Liquidity Provision and Market Fragility

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Abstract

We examine the role of short and long term traders in liquidity provision during normal times and during crashes in the spot market for stocks using a unique dataset that has trader identities. The dataset consists of orders and trades in the shares of a single actively traded firm on the National Stock Exchange of India from April to June 2006 when 116 million shares with a combined market value of 100Bn Rupees changed hands. Short term traders who carried little or no inventories overnight were important providers of liquidity and they were on one side of over 75% of the shares traded. We find that during normal times liquidity providers managed their inventory risk through *hot potato trading*, hedging using futures, and order modifications. During normal price fluctuations short term traders put in buy orders when prices declined and sold when prices rose thereby providing liquidity to the market. However, during the two fast crash days in our sample when prices declined and then recovered by more than 3% within a 15 minute interval, their buying was not enough to meet the liquidity needs of foreign institutions who sold into the crashes. Inventories of short term traders were high preceding the two crashes, indicating limited capital capacity and therefore market fragility. Buying by domestic mutual funds, which have a natural advantage in making a market in the basket of stocks they hold, 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

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 where there are no clearly designated market makers who are primarily responsible for liquidity provision, 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 75% of the shares traded. They managed their intraday inventory risk through a *hot potato trading*, hedging through futures, and order modifications.

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[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 70% of the 5-day average notional trading volume in U.S. equities on March 25, 2013 of about $209 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).

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. 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. Order modification is an important tool

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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.

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.

While STT contribute to about 75% of the total trading volume in the spot market for the stocks in our sample period, three fourth 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.

The *flash crash* of May 6, 2010 focused the attention of exchanges and regulators on the need to understand what causes market fragility[10]. 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[11] 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.[12] We add to the literature by documenting the behavior

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10 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.

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

of those who provide liquidity to the market during normal price fluctuations and during fast crashes using data from an electronic limit order book market during a time period where HFTs (as in the US markets) were not present.[13]

During the two fast crashes in our sample order modifications played an important role. 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. Section V analyzes inventory management of STT. In Section VI we study the behavior of STT during two specific days when the market crashes. We conclude in Section VII**.**

II.   Relation to the Literature

The literature on market liquidity during financial crises is growing. 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 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.

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[13] 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.

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.[14] 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 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

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[14] 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.

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 High Frequency Trading (HFT). Examining welfare implications of HFT is difficult in part due to the difficulties associated with modeling the need for liquidity and earlier resolution of uncertainties and the lack of comprehensive data. The literature is vast and we refer the interested reader to Biais, Foucault and Moinas (2013) for an excellent exposition of the issues involved.[15]

The flash crash of May 6, 2010 has focused 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.

We contribute to this literature in two ways. First, we suggest 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. Their trades amongst themselves account for a

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[15] 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.

large fraction of the total trading volume supporting the Viswanathan and Wang (2004) *hot potato* theory of market making in limit order book markets. We also develop an alternative, more direct measure of hot potato trading. When Short Term Traders' (STT) inventory levels are high, ask side liquidity worsens and bid side liquidity improves. Second, during fast crashes order modifications play an important role. We develop a method to summarize the role of order modifications that result in limit order book changes.

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.[16] 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. As can be seen from Tables III.1 and III.2, during this time 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.[17] 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.

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

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[16] Appendix A provides a detailed description of the National Stock Exchange (NSE) and market dynamics.
[17] Each contract is for 750 shares.

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.

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.

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.

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	

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

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.

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.

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.

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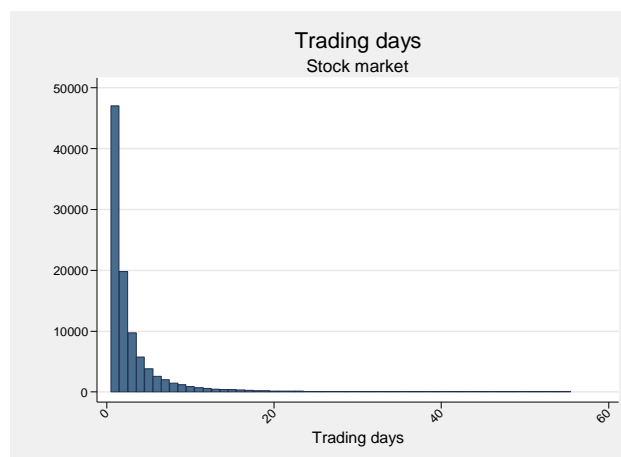
Note: Trading frequency for all spot market traders during April 3rd 2006 to June 30th 2006 time period; X axis: Trading days; Y axis: Frequency;

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 divide traders into LTT, Long Term Traders (those who carry over-night inventory) versus STT, Short Term Traders (those who do not). Next, we consider the limit order submissions. 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 is a short term trader, we denote that trader a Market Maker (MM). 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 is a long term trader, we denote that trader a Long Term Liquidity Provider (LTLP). Long term traders who are not liquidity providers are simply denoted as Other Long Term Traders (OLTT) and further subdivided into some main legal categories (category 1, 2, 4, 6, 12, 13, 99 and other). We also distinguish traders between proprietary and non-proprietary traders. A trader is called proprietary if the trade member id matches the client id; otherwise, he is classified as a non-proprietary trader.

STT who are not MM are subdivided into Passive Day Traders (PDT), if their trades are mostly passive and patient using limit orders, and Active Day Traders (ADT), if their trades are predominantly active and impatient using marketable limit orders. ADT are further sub-divided into legal categories and proprietary/non-proprietary traders.

In summary, we have 5 major categories: MM, LTLP, OLTT, PDT, ADT and 39 detailed categories: MM, LTLP, PDT, OLTTXY, ADTXY, where X denotes the legal category ("1", "2", "4", "6", "12", "13", "99", "other") and Y denotes Proprietary/non-proprietary classification ("P", " "). All categories are non-overlapping by construction.

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. For example, LTLP has 31% of probability of staying in the same category, 26.4% of becoming an ADT, 1.7% of becoming a MM, 22.6% of becoming an OLTT, and 18.4% of becoming a PDT in the next trading day. PDT has only 31.3% of probability of staying the same type, and a large 58.3% probability of becoming an ADT. On

average, many traders are more likely to become ADT compared to MM and LTLP who appear more transient.

Table IV.2 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 only three MM on May 19 and June 12, 2006. There were no LTLP on May 17 and May 19, 2006. We also tabulate results for two legal categories: category 6: Mutual Funds and category 12: Foreign Institutions. These traders belong to our OLTT category. The presence of mutual fund traders on May 19th and May 22nd, two fast crash periods in the sample, is larger than in other days. The presence of foreign institutions is relatively large on May 22nd.

In Table IV.3 we tabulate the intersection of traders in trading behavior based categories and legal categories provided by the NSE for both stock and futures markets. There is no clear mapping between these two different methods of trader categorization. Also, categorization based on trader behavior is dynamic and changes quite a bit over time, as shown in Tables IV.1, 2; however, the legal categories stay fixed throughout the sample.

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

	Current Type				
Previous Type	ADT	LTLP	MM	OLTT	PDT
ADT	84.8	0.0	0.1	9.0	6.1
LTLP	26.4	31.0	1.7	22.6	18.4
MM	42.5	0.6	15.7	8.2	32.9
OLTT	37.6	0.1	0.1	58.4	3.9
PDT	58.3	0.1	0.9	9.3	31.3
Total	74.1	0.1	0.2	17.9	7.7

 Note: Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader).

Figure IV.1: Hierarchy for Trader Categories
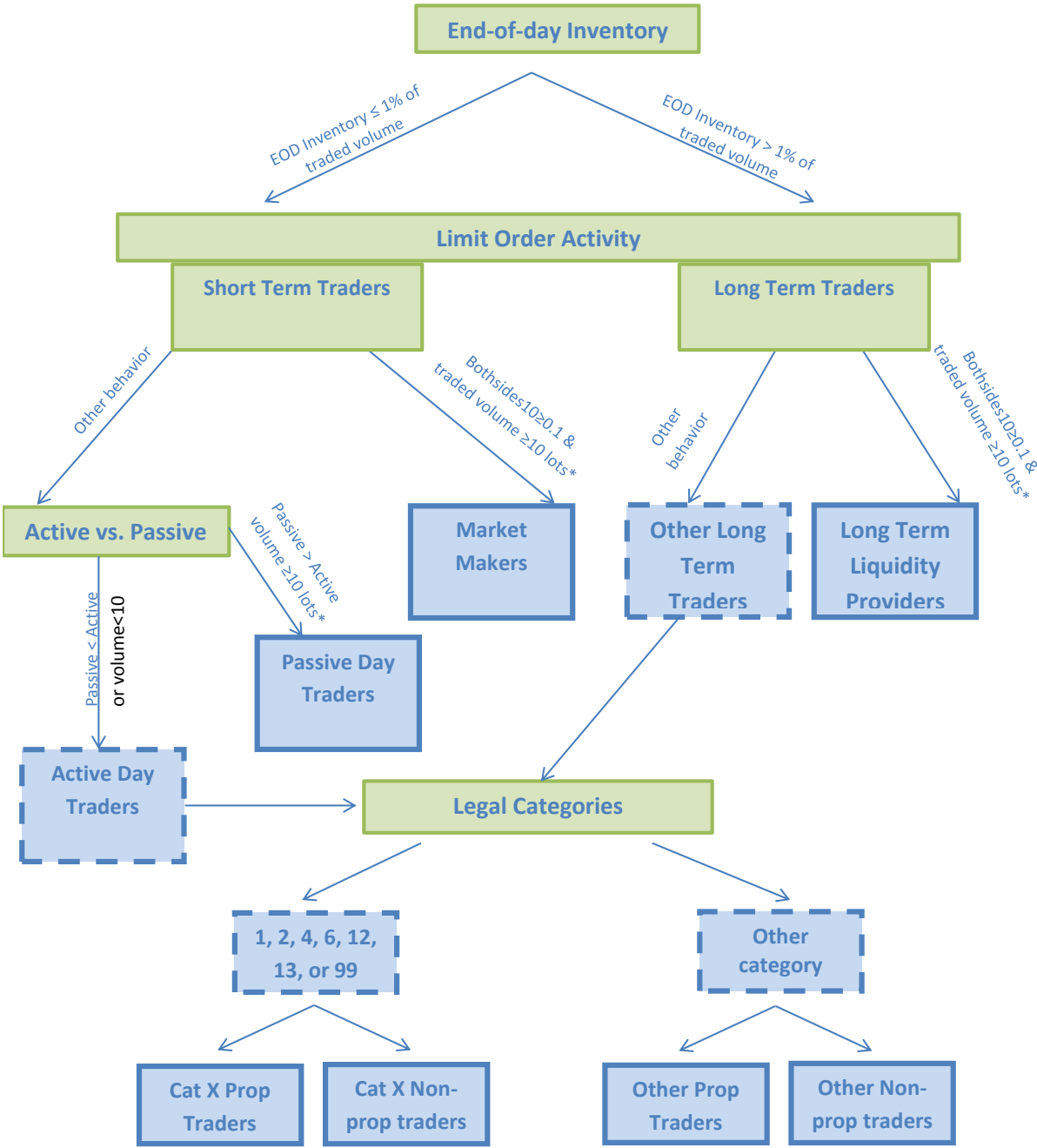
* A trading lot is defined as 10 shares in the stock market, and 750 shares in the futures market

In Table IV.4 we report the average holding time of a stock for different trader categories. Average holding time (in minutes) is computed as 3,600/(RI). RI, the rotation index, is computed as the total number of shares bought or sold on that day divided by the average daily total inventory. It is a measure of inventory turnover. The stock trades for 6 hours (3,600 minutes) on the NSE. The holding time is the average time the stock remains in the trader's portfolio.

We only have data for 3 months of trades with no information about previous inventory information. For traders that have no inventories at the end of the day, such as MM, ADT and PDT, our calculation of the average holding time will be accurate. However, we will underestimate inventories for other cases such as LTLP and OTLL traders. Therefore, we calculate average holding times using two different method and results are presented in Table IV.4. Column (1) reports holding periods based on the assumption that no inventories are carried over from one day to another, and intra-day inventories are calculated based on the trading activity during that day, and Column (2) reports holding periods based on the assumption that inventories are accumulated throughout our sample.

As expected from our definitions based on trading behavior, the average holding period for PDTs is shorter than that for other classes of traders, and the holding period is the longest for OLTT and LTLP. If we assume that no inventories are carried over from one day to another and intra-day inventories are calculated based on the trading activity during that day (Table IV.4 Column 1), we show that the average holding time for PDT is 3 minutes compared to the average holding time for OLTT of 21 minutes, i.e., the order of 7 magnitudes difference. If we assume that inventories are accumulated throughout the sample (Table IV.4 Column 2), the holding periods for LTLP and OLTT are three times as large as holding periods with no inventory carry-over assumption. This indicates that these traders tend to hold stock for longer periods of time. This is consistent with our categorization of traders depicted in Figure IV.1 as LTLP and OLTT are long term liquidity providers and other long term traders, respectively.

