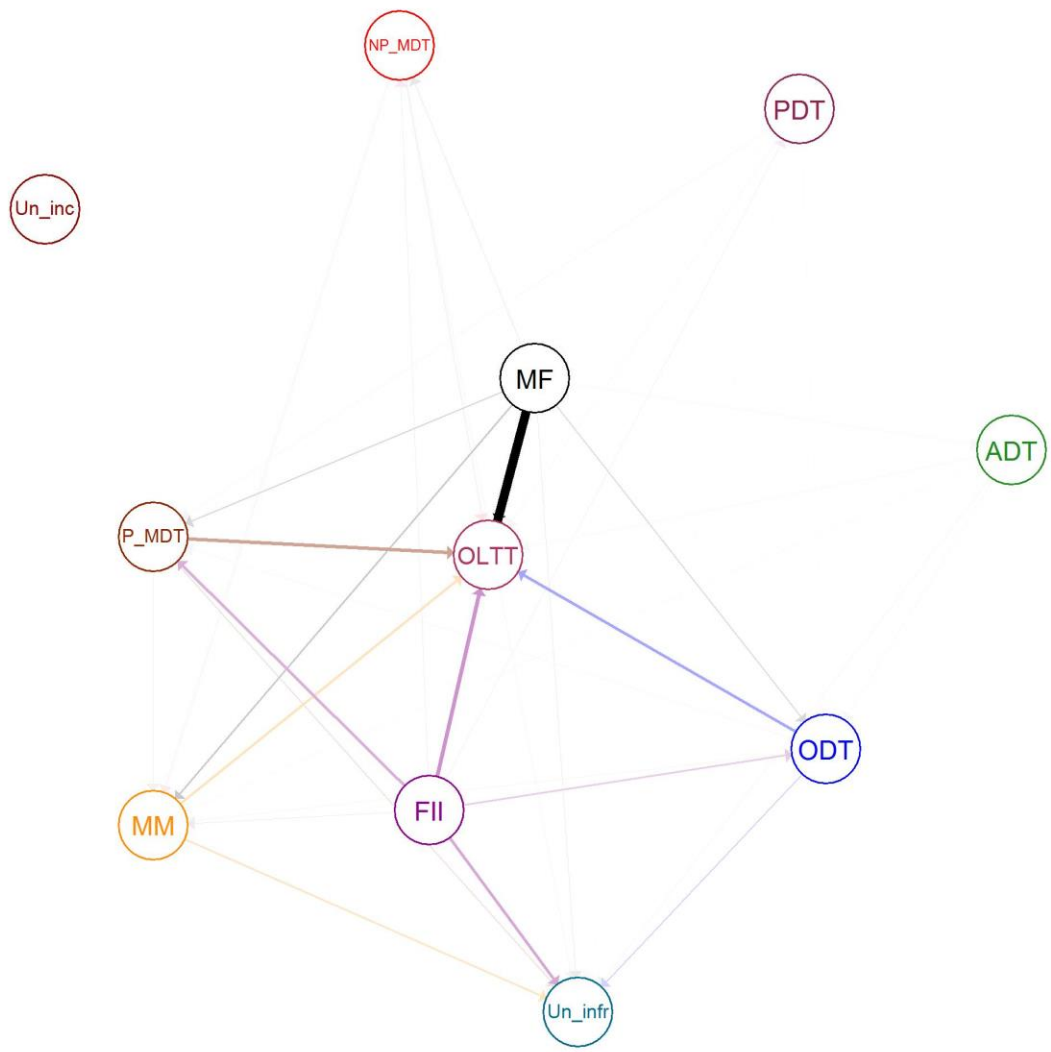
Note: Directed trading volume network for 11 non-overlapping traders categories: ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions. Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis. Thickness of each link is normalized by volume.



Network model denoting the linkages during the last 30 minutes of trading i.e 3 pm – 3:30 pm

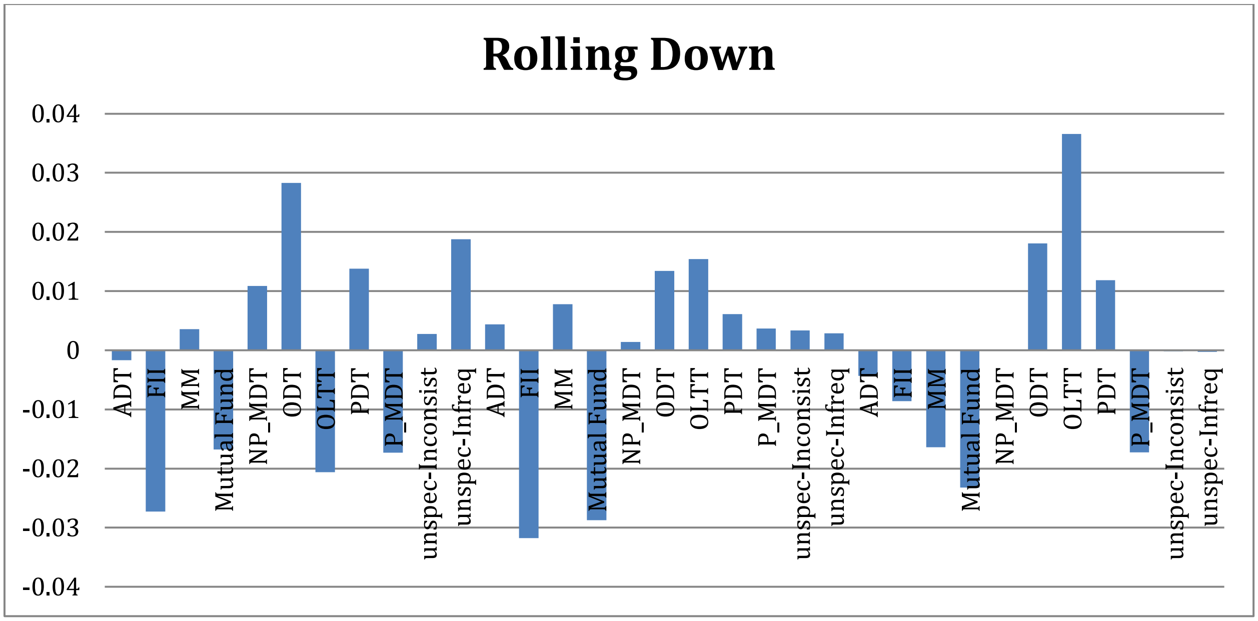


Network model denoting the linkages between the first trade and 10:30 am



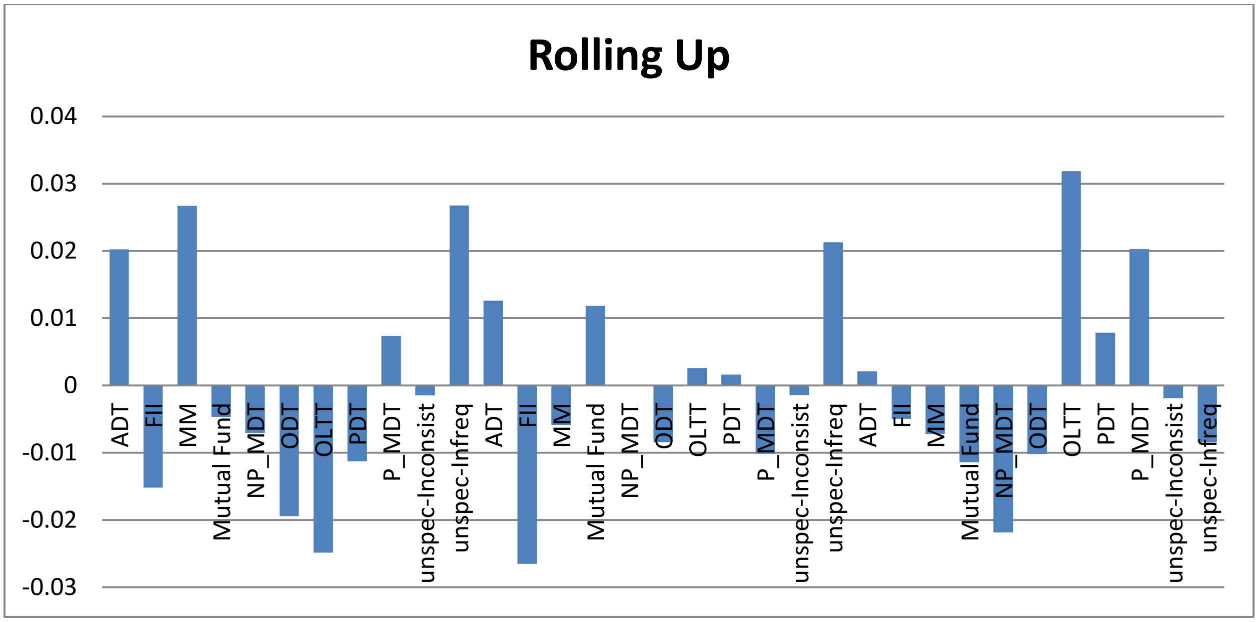
Network model denoting the linkages between 10:30 am – 3 pm