Table IV.2: Number of Traders by Trader Classification

	MM	PDT	ADT	LTLP	OLTT	MF 6	FI 12		MM	PDT	ADT	LTLP	OLTT	MF 6	FI 12
03-Apr-06	13	355	1504	9	1161	13	4	24-May-06	8	647	2766	3	2085	18	4
04-Apr-06	12	250	1084	7	910	5	4	25-May-06	9	729	3242	6	1819	13	3
05-Apr-06	17	632	2248	8	1784	8	3	26-May-06	15	936	3690	4	2034	10	1
13-Apr-06	27	1301	4306	6	2206	11	9	29-May-06	21	828	3207	4	1646	8	2
17-Apr-06	29	999	3774	5	1949	10	4	30-May-06	21	741	2981	3	1951	6	1
18-Apr-06	21	842	3252	5	2090	12	6	31-May-06	13	1024	4018	6	2301	8	15
19-Apr-06	34	1217	4459	3	2266	13	6	01-Jun-06	15	773	2907	2	1511	11	10
20-Apr-06	30	725	3283	7	1699	18	5	02-Jun-06	14	806	3086	4	2871	9	5
21-Apr-06	20	753	2907	2	1527	13	3	05-Jun-06	12	658	2571	5	1905	7	8
24-Apr-06	15	443	1791	2	1002	12	5	06-Jun-06	16	777	3047	5	1454	10	5
25-Apr-06	8	310	1524	3	1488	11	4	07-Jun-06	14	818	3200	2	1687	14	7
27-Apr-06	10	470	2070	5	1910	13	3	08-Jun-06	17	951	3834	3	2076	13	11
28-Apr-06	16	647	2594	3	1336	20	5	09-Jun-06	20	761	3078	3	2355	9	5
02-May-06	14	495	2499	6	3058	21	8	12-Jun-06	3	609	2445	7	1452	9	3
03-May-06	25	1129	4485	4	2275	11	9	13-Jun-06	15	871	3396	5	1276	10	15
04-May-06	22	777	3172	3	1791	9	13	14-Jun-06	18	871	3999	2	1386	24	5
05-May-06	25	770	2934	4	1197	9	7	15-Jun-06	15	912	3304	7	2031	14	6
08-May-06	19	568	2263	7	1893	8	5	16-Jun-06	18	935	3867	6	2028	13	5
09-May-06	16	567	2493	7	1552	13	8	19-Jun-06	22	990	4125	4	1755	11	5
10-May-06	24	534	2459	8	2327	11	11	22-Jun-06	22	765	3079	4	1726	8	5
11-May-06	16	393	1887	2	1413	10	9	23-Jun-06	16	785	3105	3	1106	16	4
12-May-06	29	990	3950	7	5555	26	3	26-Jun-06	19	534	2139	3	1389	12	7
15-May-06	17	983	3773	3	3863	19	4	27-Jun-06	7	715	2812	4	801	18	9
16-May-06	12	970	3422	2	2971	12	7	28-Jun-06	14	733	2903	7	757	10	5
17-May-06	34	818	3079	0	1960	6	0	29-Jun-06	9	455	1699	8	857	10	4
19-May-06	8	731	3037	0	4545	25	3	30-Jun-06	20	608	2318	3	2241	11	5
22-May-06	3	667	2483	1	3780	16	7								

Note: Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader). MF 6 is a legal category 6: Mutual Funds, and FI 12 is a legal category 12: Foreign Institutions.

Table IV.3: Intersection of traders in trading behavior and legal categories

	Legal Category	ADT	PDT	MM	LTLP	OLTT
1	Individual traders	2634.6	649.6	13.2	1.7	1650.9
2	Partnership firm	8.6	2.7	1.0	1.0	5.7
3	Hindu undivided family	18.9	7.3	1.1	1.0	19.7
4	Public & private companies/corporate bodies	47.8	29.5	2.8	2.1	41.5
5	Trust/society	1.1	1.0	0	0	1.3
6	Mutual fund	1.0	1.0	0	0	12.4
7	Domestic financial institution	1.0	0	0	0	1.3
8	Bank	1.0	1.0	0	0	6.3
9	Insurance	1.0	0	0	0	4.3
10	Statutory bodies	1.4	1.0	0	0	1.1
11	Non-resident Indians	1.0	1.0	0	0	16.0
12	FII Foreign Institutional Investors	1.0	0	0	0	6.0
13	Overseas corporate bodies	17.8	10.4	1.1	1.3	16.1
99	Missing	243.2	47.1	1.5	1.2	201.2
	Average Total number	2979.4	751.5	20.5	8.3	1983.7

Note: Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader).

**Table IV.4: Average holding periods for traders in trader behavior categories**

	(1)		(2)	
	Mean(minutes)	std.dev.	Mean(minutes)	std.dev.
ADT	5.24	1.22	5.24	1.22
MM	7.48	2.77	7.48	2.77
PDT	3.10	1.02	3.10	1.02
LTLP	17.94	11.55	66.31	55.20
OLTT	21.37	7.29	63.96	32.47

Note: Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader). Column (1) reports holding periods based on the assumption that no inventories are carried over from one day to another, and intra-day inventories are calculated based on the trading activity during that day, and Column (2) reports holding periods based on the assumption that inventories are accumulated throughout our sample. All holding periods are in minutes.

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.
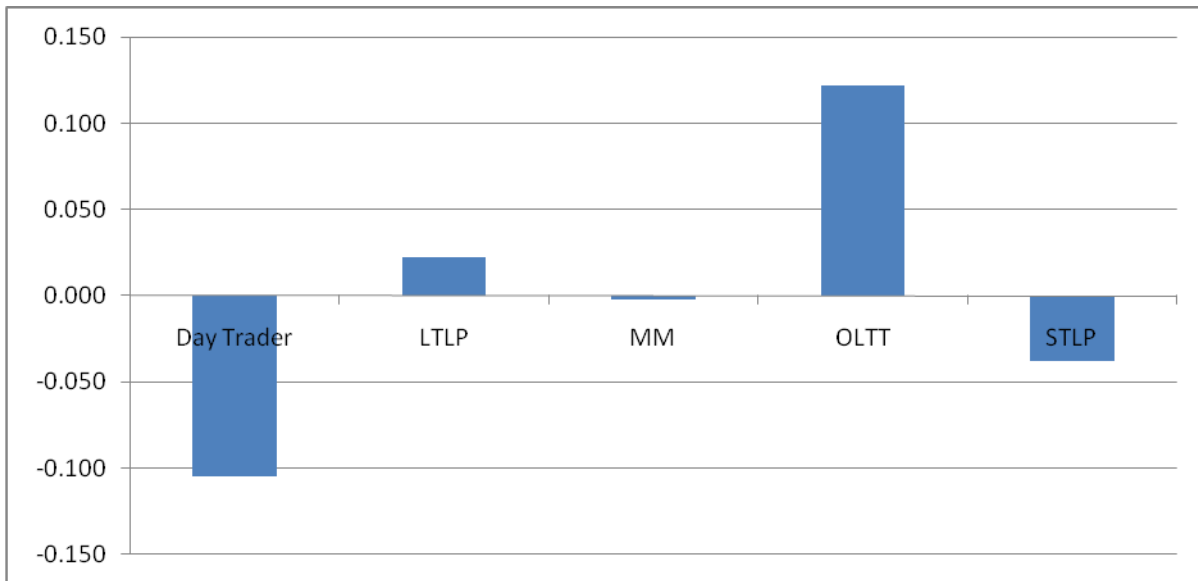
Figure IV.2: Net buys and sells during the first 30 minutes of the trading day by trader type
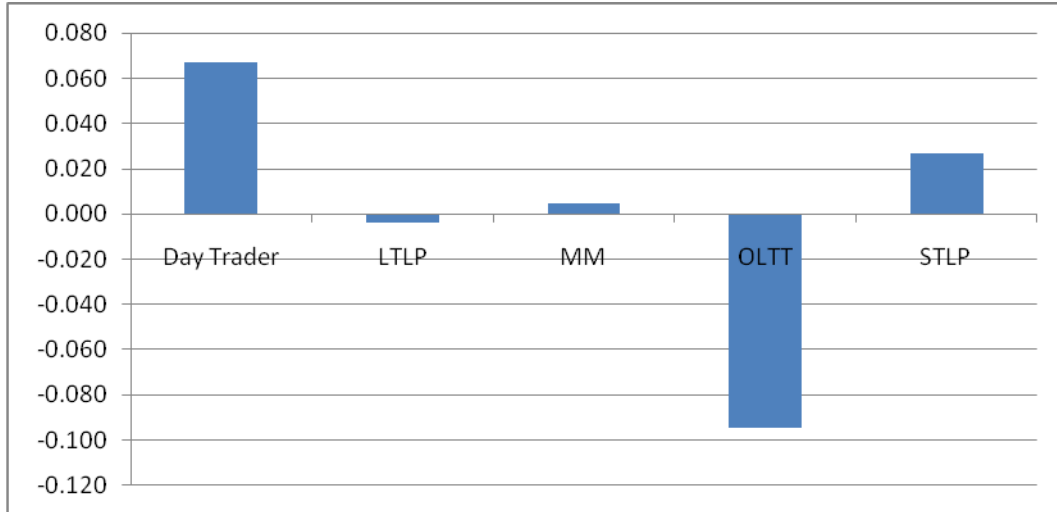
Note: Net buys and sells during the first 30 minutes of the trading day for different trader categories. Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader).

Figures IV.2 and IV.3 below 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.

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), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader).

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).

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.

In Table IV.5 we show that price elasticity (the number of shares required to be traded to move price by a given amount) 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.5.

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

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.5, there is a significant positive relationship between the price elasticity of the limit order book and the inventory levels for all the traders on the ask side with the exception of OLTPs. When the inventories are high (i.e. large and positive), the volume of shares purchased required to move prices up by 25, 50, 75, or 100bp increases. The coefficients are significantly different from zero for ADT, STLT (ADT+MM+PDT), LTLP, and PROP Traders. Conversely, the volume sold required to drive prices down by 25, 50, 75, or 100bp decreases, indicating lower liquidity on the offer side of the book, when inventories increase, for ADT, MM, STT (ADT+MM+PDT), LTLP, and PROP 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. We also use signed trading volume but it has little effect in explaining variations in the slope of the order book over time. Other long term traders (OLTT) typically are patient in their selling and buying activities. When they are buying and building up their inventories, the inventories of short term liquidity providers (PDT, ADT, MM, and PROP traders) get depleted, and hence we should expect the number of shares that will have to be bought to move prices up by a given number of basis points to fall, i.e., the coefficient for the ask side should be negative. For similar reasons we should find the coefficient on the bid side to be positive − i.e., the sign of the coefficients should be opposite for PDT, ADT, MM, and PROP traders. That is what we find.

We next examine the relation between price elasticity and inventory level of traders in legal categories and separate traders into liquidity demanders and liquidity providers, on average. Table IV.6 shows that Category 6 (Mutual funds) appear to be strongly significant liquidity demanders on the ask side (when they buy, price elasticity on the ask side rise, i.e. liquidity falls). However, they have no significant effect on the offer side of the order book. On the other hand, category 2 (Partnerships) and category 1 (Individuals) appear to hold inventories consistent with providing liquidity on the ask side of the book. Finally category 4 (Corporations) appear to be providing liquidity on the ask side of the book but demanding liquidity on the bid side of the book on average over the time period considered.

Table IV.5: Price elasticity and trader behavior based categories inventory relationships

	ask 100bp	bid 100bp	ask 75bp	bid 75bp	ask 50bp	bid 50bp	ask 25bp	bid 25bp
ADT	0.375**	-0.300	0.368***	-0.342	0.320***	-0.228	0.177***	-0.0939
Inventory	(2.60)	(-1.23)	(2.68)	(-1.39)	(3.15)	(-1.44)	(3.80)	(-1.34)
MM	0.267	-0.437**	0.303**	-0.434***	0.286***	-0.384***	0.140***	-0.284***
Inventory	(1.69)	(-2.34)	(2.28)	(-3.02)	(3.09)	(-3.42)	(3.18)	(-3.51)
PDT	0.0842	0.245	0.193	0.152	0.262	0.0827	0.275***	0.0531
Inventory	(0.71)	(1.66)	(1.21)	(1.26)	(1.81)	(0.85)	(2.93)	(0.88)
ADT+MM+PDT	0.294***	-0.271	0.324***	-0.303**	0.307***	-0.253**	0.183***	-0.163**
Inventory	(2.80)	(-1.75)	(3.41)	(-2.09)	(4.51)	(-2.38)	(5.19)	(-2.61)
MM+PDT	0.234	-0.265	0.289***	-0.286**	0.295***	-0.269**	0.185***	-0.200***
Inventory	(1.92)	(-1.74)	(2.80)	(-2.28)	(4.01)	(-2.62)	(4.35)	(-2.69)
LTLP	0.339**	-0.118	0.283	-0.113	0.196	-0.0776	0.105	-0.0296
Inventory	(2.16)	(-0.65)	(2.00)	(-0.76)	(1.80)	(-0.73)	(1.85)	(-0.48)
OLTT	-0.0164	0.0142	-0.0144	0.0195	-0.0135	0.0234**	-0.0124**	0.0262***
Inventory	(-1.76)	(1.26)	(-1.60)	(1.63)	(-1.90)	(2.09)	(-2.50)	(2.83)
PROP	0.223***	-0.129	0.226***	-0.141	0.200***	-0.119	0.115***	-0.0739
Inventory	(3.01)	(-1.39)	(3.43)	(-1.71)	(4.15)	(-1.91)	(4.35)	(-1.92)
Signed	0.0166	0.0170	0.0137	0.0170	0.00884	0.0180	0.00346	0.00643
Volume	(0.92)	(0.26)	(0.91)	(0.31)	(0.81)	(0.47)	(0.62)	(0.30)
Observations	68,935	68,877	69,000	68,994	69,000	69,000	69,000	69,000

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. The trader categories are 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). 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. $^*p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

To summarize, the results in Tables IV.5 and IV.6 support the view that when inventories of traders who provide liquidity in the market are relatively large, ask side liquidity worsens and bid side liquidity increases, consistent with various models of market making in the literature.[18] We hypothesize that the reluctance of short term traders - PDT, ADT, MM, and PROP 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 trading volumes.

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.

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.

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 VI.

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

Table IV.6: Price elasticity and legal categories inventory relationships

	ask 100bp	bid 100bp	ask 75bp	bid 75bp	ask 50bp	bid 50bp	ask 25bp	bid 25bp
Inventory Cat = 1	0.0144	-0.00880	0.0307	-0.0193	0.0426**	-0.0178	0.0316***	-0.00619
	(0.53)	(-0.34)	(1.54)	(-0.76)	(2.60)	(-0.90)	(3.09)	(-0.49)
Inventory Cat = 2	0.256**	-0.0916	0.243**	-0.112	0.160**	-0.120	0.0734**	-0.0879
	(2.06)	(-1.04)	(2.19)	(-1.34)	(2.35)	(-1.71)	(2.01)	(-1.74)
Inventory Cat = 3	3.397	-0.177	2.585	-2.582	2.034	-4.145**	0.986	-3.224***
	(1.24)	(-0.04)	(1.12)	(-0.94)	(1.26)	(-2.04)	(1.03)	(-2.76)
Inventory Cat = 4	0.0114	0.0209	0.0143**	0.0214**	0.0113**	0.0233**	0.00669**	0.0214***
	(1.57)	(1.72)	(2.21)	(2.08)	(2.01)	(2.60)	(2.24)	(3.46)
Inventory Cat = 6	-0.0256***	0.0178	-0.0233***	0.0100	-0.0181***	0.00219	-0.0127***	0.00478
	(-4.61)	(0.77)	(-4.33)	(0.60)	(-3.96)	(0.18)	(-4.75)	(0.57)
Inventory Cat = 8	-0.979	0.332	-0.840	0.222	-0.611	0.220	-0.281	0.267
	(-1.50)	(0.47)	(-1.41)	(0.36)	(-1.30)	(0.47)	(-0.90)	(1.13)
Inventory Cat = 9	-0.896	1.186	-0.767	1.258	-0.473	1.133	-0.377	1.307
	(-1.85)	(1.53)	(-1.76)	(1.43)	(-1.37)	(1.14)	(-1.64)	(1.33)
Inventory Cat = 12	0.000679	-0.00304	0.00126	-0.00301	0.000684	-0.00162	-0.00108	0.000510
	(0.33)	(-0.79)	(0.68)	(-0.89)	(0.42)	(-0.82)	(-0.88)	(0.52)
Inventory Cat = 13	0.243	0.0151	0.158	-0.0169	0.124	0.0140	0.0404	0.00504
	(1.51)	(0.11)	(1.16)	(-0.14)	(1.36)	(0.16)	(0.74)	(0.09)
Inventory Cat = 99	0.342	0.296	0.315	0.202	0.292	0.140	0.146	0.00598
	(0.56)	(1.02)	(0.57)	(0.78)	(0.75)	(0.68)	(0.84)	(0.06)
Observations	68943	68919	68986	68985	68986	68986	68986	68986

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. $* \ p < 0.05$, $** \ p < 0.05$, $*** \ p < 0.01$.

Using the Lunde and Timmermann (2004) algorithm we have identified several peaks and troughs and tabulated summary statistics in Table IV.7. During our 8 weeks of data, there is at least one peak per day and at least one peak to trough. The duration of normal boom-bust cycles vary across cycles.

Table IV.7: Characteristics of Normal Boom-Bust Cycles

Weeks	Median # of peaks per day	Median Duration of Trough to Peak (seconds)	Median # of Peaks to Troughs	Median Duration of Peak to Trough (seconds)
1	2	3,063	1	3,126
2	2	1,605	1	5,505
3	2	1,245	1	11,298
4	4	524	4	726
5	2	2,406	2	2,697
6	3	1,995	3	2,691
7	4	3,162	3	2,304
8	1	1,766	1	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.

Having identified normal booms and bust cycles, we study whether Short Term Traders (STT) tend to increase their inventories during such normal cycles. We study this question using the Probit model. Specifically, we construct a variable "rolling down", Y_t, which takes the value of 1 when prices are declining (Peak to Trough) and takes the value of 0 when prices are recovering (Trough to Peak). We then estimate the probability of a given time being a "rolling down" period using a Probit model. The explanatory variables are the inventories of liquidity providers. The Probit model specification is given below:

$Pr(Y_t=1|X) = Pr(Y^*_t > 0) = Pr(\alpha + X'_t\beta + \varepsilon_t > 0)$

where X_t is inventory Inv_t. We performed this analysis using inventories of Short Term Traders (ADT, MM, and PDT). For convenience we divided the time within a trading day into 3 minute intervals. The results are reported in Table IV.8.

It can be seen from Table IV.8, when ADT and STT are increasing their inventories, the probability of being in a "rolling down" period (peak to trough) is more likely. In contrast, when PDT are decreasing their inventories normal busts are more likely; it appears that PDT are selling into normal busts thereby demanding liquidity. Taken together, when short term liquidity traders are increasing their inventories, the probability of being in a "rolling down" period increases.

These findings are consistent with STT buying during normal busts and selling during normal booms thereby providing liquidity and stabilizing prices.

Table IV.8: Probabilities of "Rolling down" periods, Probit Model

	Probability of "Rolling down"	
	coeff	t-stat
ADT	0.035	176.5
MM	0.006	0.0
PDT	-0.007	-4.0
STT	0.009	18.8

Note: Probability of being in a "rolling down" (peak to trough) period using Probit model for ADT (Active Day Trader), MM (Market Maker), PDT (Passive Day Trader), and Short Term Traders (STT=ADT+MM+PDT). Inventory of traders is the explanatory variable. Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis.

The Probit analysis allowed us to investigate the behavior of traders during price declines and price recoveries. However, the duration of rapid downturns and recoveries in the sample differs considerably as presented in Table IV.6, i.e. the time it takes to reach the bottom of the trough of 1.5% varies. Specifically we are interested to investigate whether an increase of inventories by the short terms traders is associated with the increase of trough duration. To investigate this hypothesis we use duration analysis, which has been widely used in labor economics to study the duration of periods of unemployment and in macroeconomics to investigate the duration of expansions and contractions. In our analysis the duration variable is defined as the number of seconds that the market is in a state of peak or trough, identified using the Lunde and Timmermann (2004) algorithm as described above.

Let define T as the discrete random variable that measures the time from the trough to a point in the rolling up period (or time from the peak in to a point in time in the rolling down period) and t1, t2,. . ., tn represent the observed duration of each rolling down (peak to trough) or rolling up (trough to peak) period.

The cumulative distribution of the duration variable T (called also failure function) is formally represented as:

$$F(t) = P(T < t)$$

and measures the probability that the random variable T being smaller than a certain value t. For t equal to infinity this probability is 1 and for t equal to 0 this probability is zero. The corresponding density function is:

$$f(t) = dF(t)/dt$$

A complementary function to the failure function is the survival function

$$S(t) = \Pr(T > t) = 1 - F(t)$$

that represents the probability that the duration to a peak (or a trough) is greater or equal to t.

The hazard function is the conditional probability of having a peak (or a through) with a duration of exactly t, conditional on survival up to time t:

$$\theta(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)}$$

The model we have used to estimate the distribution parameter of the duration to a peak or a trough is the Weibull function with a characterization of the hazard rate as:

$$\theta(t, X) = \alpha t^{\alpha-1} \exp(\beta' X)$$

where β is a K x 1 vector of parameters to be estimated and X is a vector of covariates. The covariate that we consider in our analysis is the average change of inventories per periods. Our hypothesis is that the duration of a trough is longer when the liquidity providing traders that we have identified significantly increase their inventories. Results are reported in Table IV.9. Note, as above results exclude the two fast crash days (May 19 and May 22, 2006) since Section VI is specifically dedicated to the analysis of fast crashes.

As Table IV.9 shows, the inventory coefficient is always positive and significant for MM, PDT, and STT. This means that when these traders' inventories increase, the rolling down period is likely to last longer. Taken together, we find that duration of the time to recovery takes longer when liquidity providers and traders increase their inventories by a larger amount.

Finally we examine liquidity provision during normal price fluctuations that frequently occur during a trading day due surges in demand for liquidity. We denote such price fluctuations as normal booms and busts. For that purpose we classify small peaks and troughs in stock prices within each trading day (excluding the two fast crash days – May 19 and May 22, 2006) using the algorithm in Lunde and Timmerman (2004) as we described earlier with the following modification. Since some of the durations (|peak time-trough time|) are too short (2-3 seconds), we truncated the observations with durations $<10^{th}$ percentile (33 seconds). Table IV.10 provides the summary statistics of duration periods for the "rolling down", "rolling up" and for the full sample of normal busts and booms ("rolling down" and "rolling up"), after truncation.

Table IV.9: Weibull duration estimation

	Duration	
	Coeff	**z-stat**
ADT	1.00	0.45
MM	**1.01**	**3.48**
PDT	**1.01**	**9.52**
STT	**1.01**	**8.54**

Note: The impact of the change of traders' inventory on the duration of a 1.5% trough. Categories analyzed are: Active Day Traders (ADT), Market Makers (MM), Passive Day Traders (PDT), and Short Term Traders (STT=ADT+MM+PDT). Three second intervals are used for the Weibull duration analysis. Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis.

Figure IV.4 provides the number of net trades by the traders in the five behavioral categories during the beginning, middle and the end of the "rolling down" period (peak to trough) and Figure IV.5 provides this information for the "rolling up" period (trough to peak).

As can be seen, Passive Day Traders consistently provide price support (net buyers) when prices are "rolling down" during normal busts, and price recovery in such busts takes place through buying by Active Day Traders and Other Long Term Traders.

Table IV.10: Characteristics of Winsorized Normal Booms/Busts

| Peak/Trough	N	Duration Mean (In seconds)	Duration Median (In seconds)
Full Sample	254	4797.74	2296.5
"Rolling Down"	125	5208.17	2334
"Rolling Up"	129	4400.05	2142

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.

Figure IV.4: Trades in behavioral categories during the "rolling down" period
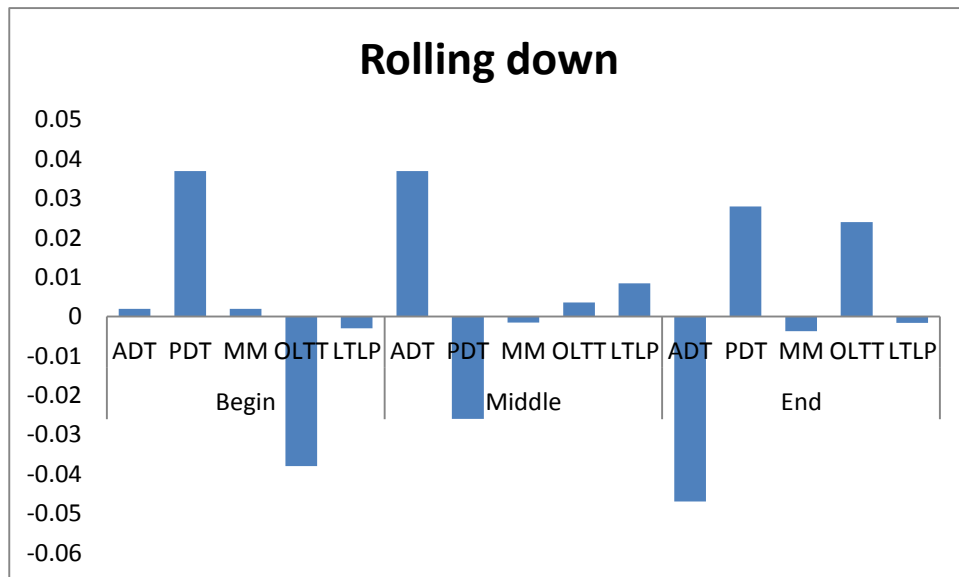
Note: Net trades during the Begin, Middle, and End "rolling down" periods for different trader behavior categories. Categories are ADT (Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader).

Figure IV.5: Trades in behavioral categories during the "rolling up" period
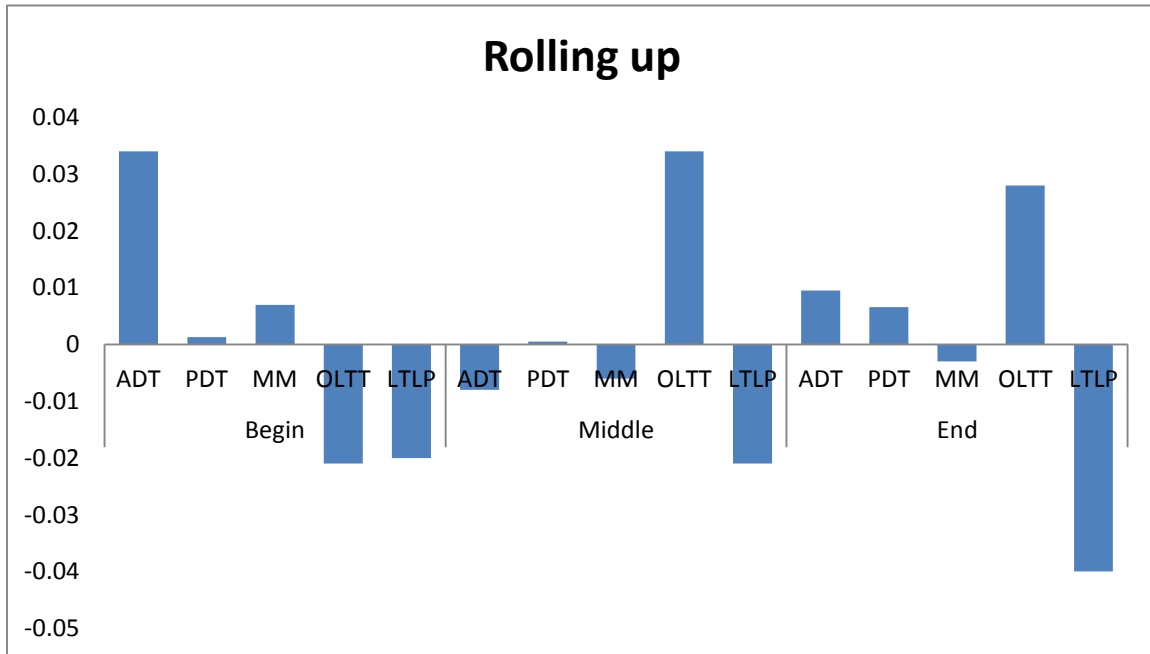
Note: Net trades during the Begin, Middle, and End "rolling up" periods for different trader behavior categories. Categories are ADT (Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader).

V.   Inventory Risk Management by Short Term Liquidity Providers

In this section we examine how those who provide short term liquidity manage their inventory risk. There are at least three ways in which short term liquidity providers can manage their intraday inventories: (i) hot potato trading, (ii) hedging through futures, and (iii) withdrawing (partially) from one side of the limit order book in order to passively adjust their inventories.

V.A "Hot Potato" Trading

As we discussed earlier, the conventional wisdom is that trading among those who make a market i.e., buy or sell through limit orders, helps dealers manage their inventory risk by reducing inventory holding periods. This inventory management behavior results in significant active

trading among market makers known as "hot potato" trading. Viswanathan and Wang (2004) model market making and trading in the presence of inventory costs and risk aversion. In this model a short term trader (could be MM, PDT, ADT, or at times a LTLP or OLTT) keeps a part of the inventory and sells the rest at the bid to other market makers. This reduces the market power of other market makers/traders, allows for better execution for the shares he sells, and generates "hot potato" trading. In general, "hot potato" trading is associated with an increased likelihood of an active sell (buy) following a passive buy (sell). We therefore examine whether there is a significant amount of "hot potato" trading in the market for the firm's shares.

V.A.1 Identification of "Hot Potato" Trading

There are several ways to identify "hot potato" trading in the market. First, at the trader level, the arrival of a large buy (sell) order (i.e. a passive trade by the liquidity provider) is likely to be followed by an active sell (buy) order and the likelihood will increase when the liquidity provider's preexisting inventory is large. Second, the fraction of the total trading volume due to trades among short term liquidity providers is an indicator of "hot potato" trading that will increase as the intensity of "hot potato" trading goes up.