Figure IV.5: Trades in behavioral categories during the "rolling down" period



Note: Net trades during the Begin, Middle, and End "rolling down" periods for different trader behavior categories. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions. Our sample includes only the 1st (bottom) quartile of the boom-bust cycles sorted by duration of the cycle.

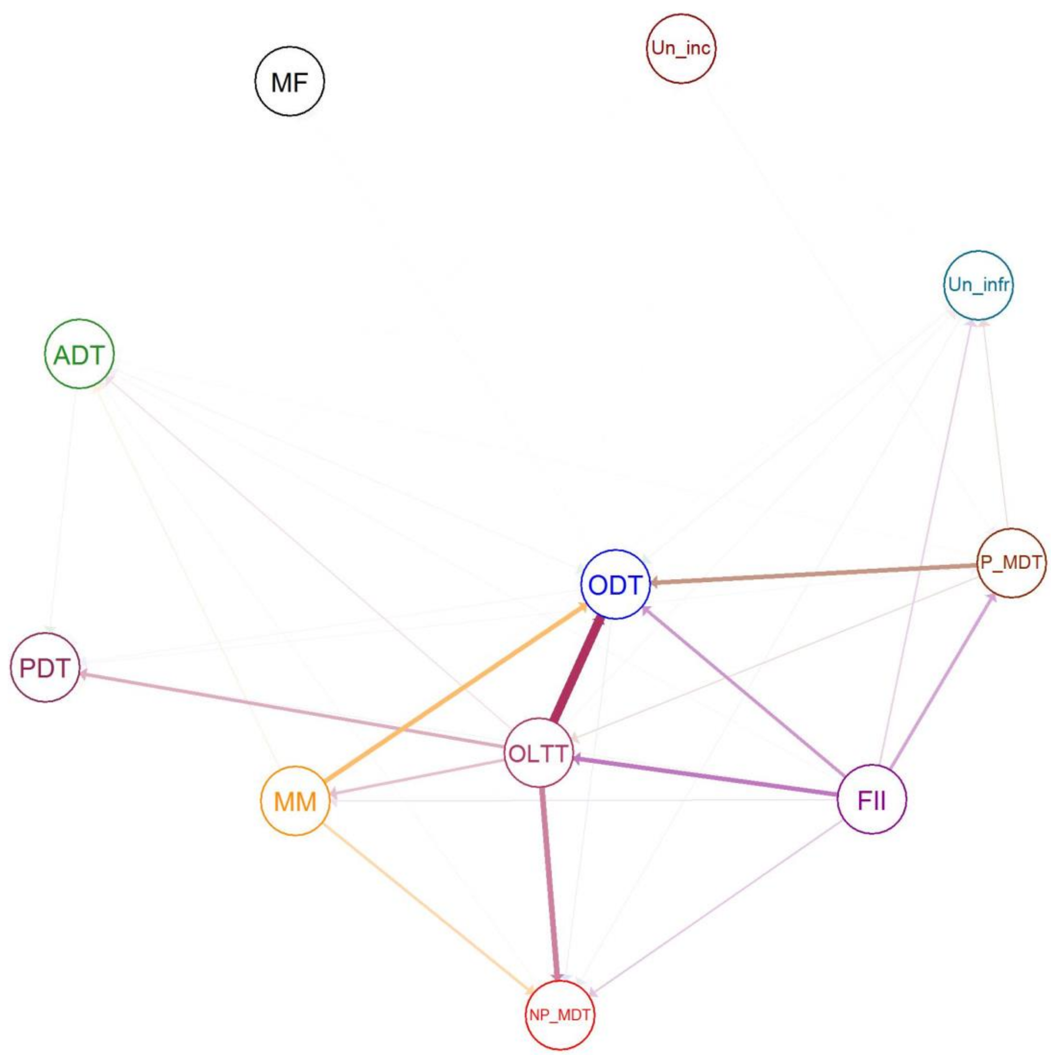
Figure IV.6: Trades in behavioral categories during the "rolling up" period



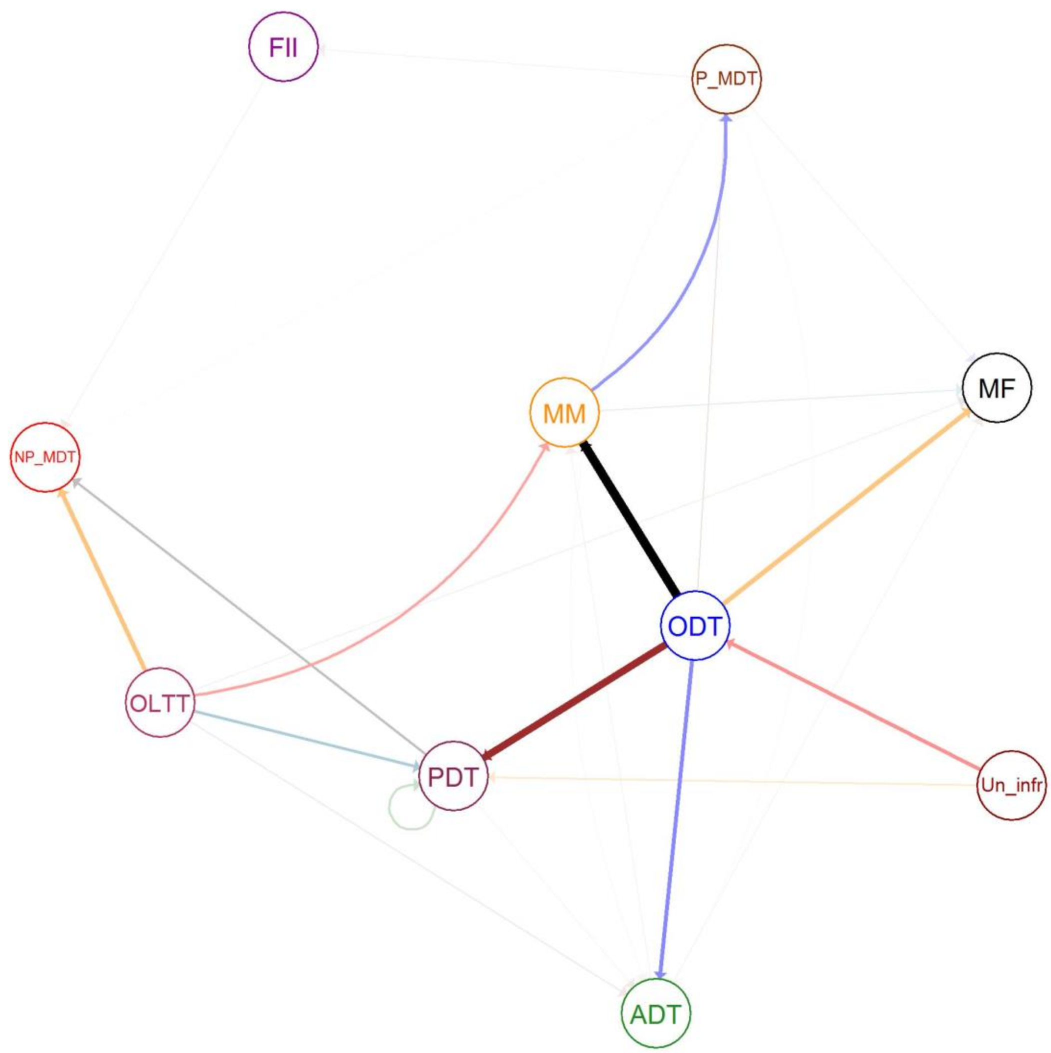
Note: Net trades during the Begin, Middle, and End "rolling up" periods for different trader behavior categories. Categories are ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions. Our sample includes only the 1st (bottom) quartile of the boom-bust cycles sorted by duration of the cycle.