To examine hot potato trading using the first trader level method, we consider trader i and split each trading day into buckets of 2 minutes (120 seconds) and record the signed active trading volume $(A_{i,t})$, the net passive trading volume $(P_{i,t})$, and the end-of-bucket inventory $(NI_{i,t})$.[19] We also define a set of time dummies, $(D_{1t},…,D_{mt})$, for each ½ hour period during the trading day to capture the effect of any systematic intraday volume and volatility patterns.

We assume that the following structural VAR (SVAR) model holds relating active and passive trading volumes:

$$\begin{bmatrix} 1 & a \\ 0 & 1 \end{bmatrix} \begin{bmatrix} A_{i,t+1} \\ P_{i,t+1} \end{bmatrix} = \Theta_1 \begin{bmatrix} A_{i,t} \\ P_{i,t} \end{bmatrix} + .. + \Theta_k \begin{bmatrix} A_{i,t-K+1} \\ P_{i,t-K+1} \end{bmatrix} + \Phi_1 [NI_{i,t}] + + \Psi_1 D_{1t} + \cdots + \Psi_m D_{mt} + \begin{bmatrix} \varepsilon_{A,i,t+1} \\ \varepsilon_{P,i,t+1} \end{bmatrix}$$

where,

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[19] If we use 30 second or 60 second windows, the results are qualitatively similar.

$$\varepsilon_{i,t+1} \sim N\left(0, \begin{bmatrix} \sigma_{i,A}^2 & 0 \\ 0 & \sigma_{i,P}^2 \end{bmatrix}\right).$$

The structural shocks of the SVAR are identified by assuming that shocks to passive trading volume ($\varepsilon_{P,t+1}$) can affect active trading contemporaneously, but active trading shocks ($\varepsilon_{A,t+1}$) have no contemporaneous effect on passive trading. We define the response of active trading to a passive trading shock ($R_{p \to a}$) as the cumulative sum of the impulse response function over a window of 2 minutes (i.e. contemporaneous plus lagged effect). A trader will then be identified as a "hot potato" trader (HPT) if $R_{p \to a}$ is more than two standard deviations below zero, indicating that during these periods passive buys (sells) lead to subsequent active sells (buys).[20]

For each trader who trades on a given day, we classify the day as being a "hot potato" trading day when the trader has significant active trades in the opposite direction following unanticipated passive trades.

V.A.2 Empirical Evidence of "Hot Potato" Trading

Using the identification presented above we tabulate the fraction of "hot potato" traders for each trader category in Table V.1. As can be seen from Table V.1, the fraction of the trader-days that are "hot potato" days are about the same, and statistically significant, for PDT and ADT, but they are not statistically significantly different from zero for MM. This indicates that "hot potato" trading strategy for inventory management is largely adopted by ADT and PDT and only marginally by MM, who potentially, as we show later on, use futures to manage their inventories.

Table V.1: Presence of "hot potato" traders

Fraction of "hot potato" traders for each trader category		
ADT	MM	PDT
0.1905	0.1376	0.1618
(0.0504)	(0.1305)	(0.0421)

Note: Fraction of the trader-days that are "hot potato" days for Short Term Traders. Categories are ADT (Active Day Trader, MM (Market Maker) and PDT (Passive Day Trader). Standard deviations are in parentheses. Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis.

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[20] During time buckets where a trader is inactive, traded volumes are set to zero to preserve an equi-spaced time grid.

Another implication of "hot potato" trading is that there will be significant trading among Short Term Traders. We thus investigate whether STT contribute to a large part of the passive volume, and whether a large part of their total trading volume is among themselves.

First, as expected, PDT engage in a large amount of passive buying and selling relative to other traders. According to Table V.2, 30.70% (30.47%) of all passive buy (sell) volume is due to PDT. This is more than twice the volume for active buys and sells for this category.

Table V.2: Active versus passive buy and sell volume for traders in trader behavior categories

	ADT	PDT	MM	LTLP	OLTT
Active_buy_vol	44.54%	13.50%	10.78%	2.68%	28.50%
Passive_buy_vol	20.56%	30.70%	9.71%	2.56%	36.46%
Active_sell_vol	42.63%	13.83%	11.23%	2.71%	29.61%
Passive_sell_vol	22.33%	30.47%	9.29%	2.49%	35.42%

Note: Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader). % represents the percentage of volume for each trader type. All rows sum up to 100%.

By looking to the volume traded in the whole sample we find that ADT accounted for 32%, MM for 10%, and PDT for 22% of the total trading volume for the firm's shares in the spot market. About 70% of volume is due to trading among STT that carry no overnight inventory, while only 30% involves trades with an "end-user".

The importance of STT can also be seen from the trading networks in Figure V.1 that provides a visual representation of the trading of STT among each other and with the rest of the market for the whole sample excluding fast crashes of May 19 and 22, 2006. The size of the arrows indicates the intensity of the trading volume, and the direction of the arrows indicates the trade side, i.e., arrows originate with a seller and reach a buyer.

Figure V.1: Directed Trading Volume Network

Active buy = passive sell	Active sell = passive buy
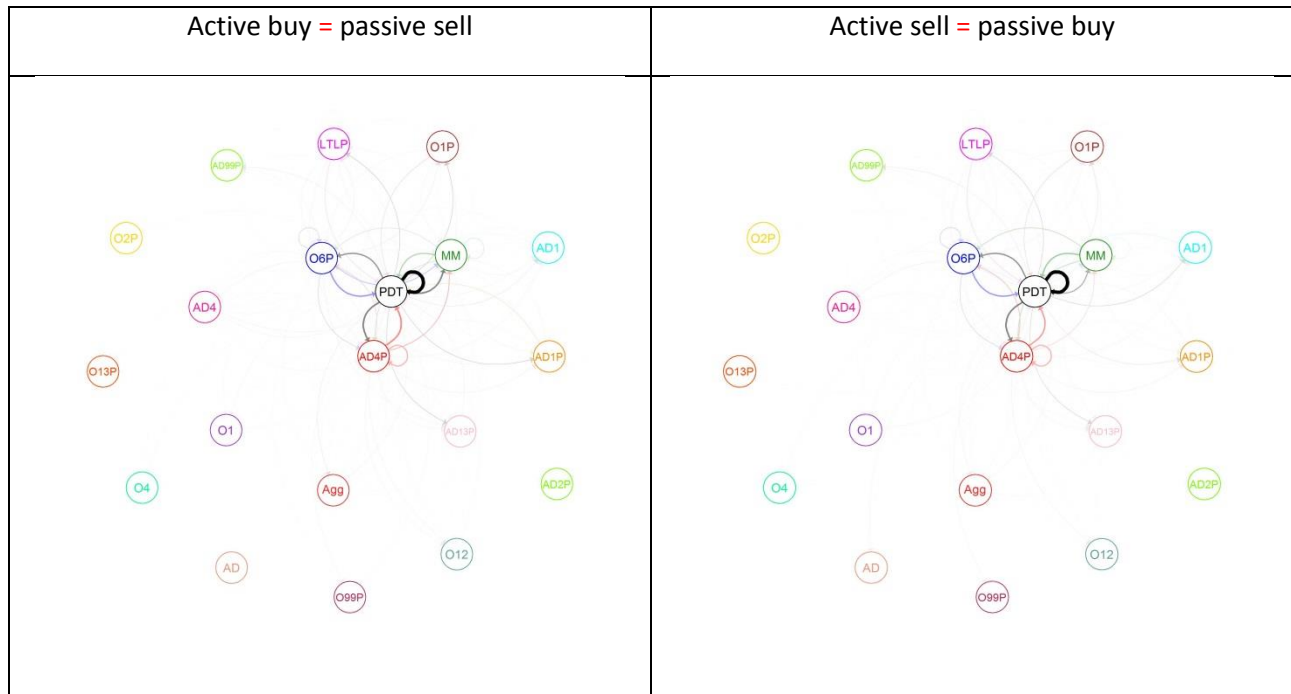
Note: Directed trading volume network for 20 non-overlapping traders categories: 3 major categories: Passive Day Traders (PDT), Market Makers (MM), Long Term Liquidity Providers (LTL) and 17 detailed categories: Active Day Traders of legal categories 1, 2 and 4 that are proprietary traders (D1P, D2P, D4P), Active Day Traders of legal categories 4, 13 and 99 that are non-proprietary traders (D4, D13, D99), Other Traders of legal category 1 that are proprietary traders (O1P), Other Traders of legal category 2 that are proprietary traders (O2P), Other Traders of legal categories 1, 4, 12, 13, 99 that are non-proprietary traders (O1, O4, O12, O13, O99). Traders that do not belong to the above classification have been included in the category "Agg". Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis.

Using the hierarchy of trading relationships presented in Figure V.1, we provide a network of trading relationships between non-overlapping trader categories. We use the first three letters in the trading behavior based classes. We focus on PDT (PDT), LTLP (LTL), ADTs (D), and Other Traders (O). D and O are further classified into legal categories. For example D4P denotes day traders who are in the legal category 4 (public and private companies/corporate bodies) and are also prop traders trading on their own account (D4P). Day traders who are in legal category 4, but not prop traders are labeled as D4.

We find that PDTs, MMs, and prop traders who could also be day traders are important contributors to trading volume (indicated by the thickness of the directed line). Most of the active buys (passive sells) and active sells (passive buys) took place among PDTs, MMs, and prop traders (D4P, O6P, and D1P). PDTs appear to be more central to the network in all time periods. The patterns in the two directed network graphs are consistent with the trading behavior of "hot

potato traders": that Short Term Traders (STT) contribute to a major part of the trading volume and a major part of that due to STT trading among themselves.

An examination of the graphs in Figure V.1 leads us to conjecture that STT (i.e. ADT, PDT and MM) are the primary providers of immediacy in the market, and they have limited capital available at their disposal. The implication is that when their inventory position gets large relative to their capital buffer, liquidity for the stock will be adversely affected with the result that investors who require immediacy will have to pay more for it through increased price concessions.[21]

Table V.3: Probabilities of "Rolling down" periods, Probit Model

	Probability of "Rolling down"	
	Coeff	t-stat
ADT	-0.002	5.76
MM	-0.001	1.68
PDT	-0.002	13.27
STT	-0.001	14.33

Note: Probability of being in a "rolling down" (peak to trough) period using Probit model for ADT (Active Day Trader), MM (Market Maker), PDT (Passive Day Trader), and Short Term Traders (STT=ADT+MM+PDT). The ratio of the volume traded among ADT, MM, PDT and STT respectively for each three seconds over the total volume of trades in the same interval is the explanatory variable. Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis.

Finally, we examine the behavior of the STT during market "rolling up" and "rolling down" periods. We repeat the Probit and Weibull analyses performed in Section IV by using the ratio of volume traded among STT each three seconds and the total volume in the same time interval as an explanatory variable. Results of the Probit analysis are reported in Table V.3.

Table V.3 shows that the probability of a "rolling down" period is lower when trading among STT has increased. This is confirmed for all the three categories of STT considered at 99% for ADT and PDT and at 90% confidence levels for MM. It is interesting to observe that the most significant variable is STT, i.e., when we consider the total volume traded among all STT categories, we get the largest decrease in the probability of a "rolling down" period. This is what

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[21] See Amihud Mendelson (2003) and Naik and Yadav (2003).

we should expect to find. When all STT are near their inventory capacity, "hot potato" trading does not help much in sharing inventory risk and is reduced. Those are the times when "rolling down" periods are likely to occur.

Table V.4: Weibull duration estimation of "Hot potato" trading

	Duration	
	Coeff	z-stat
ADT	1.00	2.53
MM	1.01	6.24
PDT	1.01	1.13
STT	1.01	4.66

Note: The impact of the volume traded among Short Term Traders (STT) over total volume on the duration of a 1.5% trough. Categories analyzed are: Active Day Traders (ADT), Market Makers (MM), Passive Day Traders (PDT), and Short Term Traders (STT=ADT+MM+PDT). Three second intervals are used for the Weibull duration analysis. Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis.

We also investigate the relationship between the duration of "rolling down" periods and the volume traded among STT. Conditional on being in a "rolling down" period, we should expect to find a positive association between the duration of the trough and "hot potato" trading for reasons we will discuss shortly. For this reason we performed the Weibull-duration analysis – i.e., we examine the duration of the "rolling down" period conditional on being t seconds into the "rolling down" period -- and use as explanatory variable the ratio of the volume traded among STT each three seconds and the total volume of trades in the same interval. Results of the Weibull analysis are reported in Table V.4.

Table V.4 shows that when the volume traded among STT is large, the duration of a "rolling down" period is longer indicating that more "hot potato" trading is needed – i.e., shares have to pass through a number of short term traders before finding the one who has sufficient inventory capacity to hold on to the shares -- and since the risk (inventory) bearing capacity is being breeched, duration becomes longer. When all liquidity providers have large inventory levels "hot potato" trading does not help and comes down. This happens at the same time when liquidity is

in short supply. This result is also confirmed if we examine the distribution of different "rolling down" periods in the sample.   In Table V.5 we tabulate the average ratio of the volume of trades among STT with respect to the total volume of the market for "rolling down" periods that are very short (first quartile) and those that are very long (fourth quartile).

Table V.5: Average ratio of the volume traded by STT

	"Rolling down"			"Rolling up"		
	Mean	1st Q	4th Q	Mean	1st Q	4th Q
MM	0.04	0.01	0.13	0.03	0.01	0.13
PDT	0.08	0.01	0.23	0.08	0.01	0.22
ADT	0.13	0.01	0.34	0.14	0.01	0.35
STT	0.49	0.09	0.88	0.52	0.13	0.90

Note: Average of the ratio of the volume traded among ADT, MM, PDT, and STT respectively for each three seconds over the total volume of trades in the same interval for ADT (Active Day Trader), MM (Market Maker), PDT (Passive Day Trader), and Short Term Traders (STT=ADT+MM+PDT). Fast crashes occurring on May 19 and May 22, 2006 are excluded from this analysis.

As Table V.5 shows, the largest ratio refers to the volume traded among the three categories of STT considered. In fact on average this ratio during "rolling down" period is 49% of the total volume traded each three seconds for STT and the ratio within the three categories separately is 25% (i.e. 4% MM, 8% PDT and 13% ADT). On average there is not a large difference between the ratio in the "rolling down" and "rolling up" periods. Nevertheless, there is a large difference among "rolling down" periods and "rolling up" periods that are very short (the ratio for STT in this case is on average 9% for the rolling down and 13% for the rolling up) and those that are very long (88% in the rolling down and 90% in the rolling up). This indicate that when STT trade a lot among each other the duration of both "rolling down" and "rolling up" is larger.

V.B Hedging through futures

A second strategy used by STT to manage their inventories is by using futures. We investigate first how many of the STT trade in both markets on the days when they provide liquidity to the market. Table V.6 reports statistics on the contemporaneous trading in both the markets.

Table V.6: STT active in both spot and futures markets STT

	ADT	PDT	MM	STT
Fraction of traders active in both spot and futures markets				
Mean	2.3%	5.6%	19.2%	9.1%
Std	0.64%	1.50%	11.61%	4.6%
max	3.7%	9.3%	71.4%	71.4%
Min	1.1%	3.1%	0.0%	0.0%
Volume by traders active in both markets as fraction of total spot volume				
Mean	30.8%	30.4%	84.3%	48.5%
std	9.77%	10.5%	21.57%	14.0%
max	54.4%	57.2%	99.7%	99.7%
min	8.9%	6.0%	0.0%	0.0%
Fraction of trading volume associated with hedging				
Mean	18.9%	15.4%	74.0%	36.1%
std	9.68%	9.34%	31.18%	16.7%
max	42.9%	42.9%	98.8%	98.8%
min	4.2%	2.8%	0.0%	0.0%

Note: We report the fraction of STT (i.e. traders identified as ADT, PDT or MM on a given day) that are active in both markets . ADT are Active Day Traders, PDT are Passive Day Traders, and MM are Market Makers.

As Table V.6 shows, only a small fraction of STT trade in both markets. However, it is important to evaluate also the volume traded by those who trade in both the market with respect to the total volume traded by each of the three categories considered in the spot market. Table V.6 indicates that on average ADT and PDT who are active in both markets represent about 30% of the total volume traded by these categories. MM are those that largely participate in both markets (84% of the volume traded by MM is generated by traders that trade in both markets). This is consistent with the MM category comprising the largest traders.

However, being present in both markets does not necessarily indicate that traders are using futures to manage/hedge their inventories in the spot markets. We have therefore calculated the maximum spot and futures inventories each day for each trader. We consider a trader engaged in hedging his spot positions through futures when we observe the reduction in the net positions. We find that the volume traded in the spot market over the total volume traded is less than 20% for ADT and PDT, but is quite large for MM indicating MM are heavily relying on futures to adjust their exposures. However, we note that the standard deviations are quite large too, so traders use futures to adjust their inventories on some days but not in others**.**

V.C Being on one side of the market to adjust their inventories

STT provide liquidity in the market by building up their inventories and then they have to manage the risk of these inventories. A simple way to manage inventories is largely being on one side of the market. For example, ADT and PDT might build up their inventories during the day and unwind them at the end of the day.

Figure V.2: Net buys and sells during each 30 minutes interval of the trading day by trader type
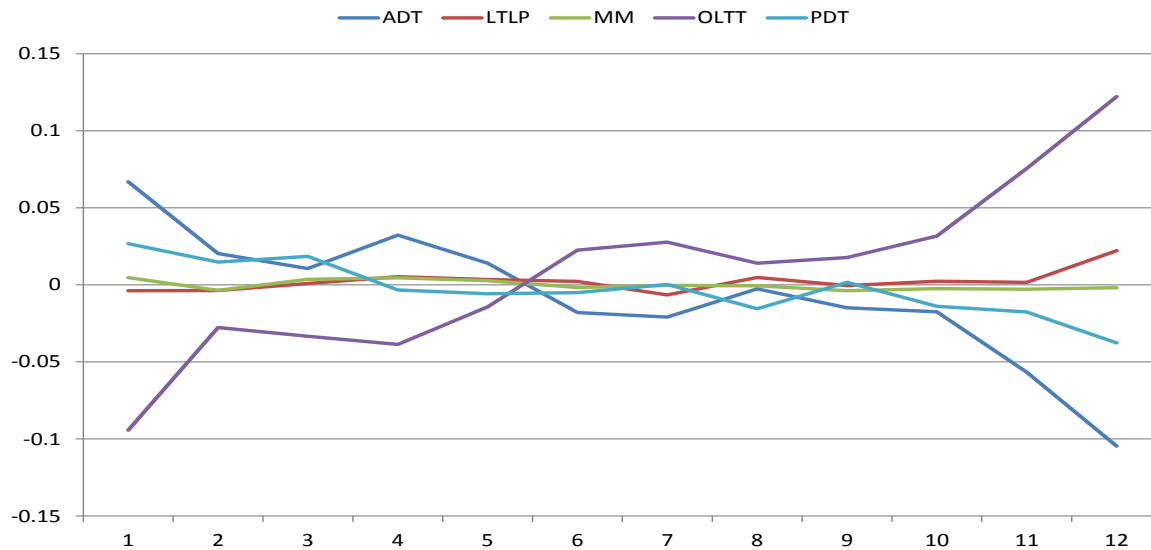
Note: Net buys and sells during each 30 minutes interval of the trading day for different trader categories. Trader categories are based on trader behavior. Categories are ADT (Active Day Trader), LTLP (Long Term Liquidity Provider), MM (Market Maker), OLTT (Other Long Term Trader), and PDT (Passive Day Trader). Units are in terms of fraction of total trading volume during the each time interval

To examine this hypothesis we divide the trading day into twelve thirty minute intervals and examine the net buys and sells during each of these 30 minute intervals on all trading days in our sample excluding May 19 and May 22. Figure V.2 provides the net buys and sales by the five behavioral categories during each 30 minutes interval of each trading day.

Consistent with our expectations, Figure V.2 shows that Active Day Traders (ADT) are net buyers during the beginning of the day and net sellers towards the end of the day. The same is also true to a lesser extent for PDT. The converse pattern is true for OLTT who hold overnight inventory and are the net sellers early in the day and net buyers towards the end of the day. It is interesting to observe that MM, which also carry no over-night inventories, are strategically trading differently as their trades are balanced throughout the trading day.

VI.   Behavior of Traders During Fast Crashes and Recoveries

As we noted in section IV, short term traders on average hold their positions for less than ten minutes and rarely carry inventories over night. 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.

VI.1 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 VI.1 below gives the inventory behavior on May 19 and Figure VI.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 FIs. 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.

Figure VI.1: Inventory of FI, Mutual funds, and STT on May 19th, 2006
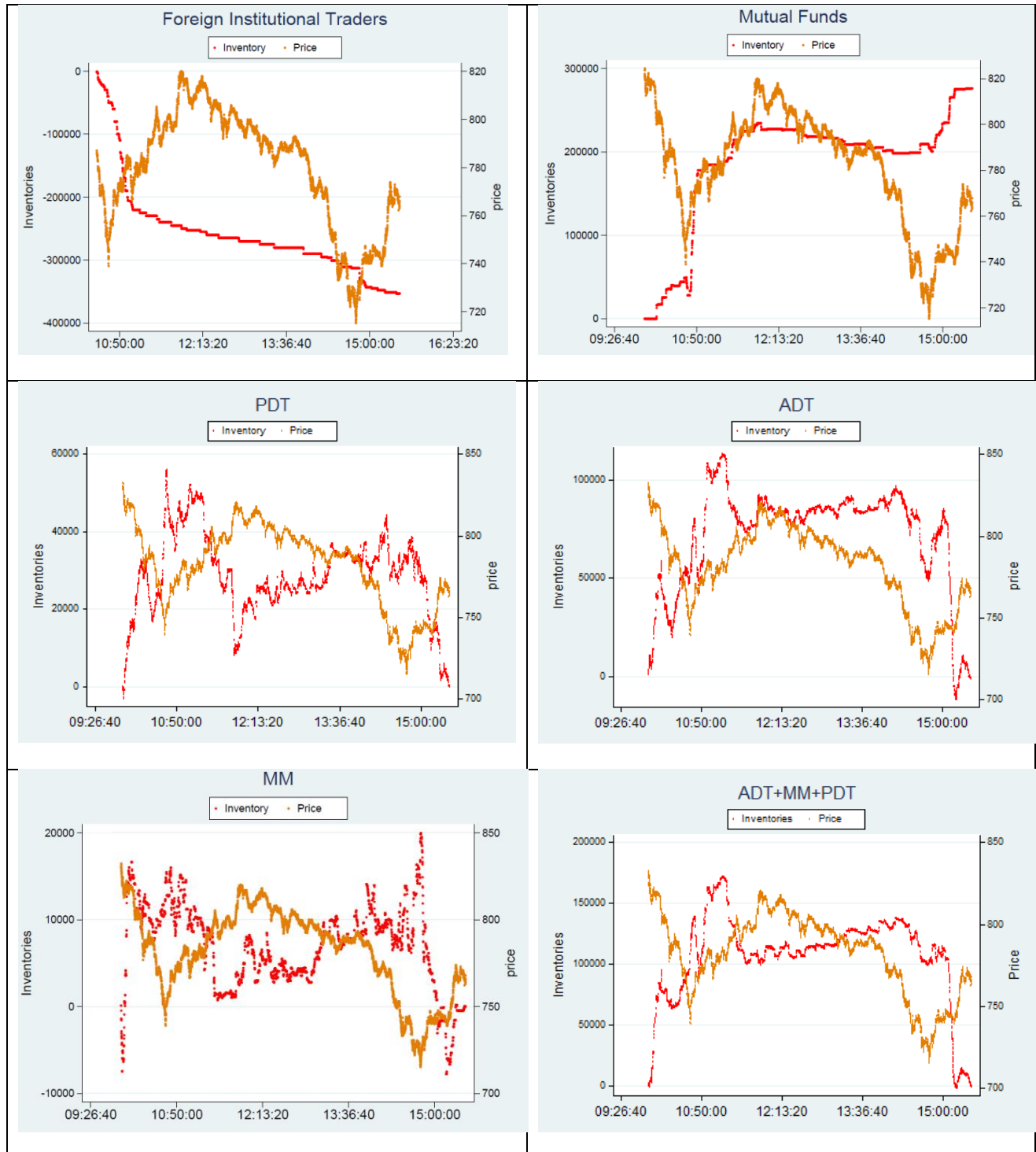
Note: Intra-day inventories and prices for Foreign Institutional Traders, Mutual Funds, Passive Day Traders (PDT), Active Day Traders (ADT), Market Makers (MM), and Short Term Traders (ADT+MM+PDT) on May 19, 2006.

Figure VI.2: Inventory of FI, Mutual funds, and STT on May 22nd, 2006
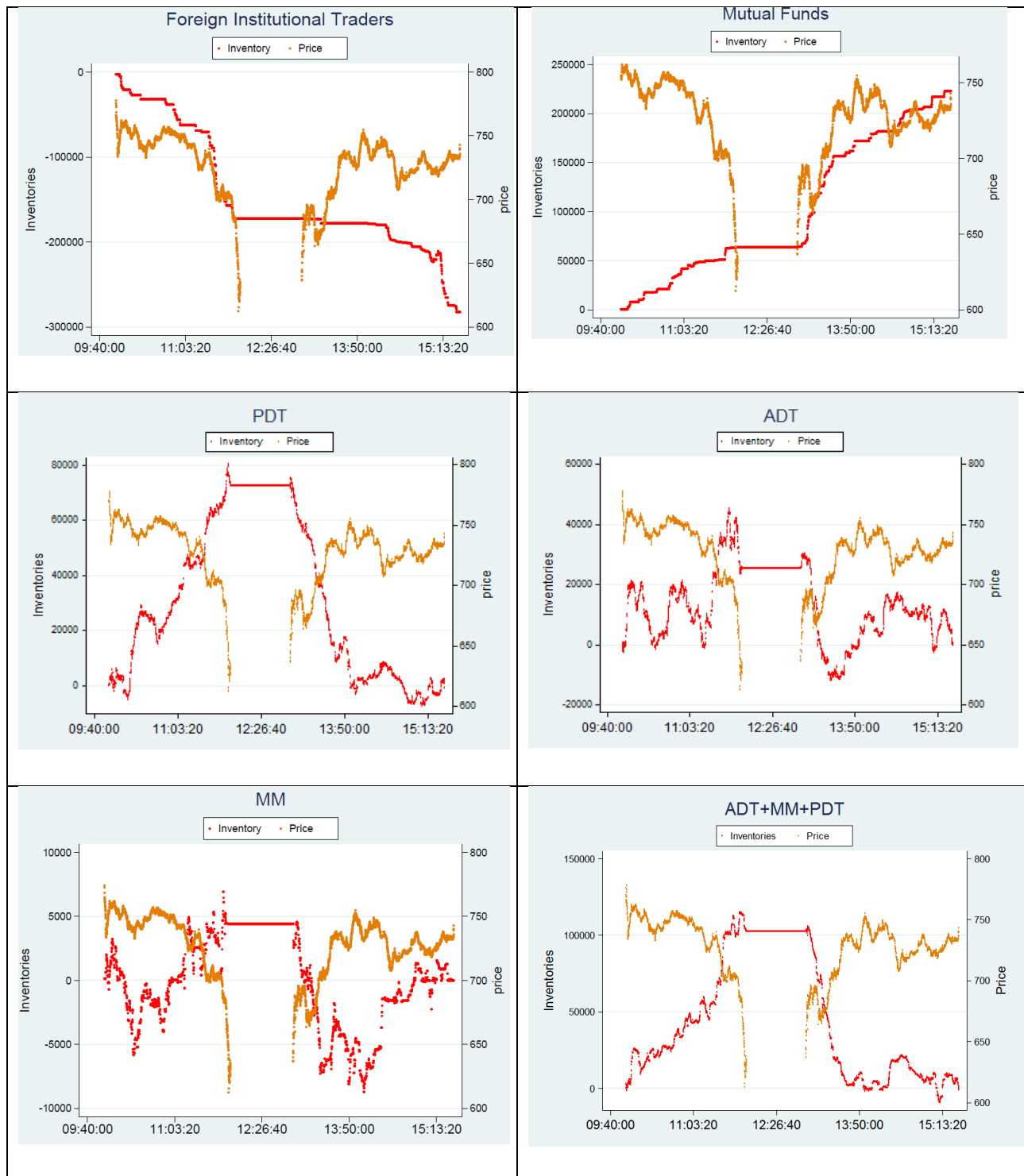
Note: Intra-day inventories and prices for Foreign Institutional Traders, Mutual Funds, Passive Day Traders (PDT), Active Day Traders (ADT), Market Makers (MM), and Short Term Traders (ADT+MM+PDT) on May 22, 2006.

VI.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.