Figure IV.7: Directed Trading Volume Network

Note: Directed trading volume network for 11 non-overlapping traders categories: ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), and Unspec_Infreq (infrequent traders with no specified category). MF is a legal category 6: Mutual Funds, and FII is a legal category 12: Foreign Institutions. Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis. Thickness of each link is normalized by volume.

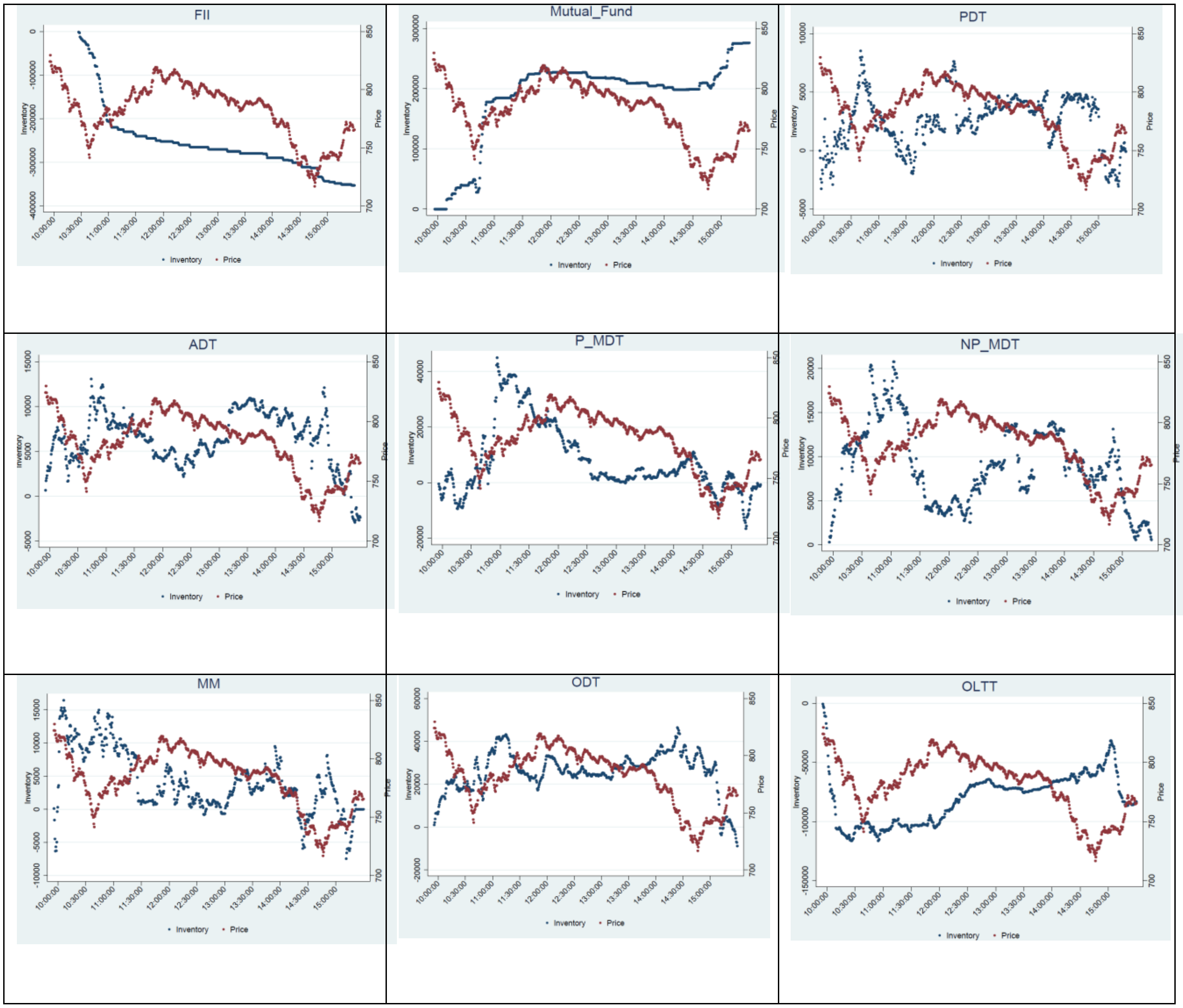


Network model denoting the linkages during the "rolling down" period as per the Timmermann and Lunde (2004) algorithm



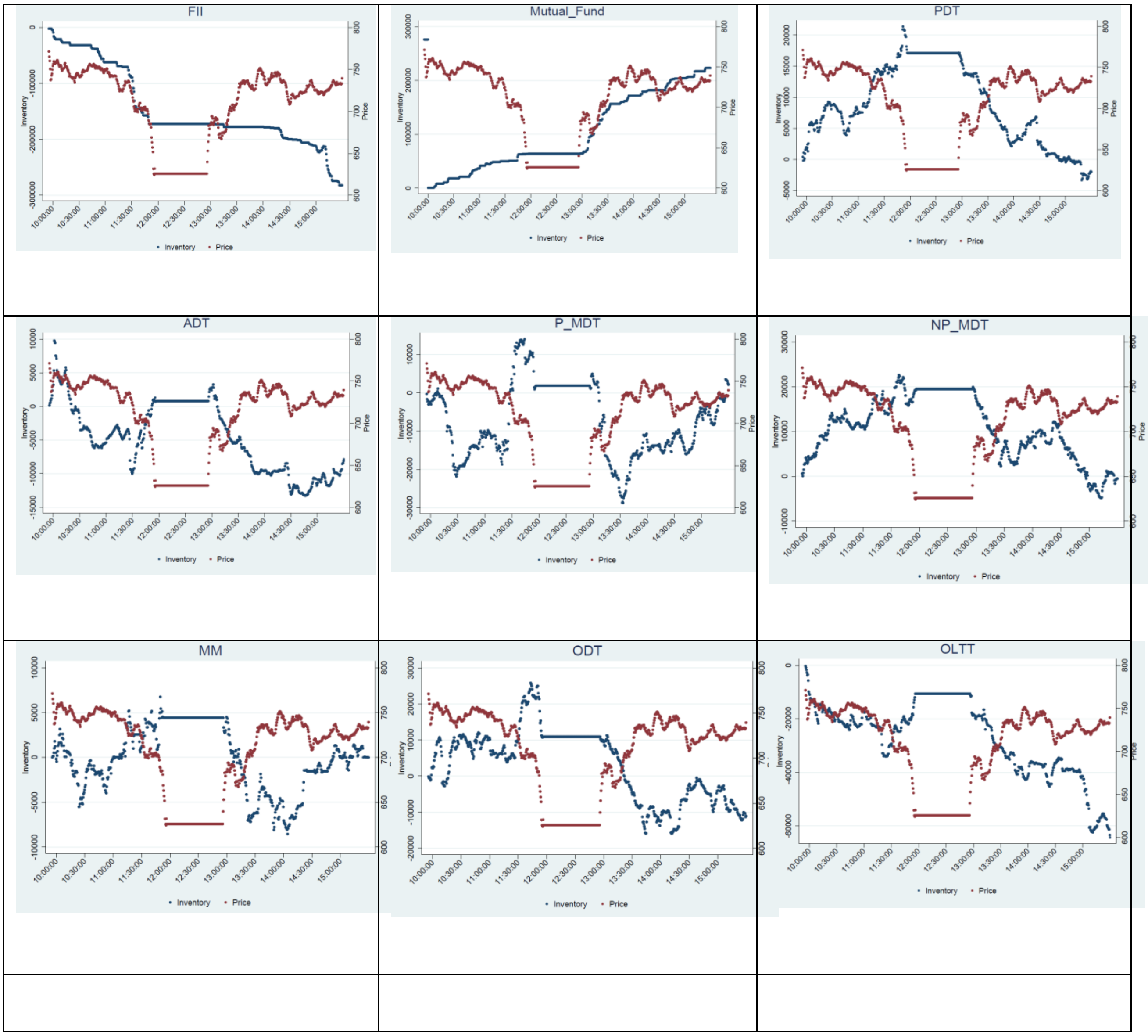
Network model denoting the linkages during the “rolling up” period as per the Timmermann and Lunde (2004) algorithm.