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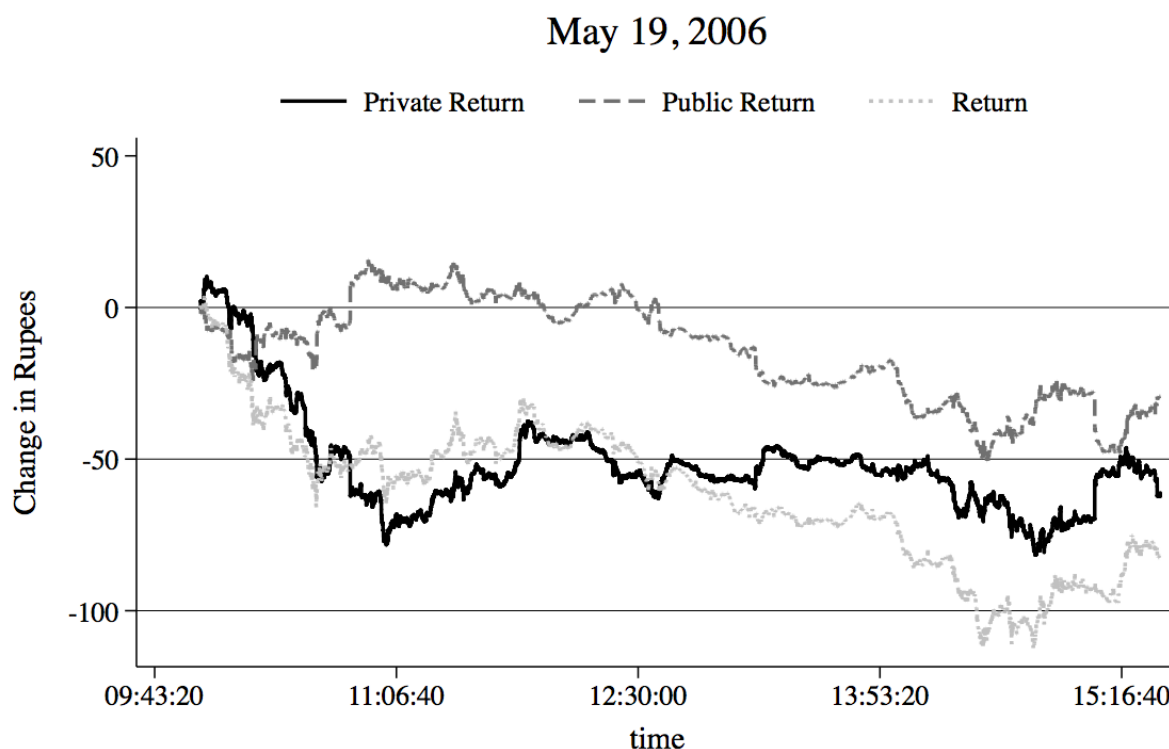
May 19, 2006

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

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. By looking at the sequence in which the buy and the sell orders arrived, we can determine whether the buy or the sell order initiated the trade, i.e., the market order (or marketable limit order).

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

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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.

**Figure VI.4: Price change decomposition on May 22, 2006**
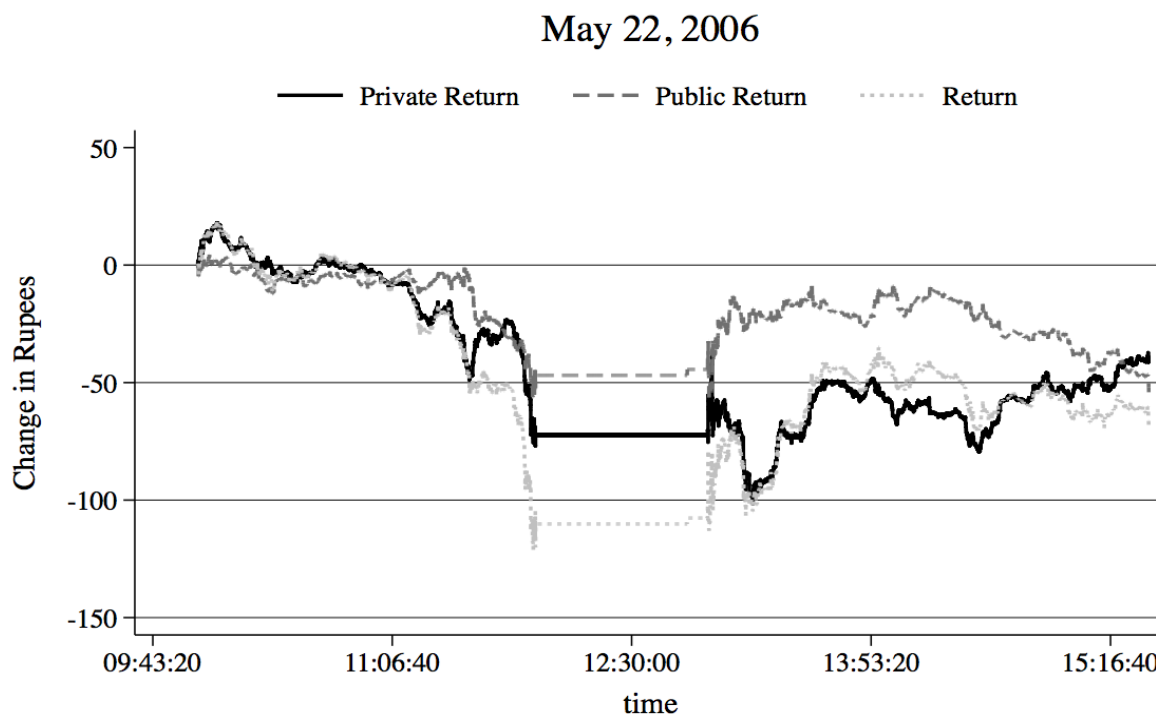
Note: The cumulative price change into private and public components for May 22, 2006.

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 VI.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 VI.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. The pattern that emerges from these figures is consistent with the inventory behavior in Figures VI.2 and VI.3 discussed in section VI.1.

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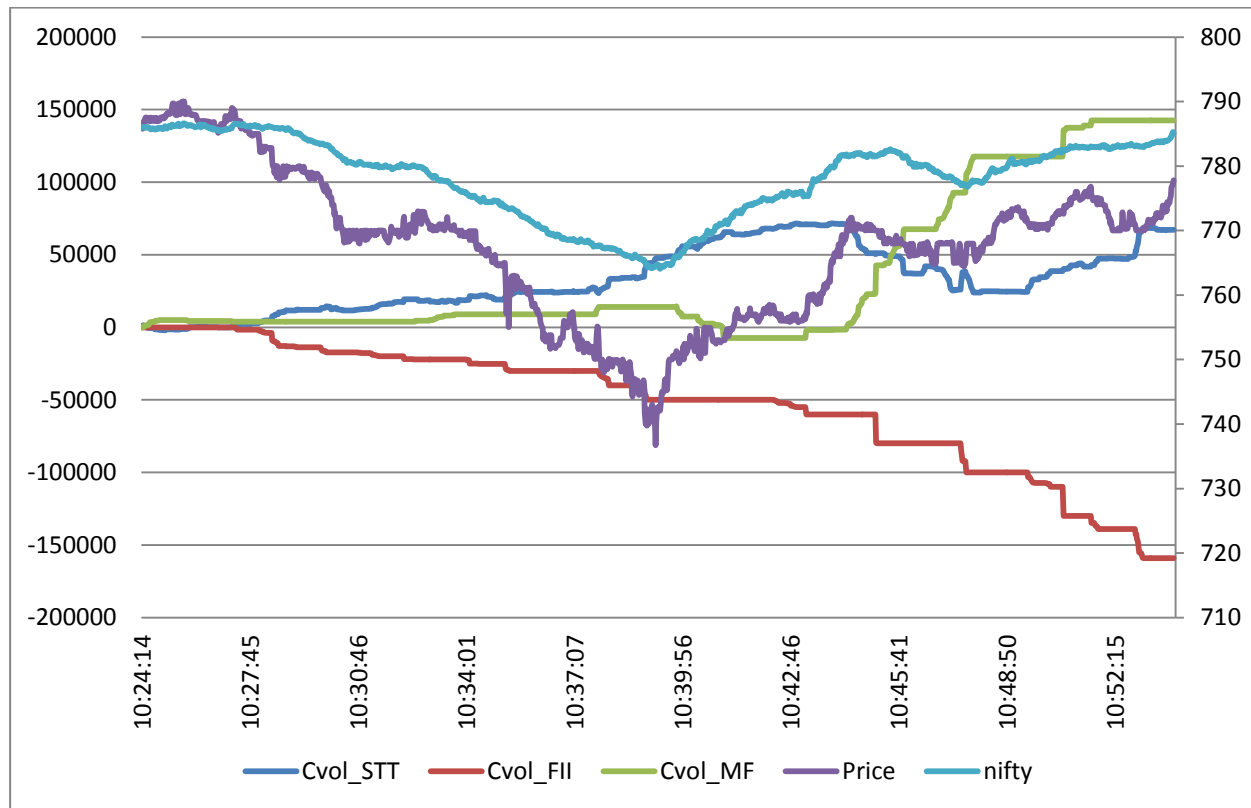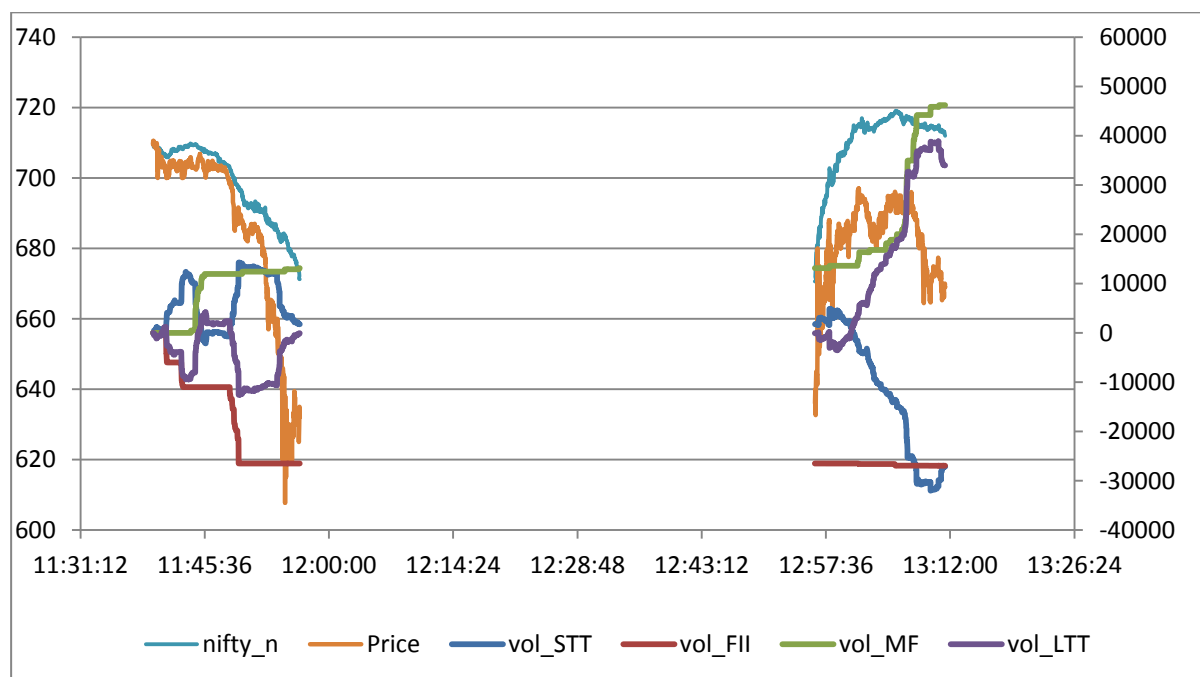

Note: Stock price (right vertical axis) and buy and sell (negative) volume in number of shares (left vertical axis) for Short Term Traders (STT), Foreign Institutions (FII), and Mutual Funds (MF) during the fast crash of May 19, 2006. Stock and NIFTY prices are depicted as well.

Finally 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 VI.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

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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 VI.3, and specifically indicates who are the main actors that generates the pattern of private returns.

Figure VI.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.

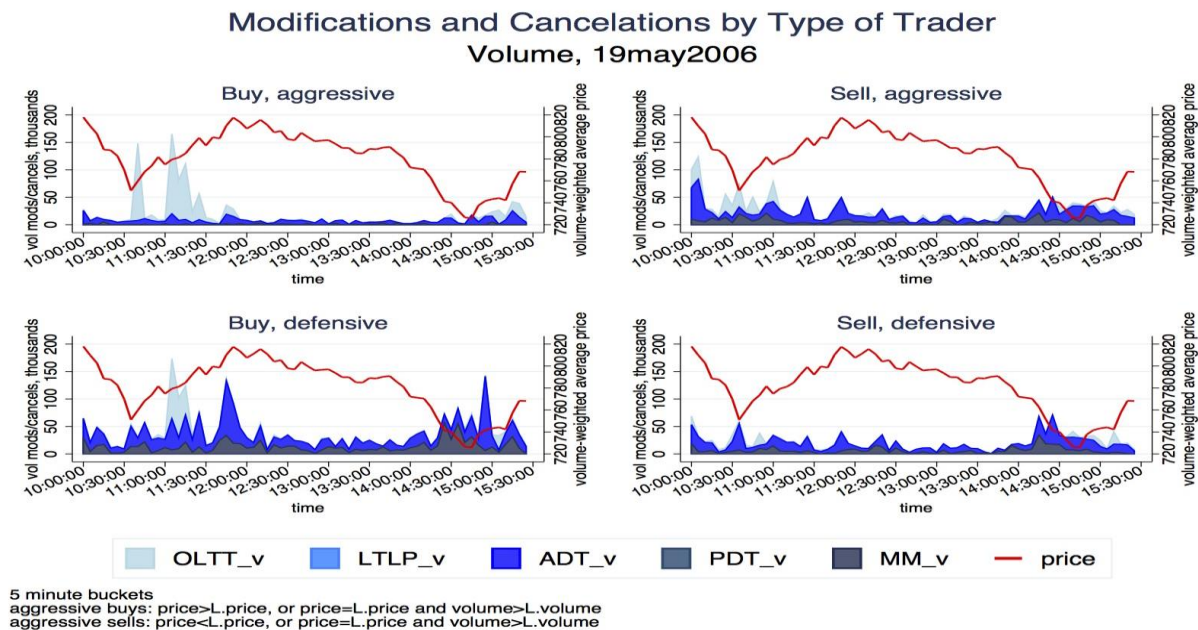**Figure VI.7: Order modifications and cancellations by trader types on May 19, 2006**