Figure V.1: Inventory of FI, Mutual funds, and STT on May 19th, 2006



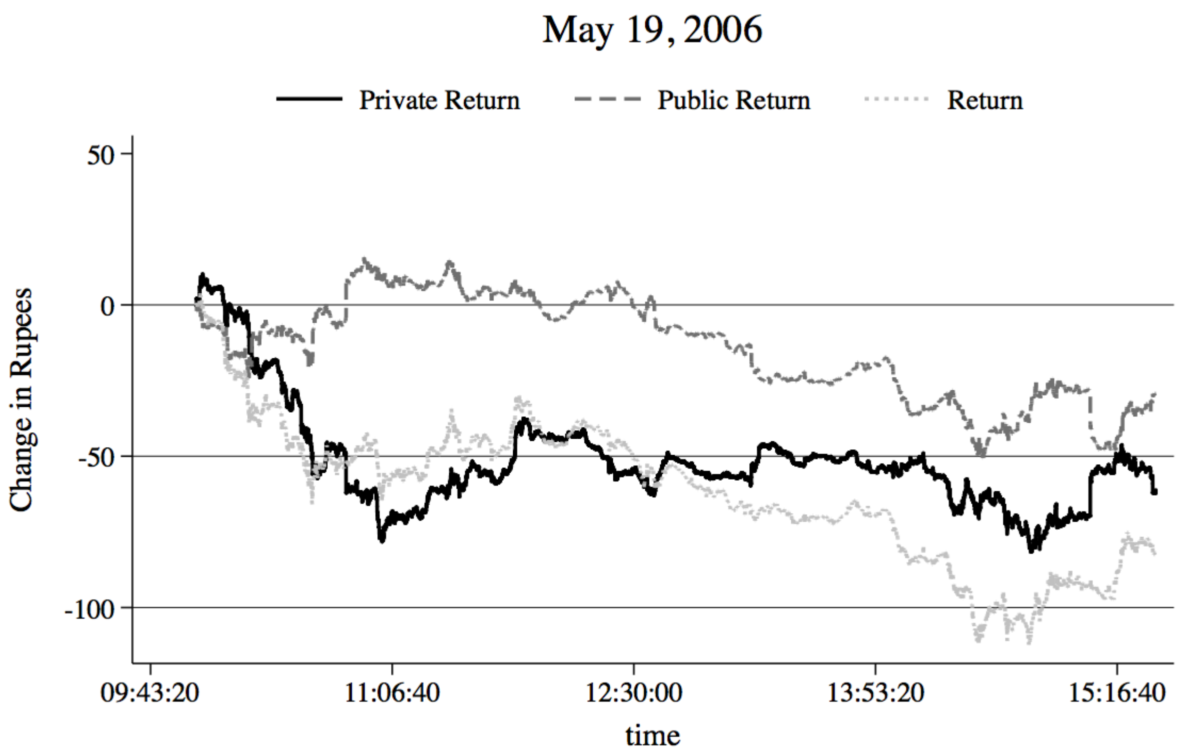
Note: Intra-day inventories and prices for ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), Unspec_Infreq (infrequent traders with no specified category), MF (Mutual Funds), and FII (Foreign Institutions) on May 19, 2006.

Figure V.2: Inventory of FI, Mutual funds, and STT on May 22nd, 2006



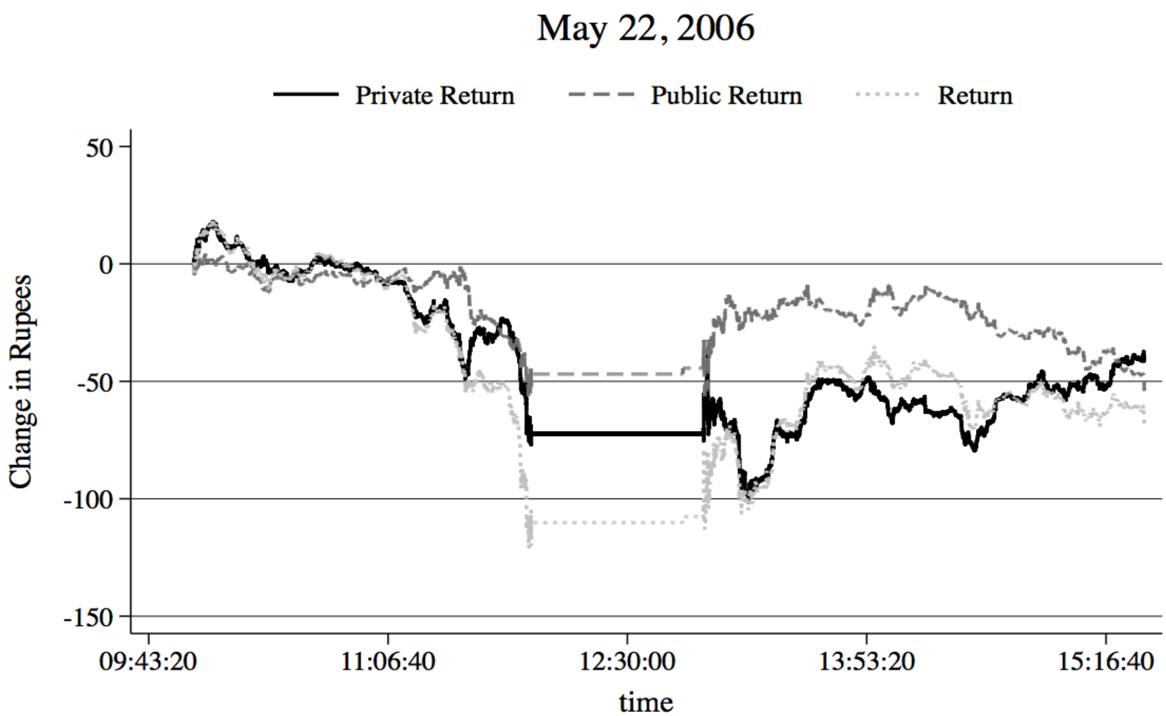
Note: Intra-day inventories and prices for ADT (Active Day Trader), P_MDT (Proprietary Medium Day Trader), PDT (Passive Day Trader), MM (Market Maker), NP_MDT (Non-Proprietary Medium Day Trader), ODT (Other Day Trader), OLTT (Other Long Term Trader), Unspec_Inconsist (frequent traders with no specified category who are not consistent day traders), Unspec_Infreq (infrequent traders with no specified category), MF (Mutual Funds), and FII (Foreign Institutions) on May 22, 2006.

Figure V.3: Price change decomposition on May 19, 2006



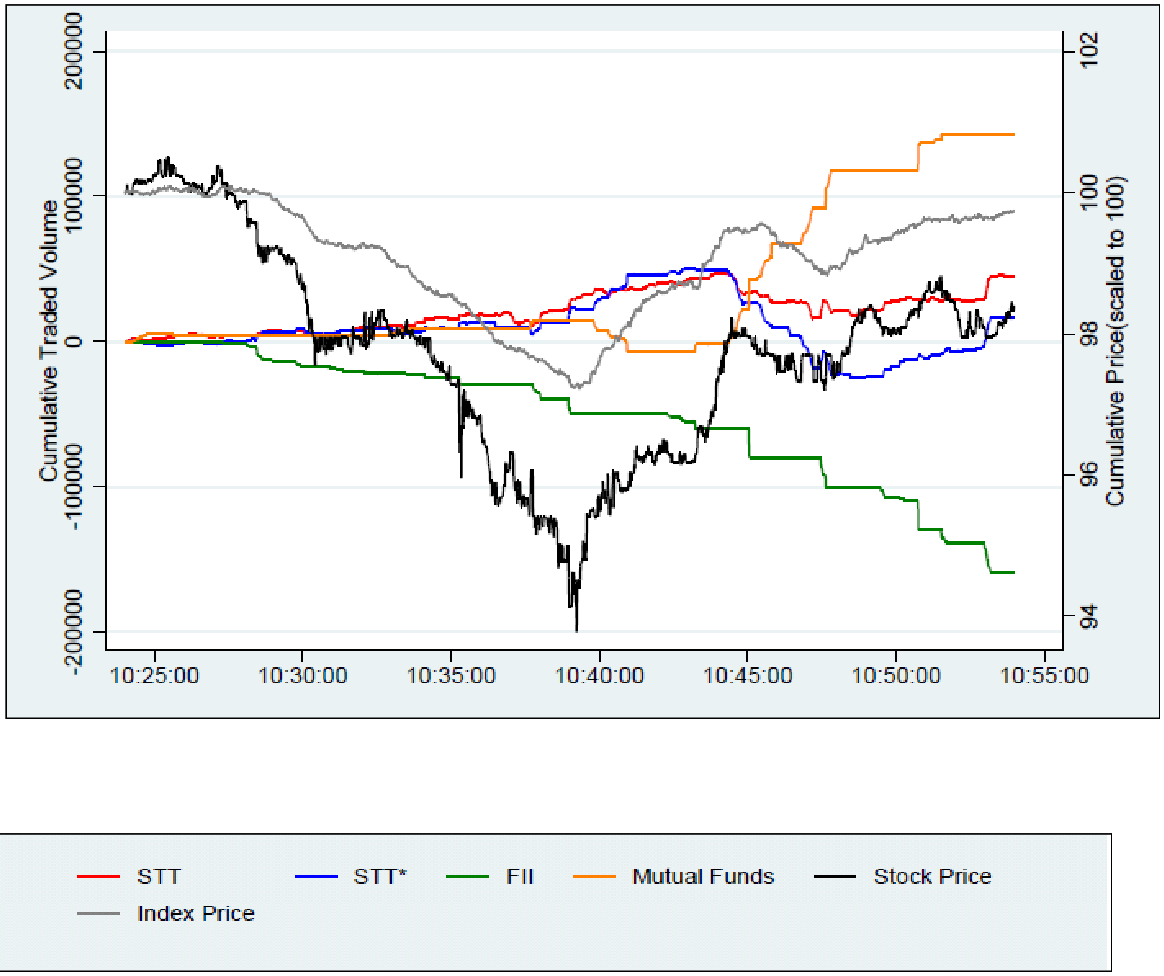
Note: The cumulative price change into private and public components for May 19, 2006.

Figure V.4: Price change decomposition on May 22, 2006



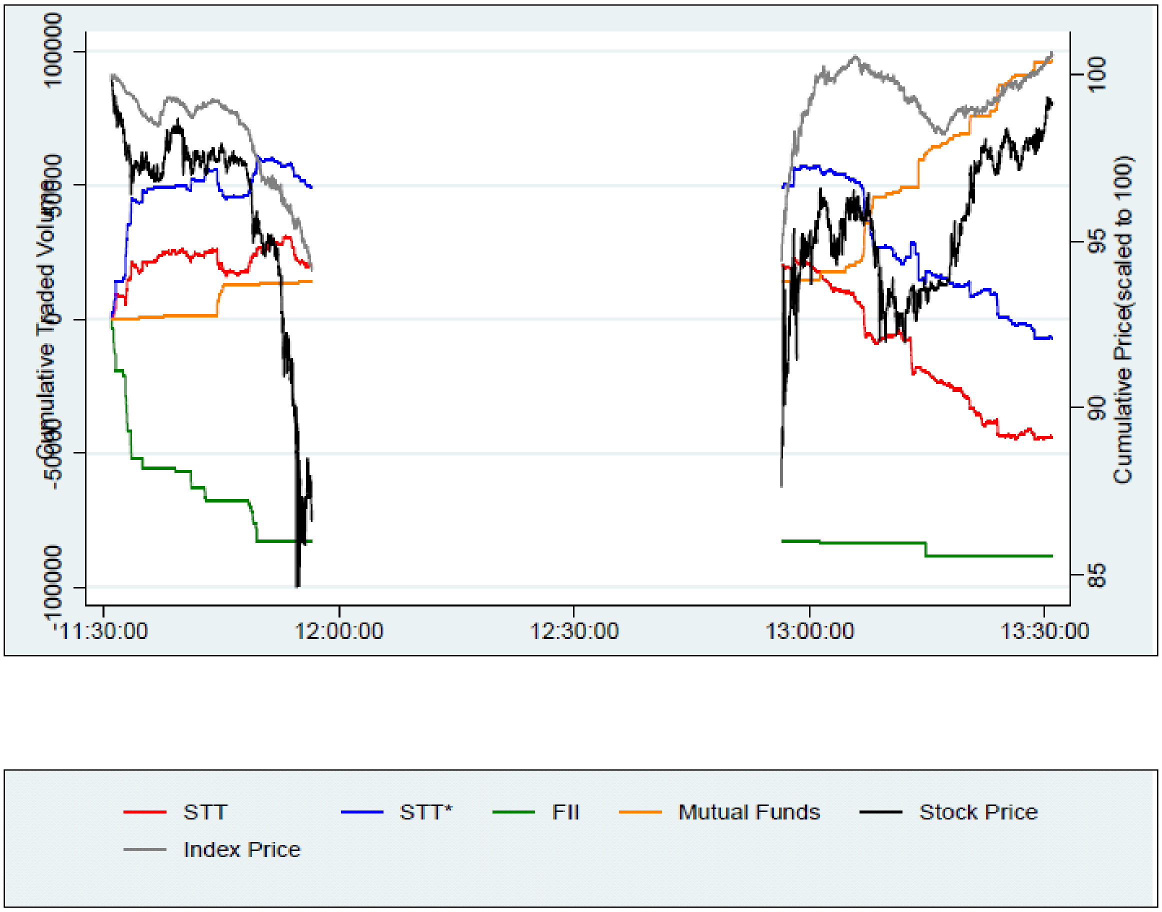
Note: The cumulative price change into private and public components for May 22, 2006.