Modifications and Cancelations by Type of Trader
Volume, 19may2006

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

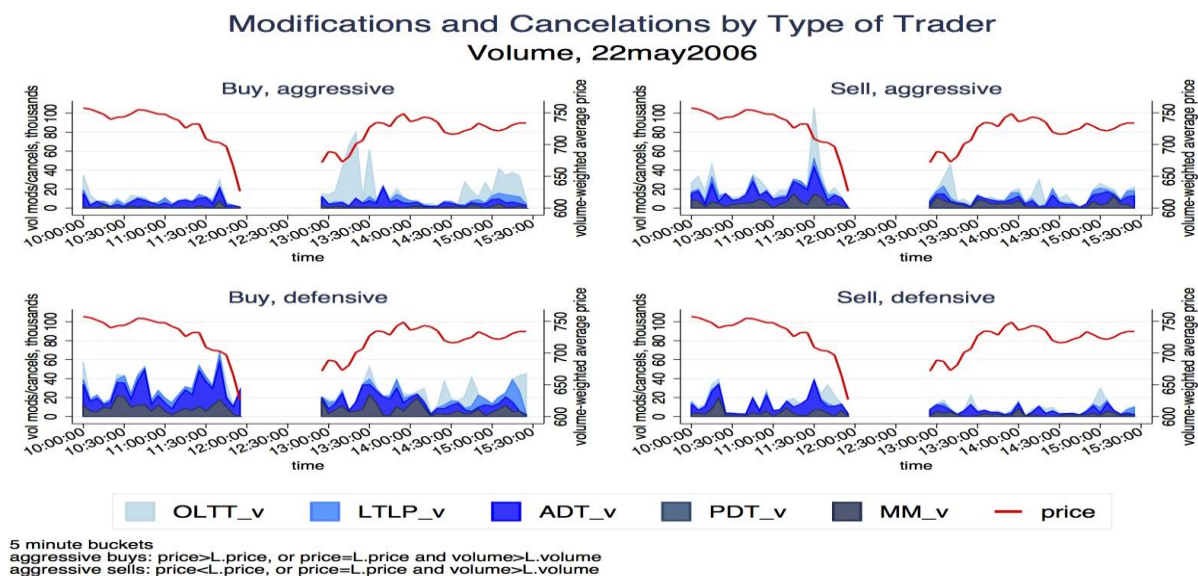Modifications and Cancelations by Type of Trader
Volume, 22may2006

Figure VI.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 VI.4.

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

Table VI.1 gives details of buyers and sellers during the two flash crash days and during 36 more severe of the 80 price declines that occurred on other days during the normal price declines 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. A common pattern emerges. As can be seen from Table VI.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.

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

19-May			
Crash/Recovery	**vol_FII**	**vol_MF**	**vol_STT**
Price Crash	-50,000	13,979	46,811
Price Recovery	-109,026	128,673	20,406

22-May			
Crash/Recovery	**vol_FII**	**vol_MF**	**vol_STT**
Price Crash	-26,493	12,428	4,830
Price Recovery	-457	33,772	-31,964

36 Normal cycles			
Fall/Rise	**vol_FII**	**vol_MF**	**vol_STT**
Price Decline	-5,399	2,139	4,190
Price Rise	-7,383	6,677	-511

Note: Signed trading volume for Short Term Traders (STT), Foreign Institutions (FII), and Mutual Funds (MF) during the fast crashes of May 19 and May 22, 2006, and during 36 normal cycles.

It is interesting to note that FII sold into the normal busts in the 36 more severe 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.

Table VI.2: Legal Trader Categories Re-categorization

Data coding	Legal Trader Category	Broader Trader Category
1	individual traders	1
2	partnership firm	2
3	Hindu undivided family	1
4	Public & private companies/corporate bodies	2
5	trust/society	2
6	mutual fund	3
7	domestic financial institution	3
8	Bank	3
9	Insurance	3
10	statutory bodies	5
11	Non-resident Indians	1
12	FII Foreign Institutional Investors	4
13	overseas corporate bodies	5
99	Missing	5

Note: Re-categorization of legal trader categories into 5 broader trader categories.

Table VI.3: May 19 Buyers and Sellers during Steep Decline, traders in legal categories

Legal Group	P-Buy	A-Buy	P-Sell	A-Sell	Buy-Sell
1	0.17	0.36	0.06	0.30	0.17
2	0.14	0.18	0.08	0.19	0.04
3	0.07	0.02	0.01	0.00	0.09
4	0.00	0.00	0.12	0.10	-0.23
5	0.04	0.02	0.06	0.08	-0.07
Sum	0.42	0.58	0.33	0.67	0.00

Note: Passive/active buyers/sellers during the steep decline (period 3) of May 19th, 2006 fast-crash. Traders in 5 broader categories based on legal categories are analyzed.

We next proceed to analyze the behavior of the different types of traders during May 19 and May 22 in greater detail. We find that traders use a judicious combination of passive and active trading to be effectively on one side of the market to manage inventory positions and risk. To analyze their passive and active order placement behavior, for convenience, we also group various traders in 13 legal categories into five legal classes. Table VI.2 below categorizes the five classes. On May 19, the tail end of the price decline and the initial phase of the recovery are both rather steep.

Table VI.4: May 19 Buyers and Sellers during Recovery, traders in legal categories

Legal Group	P-Buy	A-Buy	P-Sell	A-Sell	Buy-Sell
1	0.08	0.25	0.07	0.21	0.06
2	0.06	0.20	0.06	0.18	0.01
3	0.23	0.14	0.03	0.02	0.32
4	0.00	0.00	0.24	0.08	-0.32
5	0.01	0.04	0.04	0.07	-0.06
Sum	0.37	0.63	0.44	0.56	0.00

Note: Passive/active buyers/sellers during recovery (period 4) of May 19th, 2006 fast-crash. Traders in 5 broader categories based on legal categories are analyzed.

Table VI.5: Buyers and Sellers during Steep Decline, traders in categories based on trader behavior

Trader Type	P-Buy	A-Buy	P-Sell	A-Sell	Buy-Sell
ADT	0.10	0.31	0.04	0.28	0.10
MM	0.03	0.02	0.03	0.01	0.01
OLTT	0.10	0.14	0.18	0.26	-0.21
PDT	0.17	0.13	0.10	0.09	0.10
Sum	0.40	0.60	0.36	0.64	0.00

Note: Passive/active buyers/sellers during the steep decline (period 3) of May 19th, 2006 fast-crash. Traders in ADT (Active Day Trader), MM (Market Maker), OLTT (Other Long-Term Trader), and PDT (Passive Day Trader) are analyzed.

Table VI.6: May 19 Buyers and Sellers during Recovery, traders in categories based on trader behavior

Trader Type	P-Buy	A-Buy	P-Sell	A-Sell	Buy-Sell
ADT	0.05	0.34	0.04	0.24	0.11
MM	0.02	0.04	0.02	0.04	0.00
OLTT	0.14	0.27	0.22	0.30	-0.10
PDT	0.07	0.08	0.10	0.05	-0.01
Sum	0.28	0.72	0.37	0.63	0.00

Note: Passive/active buyers/sellers during recovery (period 4) of May 19th, 2006 fast-crash. Traders in ADT (Active Day Trader), MM (Market Maker), OLTT (Other Long-Term Trader), and PDT (Passive Day Trader) are analyzed.

Tables VI.4 and VI.5 identify providers and demanders of liquidity (legal categories) during the steep decline and the recovery during the fast crash of May 19. Group 4 (FII) were net sellers during the steep decline period, and they used both market and limit orders to sell. Group 1 (mostly individual investors) were net buyers and provided liquidity. Buying by group 3 (mostly mutual funds, who are stand by liquidity providers who are slower to move in) helped price recovery during the min crash. Group 4 were net sellers using passively limit orders during the recovery period. Tables VI.5 and VI.6 summarize buyers and sellers by behavioral trader groups.

As can be seen from the tables, Other Long Term Traders (OLTT) were the liquidity demanders during the steep crash, and ADT and PDT were on the other side. ADT were the primary net buyers during the recovery period and OLTT continued to be net sellers.

We now proceed to analyze who were demanding liquidity during the steep fall in prices towards the end of the crash that led to a halt in trading on May 22 and who were the net buyers during the recovery following the resumption of trading. Tables VI.7 and VI.8 provide the details on buyers and sellers by legal groups and Tables VI.9 and VI.10 provide details on buyers and sellers by behavioral categories.

Table VI.7: May 22 Buyers and Sellers during Steep Decline, traders in legal categories

Legal Group	P-Buy	A-Buy	P-Sell	A-Sell	Buy-Sell
1	0.21	0.43	0.06	0.43	0.14
2	0.13	0.16	0.10	0.23	-0.04
3	0.02	0.00	0.00	0.00	0.02
4	0.00	0.00	0.06	0.07	-0.13
5	0.03	0.03	0.03	0.02	0.01
Sum	0.18	0.18	0.19	0.32	0.00

Note: Passive/active buyers/sellers during the steep decline (period 4) of May 22th, 2006 fast-crash. Traders in 5 broader categories based on legal categories are analyzed.

Table VI.8: May 22 Buyers and Sellers during Recovery, traders in legal categories

Legal Group	P-Buy	A-Buy	P-Sell	A-Sell	Buy-Sell
1	0.08	0.41	0.09	0.46	-0.07
2	0.08	0.15	0.12	0.28	-0.18
3	0.17	0.05	0.00	0.00	0.22
4	0.00	0.00	0.00	0.00	0.00
5	0.04	0.02	0.03	0.01	0.03
Sum	0.30	0.22	0.16	0.30	0.00

Note: Passive/active buyers/sellers during recovery (period 5) of May 22th, 2006 fast-crash. Traders in 5 broader categories based on legal categories are analyzed.

Again, Group 4 in the legal category (FII) were demanding liquidity and those in Group 1 in the legal category were providing liquidity. However, as we noted earlier, most of the steep drop in the price during the crash was due to revision in the order book and not due to selling. During recovery (period 5) those in category 3 (mostly mutual funds) were buying (passive but through order revision) aiding in recovery.

Table VI.9: May 22 Buyers and Sellers during Steep Decline, categories based on trader behavior

Trader Type	P-Buy	A-Buy	P-Sell	A-Sell	Buy-Sell
ADT	0.09	0.33	0.06	0.42	-0.06
LTLP	0.01	0.00	0.00	0.00	0.00
MM	0.04	0.03	0.02	0.03	0.01
OLTT	0.10	0.09	0.08	0.14	-0.03
PDT	0.20	0.10	0.13	0.11	0.07
Sum	0.44	0.56	0.29	0.71	0.00

Note: Passive/active buyers/sellers during the steep decline (period 4) of May 22th, 2006 fast-crash. Traders in ADT (Active Day Trader), MM (Market Maker), OLTT (Other Long-Term Trader), and PDT (Passive Day Trader) are analyzed.

Table VI.10: May 22 Buyers and Sellers during Recovery, categories based on trader behavior

Trader Type	P-Buy	A-Buy	P-Sell	A-Sell	Buy-Sell
ADT	0.04	0.24	0.06	0.29	-0.06
LTLP	0.02	0.01	0.03	0.03	-0.03
MM	0.02	0.02	0.03	0.05	-0.04
OLTT	0.23	0.22	0.03	0.16	0.26
PDT	0.10	0.09	0.19	0.14	-0.13
Sum	0.41	0.59	0.34	0.66	0.00

Note: Passive/active buyers/sellers during recovery (period 5) of May 22th, 2006 fast-crash. Traders in ADT (Active Day Trader), MM (Market Maker), OLTT (Other Long-Term Trader), and PDT (Passive Day Trader) are analyzed.

VII. 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 75% of the total trading volume; and over 75% 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.

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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.

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[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.

Figure A.1: Price of the stock and the trading volume in the spot market
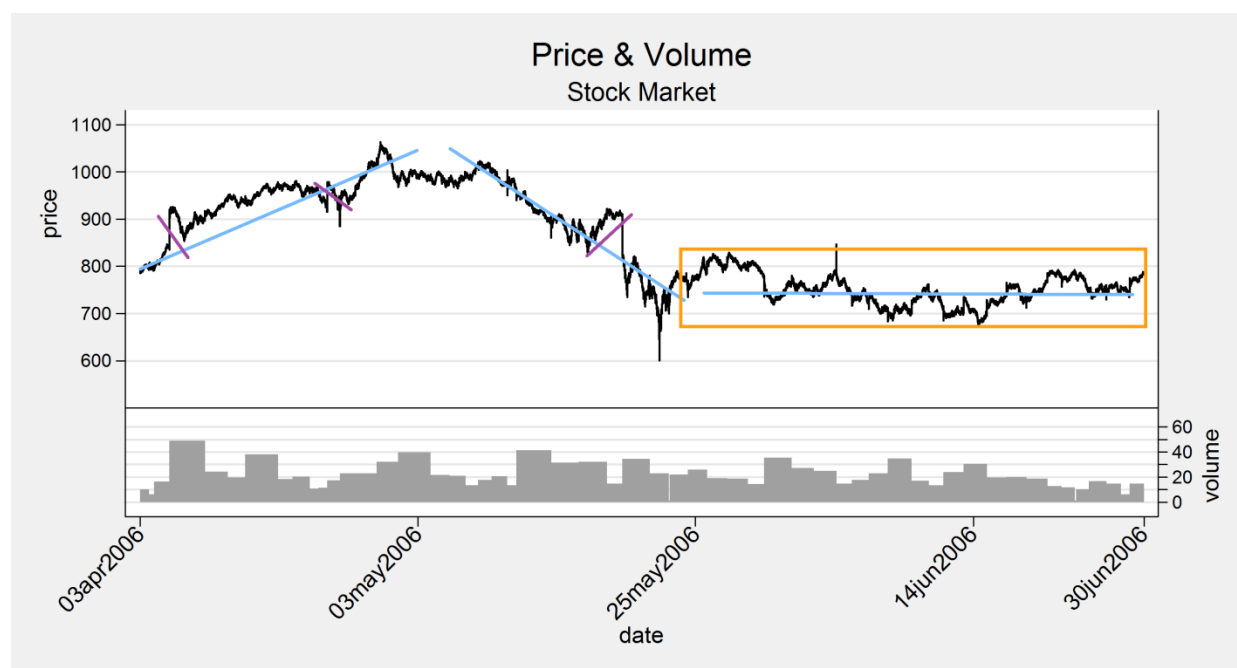
Note: Volume data refer to the daily number of shares sold and bought (in 100,000 shares); Upper panel, y axis: price; Lower panel, y axis: trading volume;

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

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[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.