Figure V.5: Trading by STT, FII and MF on May 19, 2006



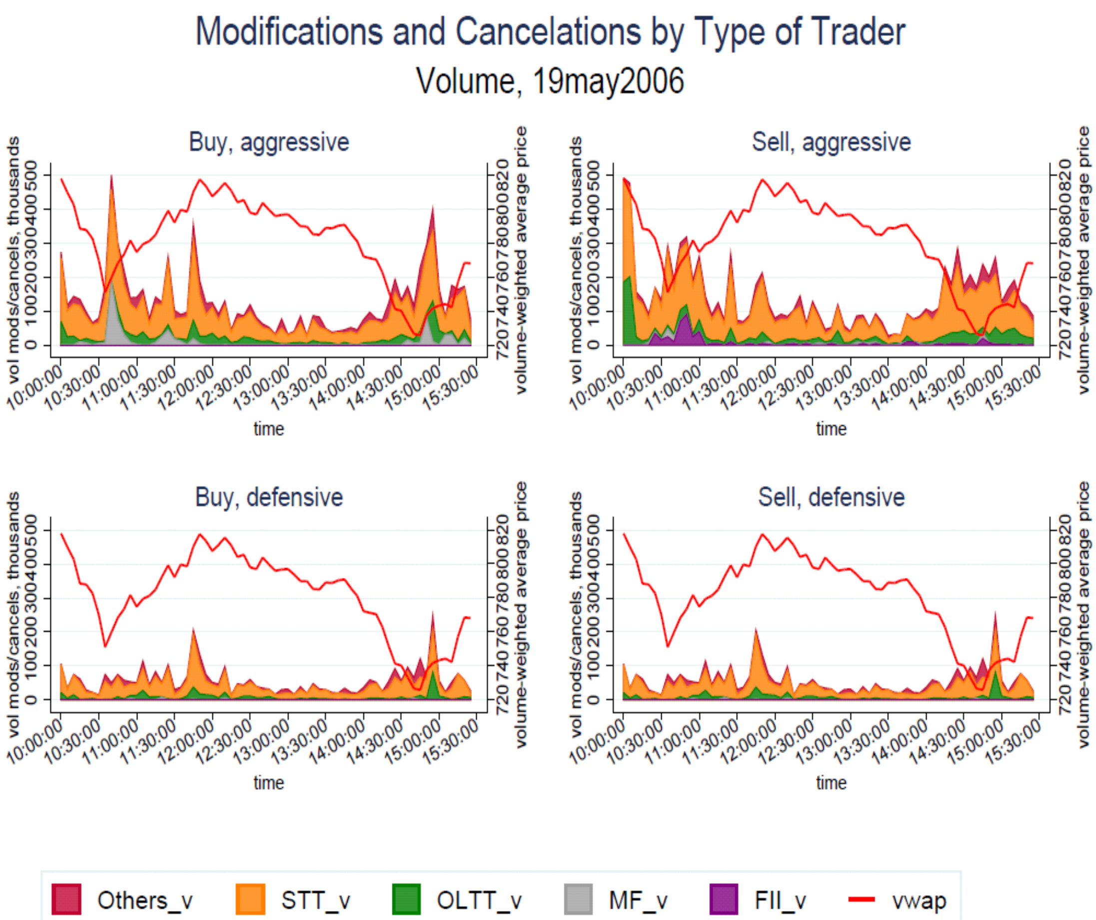
Note: Stock price (right vertical axis) and buy and sell (negative) volume in number of shares (left vertical axis) for Short Term Traders (STT), Foreign Institutions (FII), and Mutual Funds (MF) during the fast crash of May 19, 2006. Stock and NIFTY prices are depicted as well.

Figure V.6: Trading by STT, FII and MF on May 12, 2006



Note: Stock price (right vertical axis) and buy and sell (negative) volume in number of shares (left vertical axis) for Short Term Traders (STT), Foreign Institutions (FII), and Mutual Funds (MF) during the fast crash of May 22, 2006. Stock and NIFTY prices are depicted as well.

Figure V.7: Order modifications and cancellations by trader types on May 19, 2006

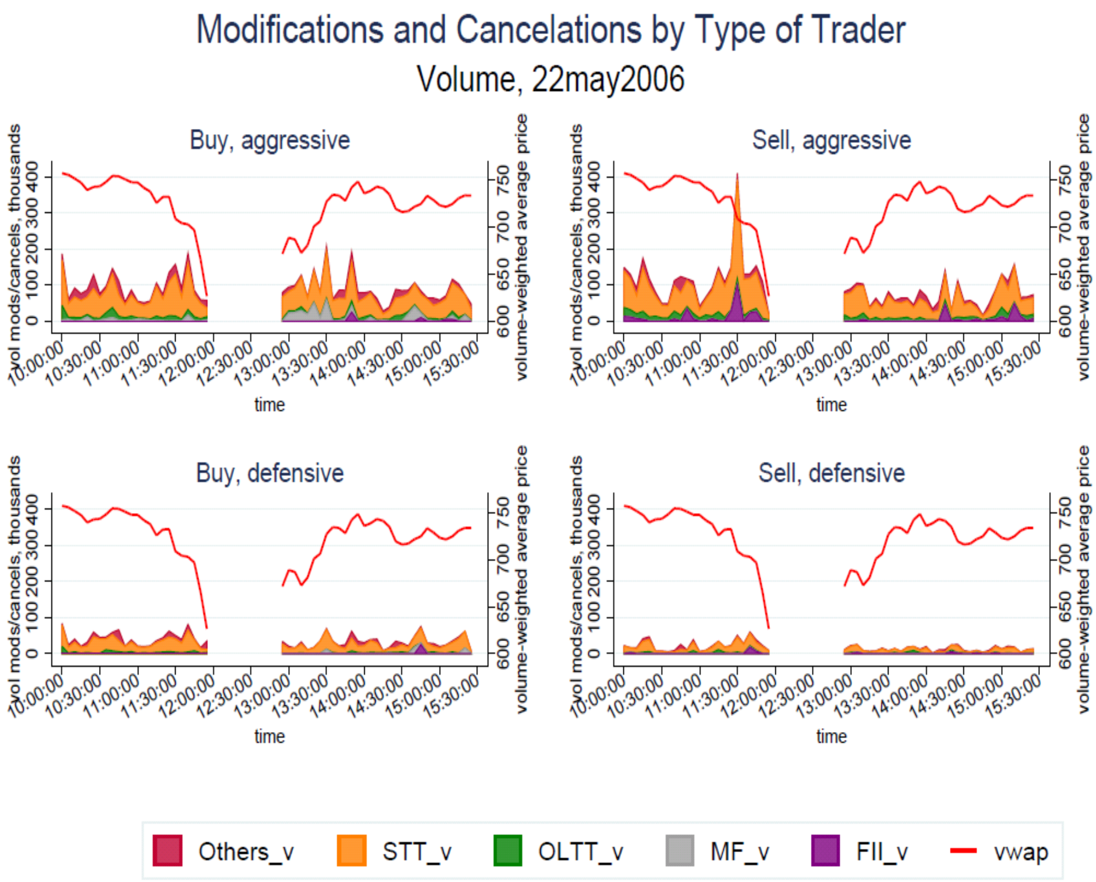


STT - as per new classification and includes ADT + MM + NP_MDT + P_MDT + PDT

Others – includes ODT + Unspec. Inventory Inconsistent + Unspec.

STT* - includes STT + Others

Figure V.8: Order modifications and cancellations by trader types on May 22, 2006

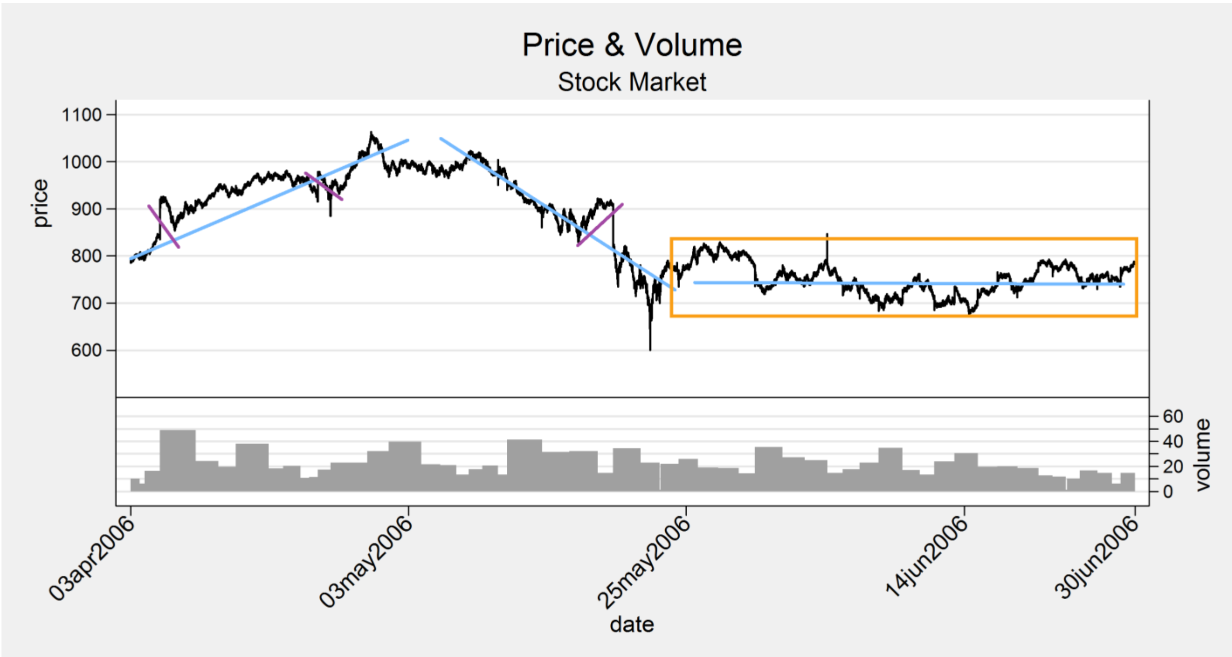


STT - as per new classification and includes ADT + MM + NP_MDT + P_MDT + PDT

Others – includes ODT + Unspec. Inventory Inconsistent + Unspec.

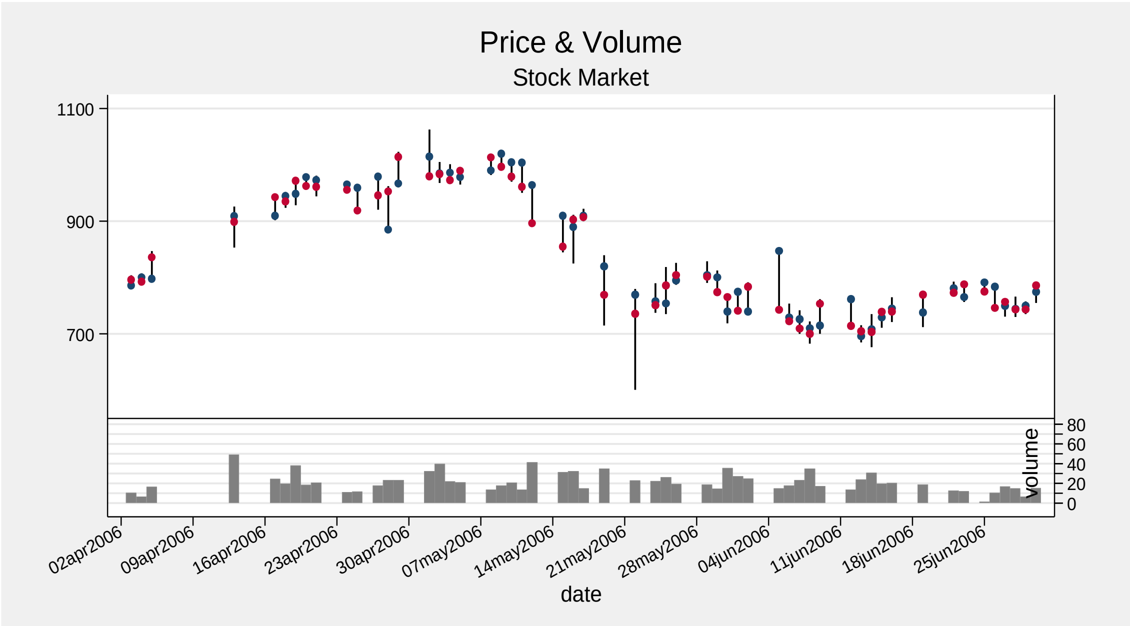
STT* - includes STT + Others

Figure A.1: Price of the stock and the trading volume in the spot market



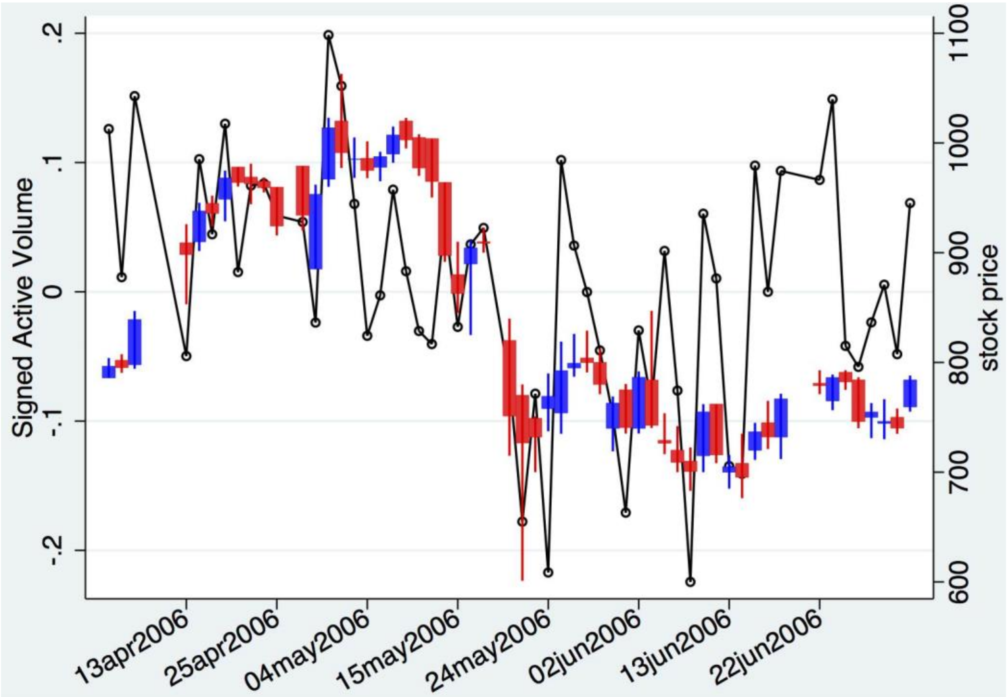
Note: Volume data refer to the daily number of shares sold and bought (in 100,000 shares); Upper panel, y axis: price; Lower panel, y axis: trading volume;

Figure A.2: Stock price and volume bar chart



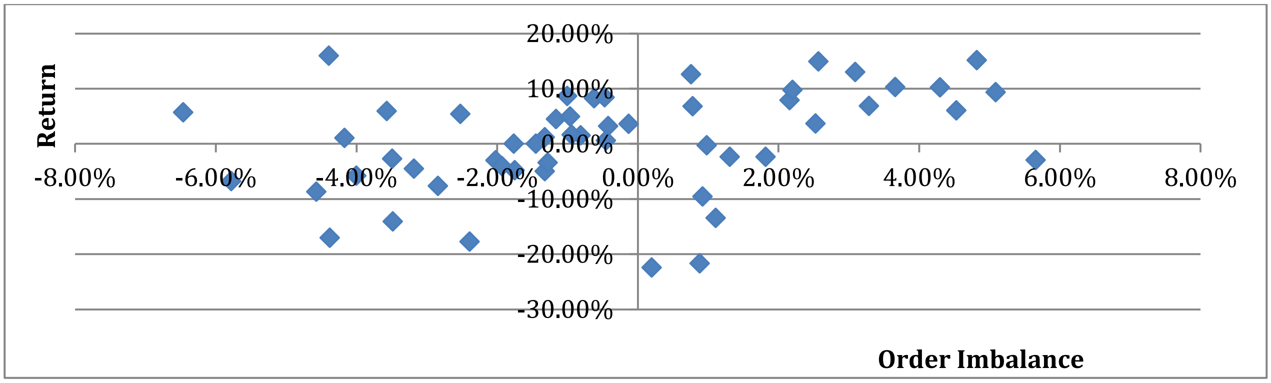
Note: Blue circles: opening price; Red circles: closing price. Bar: indicates maximum and minimum daily prices; Volume data refer to the daily number of shares sold and bought (in 100,000 shares). Upper panel, y axis: share price; Lower panel, y axis: volume.