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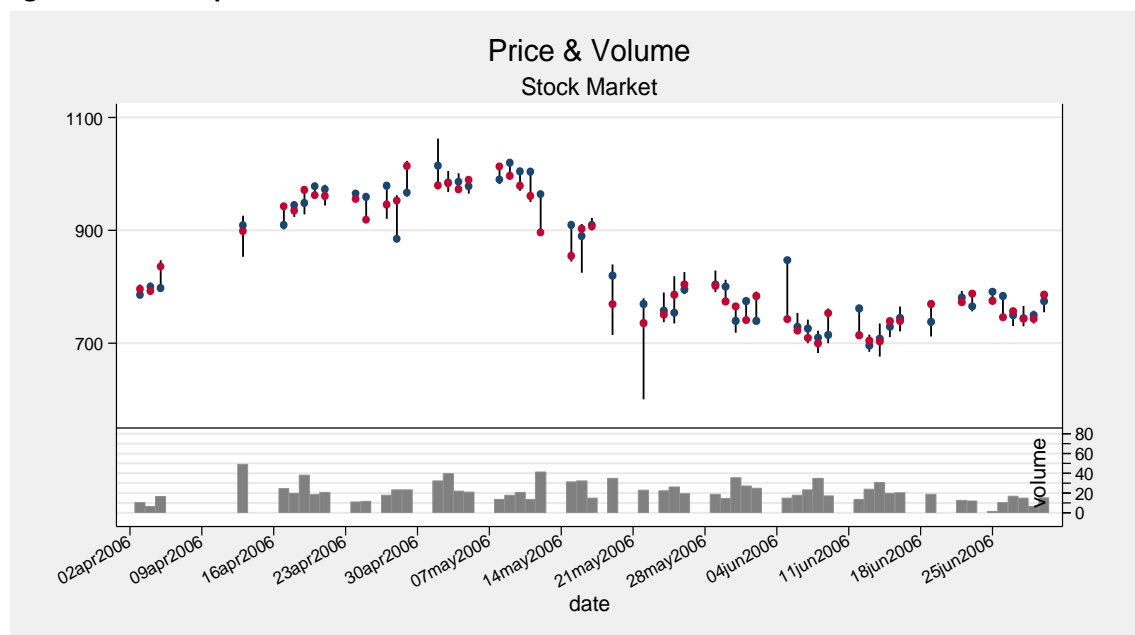
Note: Blue circles: opening price; Red circles: closing price. Bar: indicates maximum and minimum daily prices; Volume data refer to the daily number of shares sold and bought (in 100,000 shares). Upper panel, y axis: share price; Lower panel, y axis: volume.

Figure A.3 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

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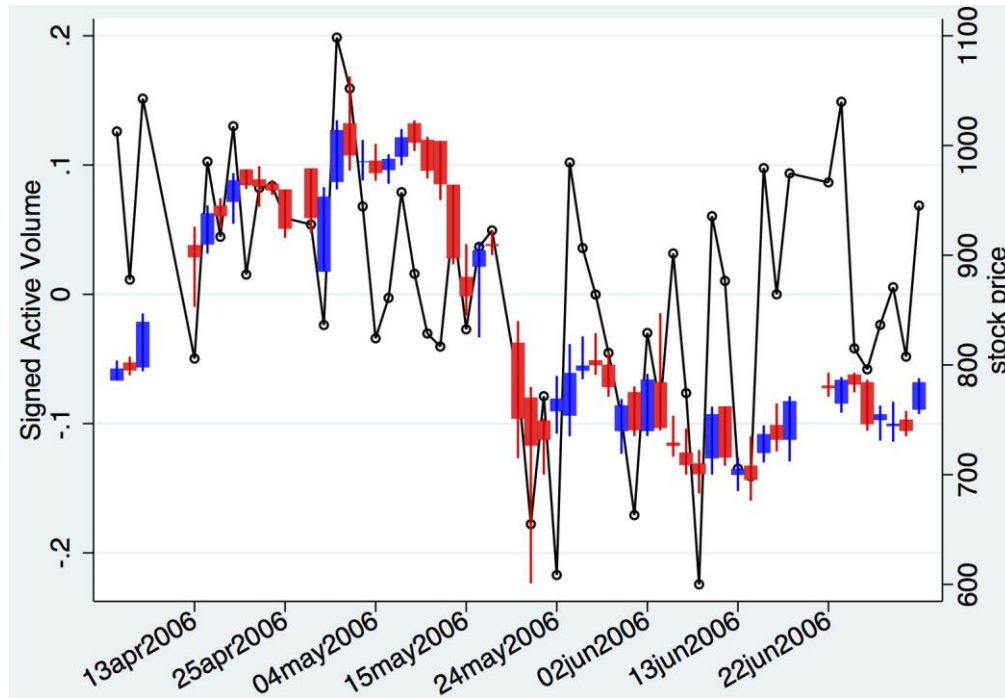
Note: Bar indicates maximum and minimum daily prices (right y-axis); Body of the candlestick indicates opening and closing prices. The candlestick is blue (red) if stock closed lower (higher). Signed active volume refers to the net active trading imbalance as a fraction of daily volume: $\frac{buyer\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

Figure A.4: Stock Returns vs. order imbalance
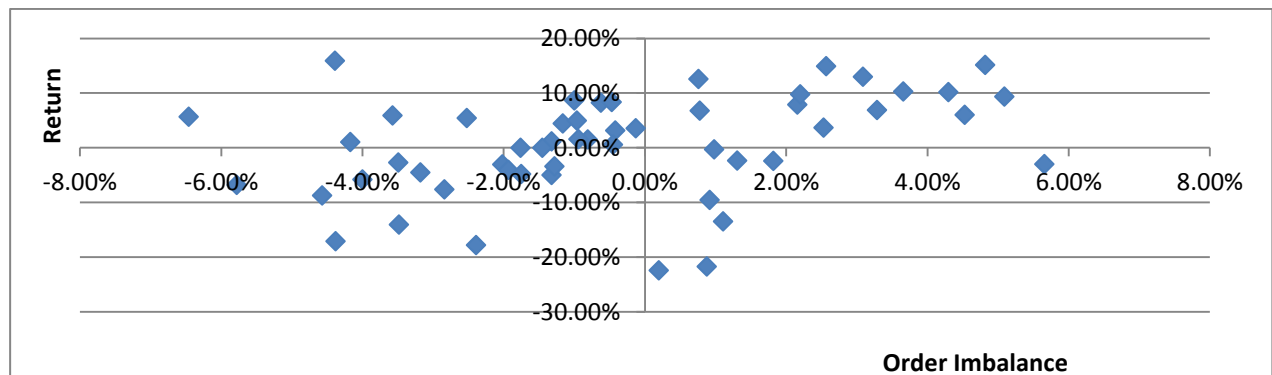
Note: Stock returns versus order imbalance during April 3rd 2006 - June 30th 2006 time period. Stock returns are calculated daily. Daily order imbalance is measured as (buy-sell)/(buy+sell), i.e., buyer initiated volume minus the seller initiated volume divided by the total volume during that day.

Figure A.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.

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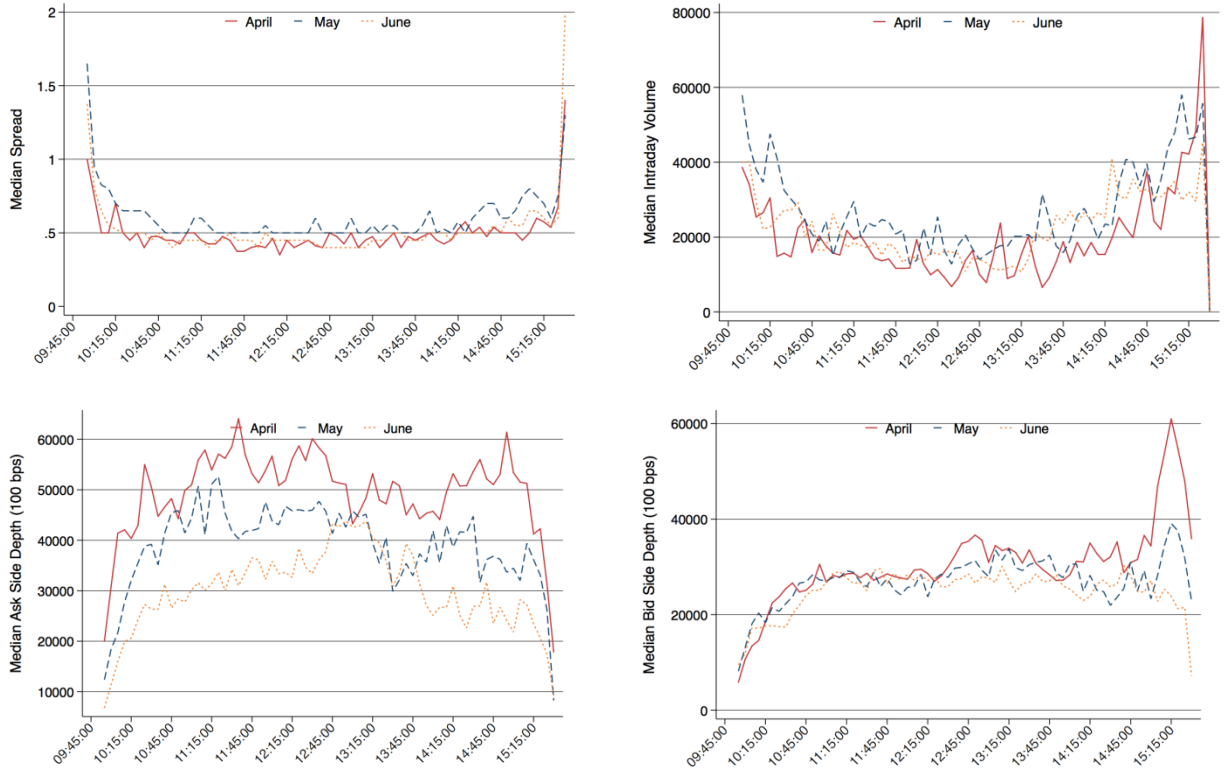
Note: Liquidity measures for the spot market: median intraday bid-ask spreads, median intraday volume, and median bid and ask side depths. X-axis indicates 5-minute partitions of a daily trading session.

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.

Figure A.6: Depth of the limit order book
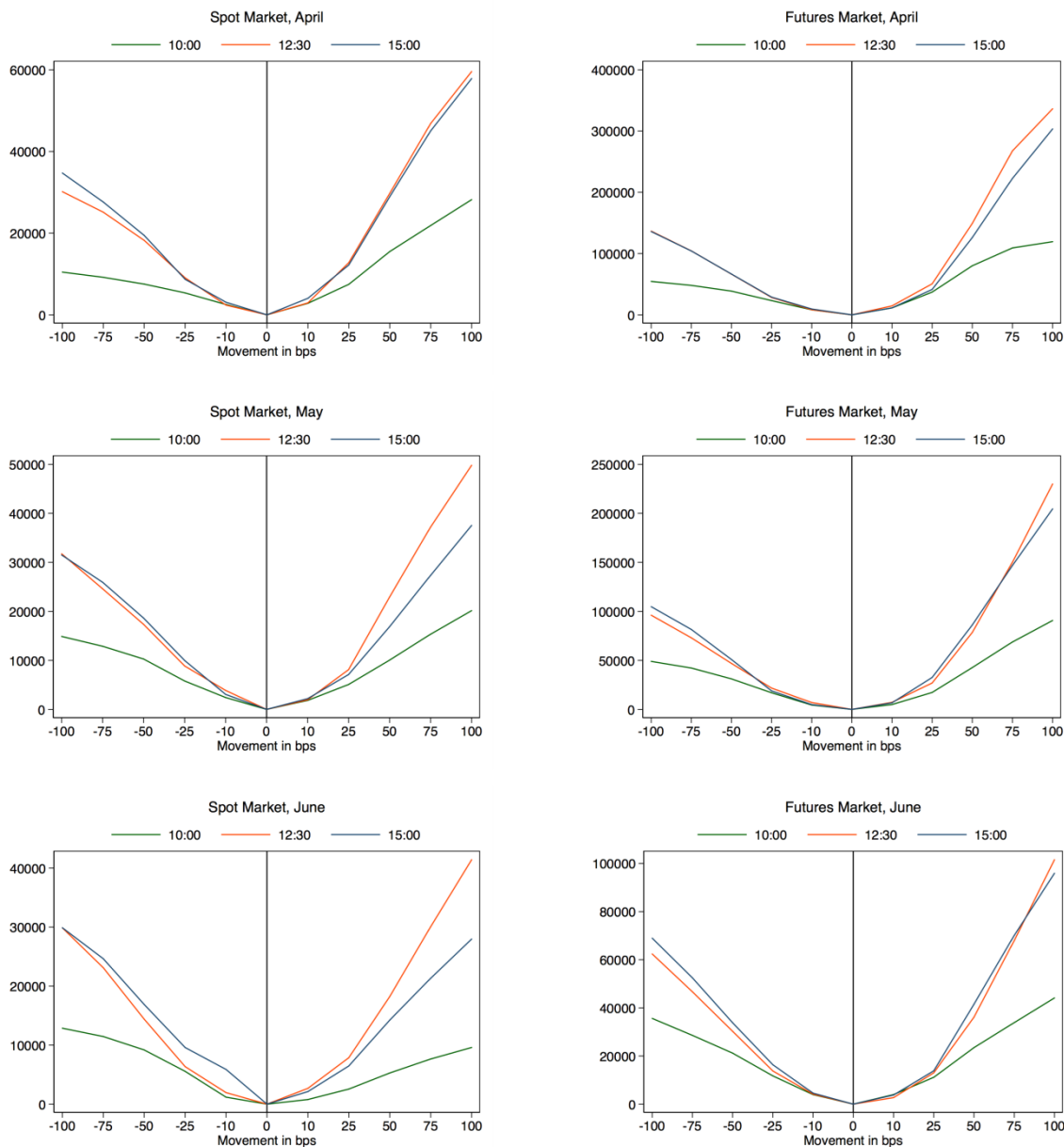
Note: Depths of the limit order book for spot and futures markets for April, May, and June 2006. Depths of the limit order book are separated by bid and ask sides and by times: 10 am, 12:30 pm, and 15:00 pm. y-axis: the number of shares it takes to move ask or bid price by the number of basis points 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.

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.