Figure A.3: Open, Close, Intra-day Max and Min Prices, Buy-Sell Volume



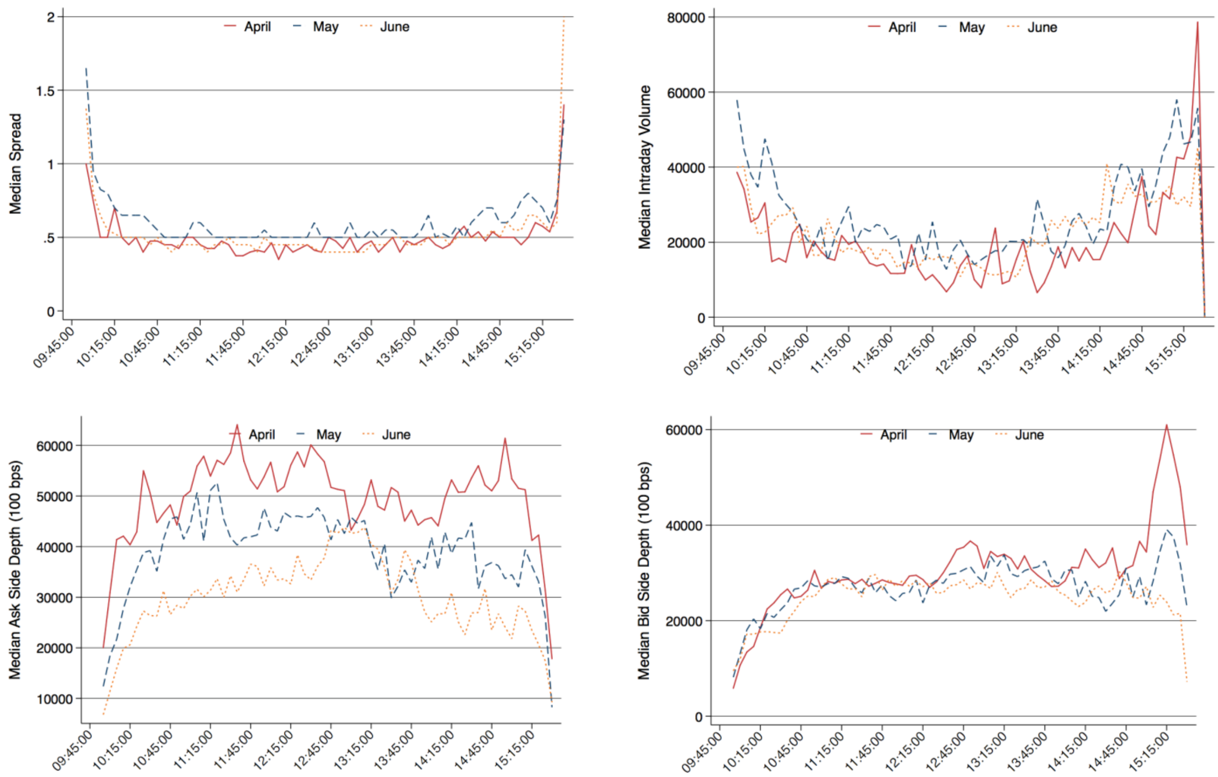
Note: Bar indicates maximum and minimum daily prices (right y-axis); Body of the candlestick indicates opening and closing prices. The candlestick is blue (red) if stock closed lower (higher). Signed active volume refers to the net active trading imbalance as a fraction of daily volume: $\frac{buyer\ initiated - seller\ initiated}{total\ volume}$ (left y-axis).

Figure A.4: Stock Returns vs. order imbalance



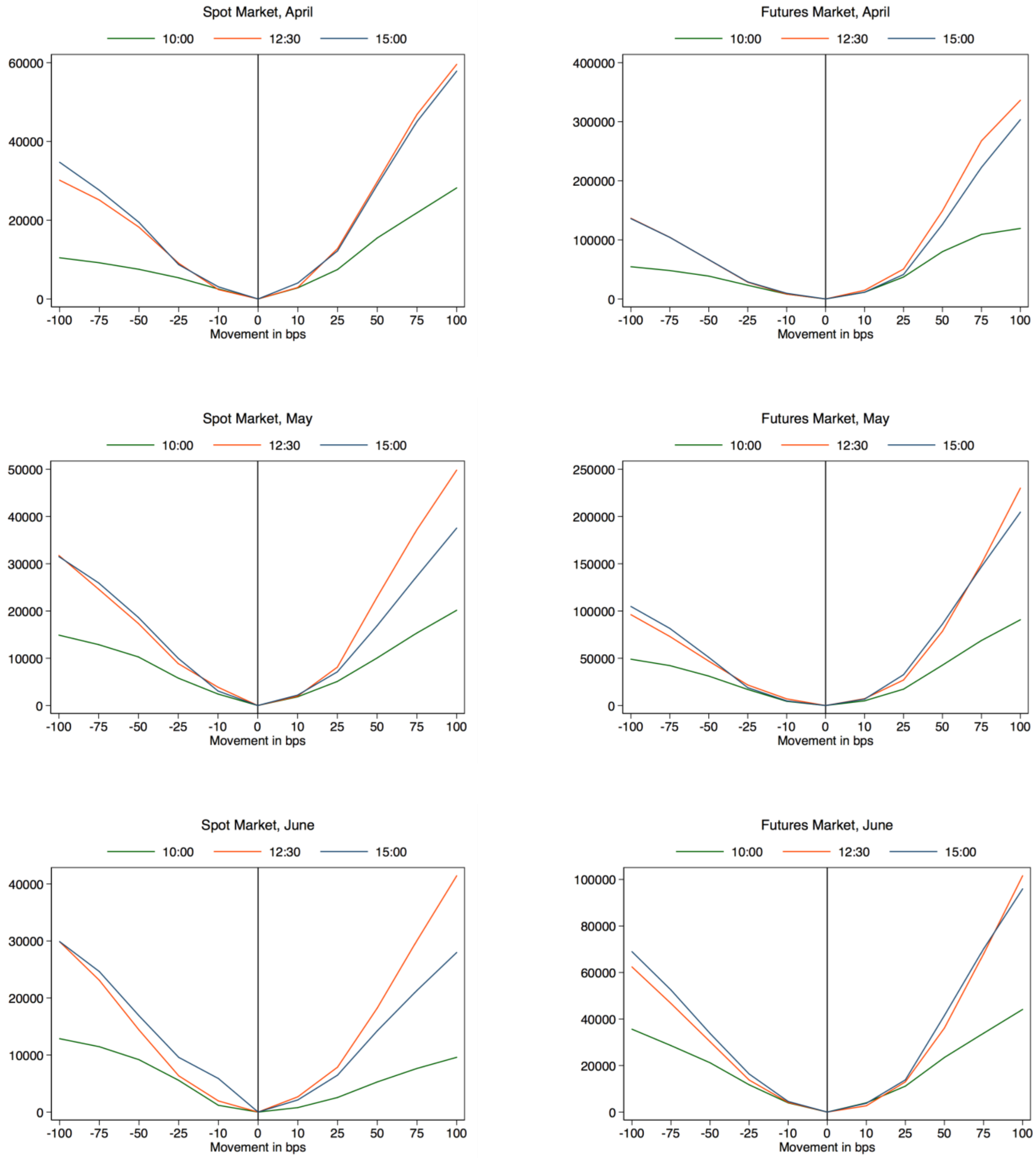
Note: Stock returns versus order imbalance during April 3rd 2006 - June 30th 2006 time period. Stock returns are calculated daily. Daily order imbalance is measured as (buy-sell)/(buy+sell), i.e., buyer initiated volume minus the seller initiated volume divided by the total volume during that day.

Figure A.5: Liquidity Measures for the Spot Market



Note: Liquidity measures for the spot market: median intraday bid-ask spreads, median intraday volume, and median bid and ask side depths. X-axis indicates 5-minute partitions of a daily trading session.

Figure A.6: Depth of the limit order book



Note: Depths of the limit order book for spot and futures markets for April, May, and June 2006. Depths of the limit order book are separated by bid and ask sides and by times: 10 am, 12:30 pm, and 15:00 pm. y-axis: the number of shares it takes to move ask or bid price by the number of basis points depicted in the x-axis. On the x-axis, points to the left of zero correspond to the bid side of the book and points to the right of zero correspond to the ask side.