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STOCK PRICE CRASHES:
ROLE OF CAPITAL CONSTRAINED TRADERS

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ABSTRACT

We study two fast crashes using orders/cancellations/trades data with trader identities for a stock trading in the spot and single stock futures markets on the National Stock Exchange of India during April-June/2006 when there was no algorithmic trading. Spot (futures) prices fell by 6.1% (4.6%) and 11.1% (12.3%) within 15 minutes during crashes. Buying by capital constrained short-term-traders who were the primary intraday liquidity providers was not sufficient to halt price decline. Domestic mutual funds, slow to move in, bought sufficient quantities leading to price recovery. Crashes and recoveries began in the spot market though volume was higher in futures.

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The "Flash Crash" of May 6, 2010 focused the attention of exchanges and regulators on the need to understand what causes market fragility. According to SEC/CFTC report (CFTC and SEC (2010)), there was a large institutional sell order (more than 4 billion USD) for E-mini S&P 500 futures that was quickly executed via algorithmic trading starting at 2:32 pm EDT on May 6, 2010. As a result of this order execution, within 30 minutes U.S. stock market had dropped by more than 9% before bouncing back. Regulators have since focused their attention on understanding the role of algorithmic traders who trade at high frequencies in precipitating fast crashes. SEC (2010) defines High Frequency Traders (HFT) as a subgroup of algorithmic traders characterized by superior speed relative to other market participants who hold little intraday as well as end-of-day inventory positions, indicating that they are capital constrained.

Easley, Lopez de Prado, and O'Hara (2011), using their VPIN metric of "order flow toxicity" developed in Easley, de Prado, and O'Hara (2012), argue that order flow toxicity – the likelihood of a trader who provides liquidity trading against a better informed trader – spiked before the Flash Crash occurred.[1] To the extent HFT might be better informed due to their superior ability to collect, process, and act on information from the order flow and news feeds,[2] one may suspect that HFT may have contributed to increased order flow toxicity. Interestingly, Kirilenko, Kyle, Samadi, and Tuzun (2017), using transaction-level data for the E-mini S&P 500 futures, conclude that HFT did not trigger the May 6, 2010 Flash Crash. Moreover, HFT did not behave differently during the Flash Crash as compared to other times.

In this paper, we contribute to this debate. In order to examine the role of limited market making capital available to traders, i.e. capital constrained traders, who are the primary providers of intraday liquidity during fast crashes, we use data provided by the National Stock

[1]However, their findings are subject to debate – Andersen and Bondarenko (2014) come to a different conclusion.

[2]See Cespa and Foucault (2011); Scholtus, van Dijk, and Frijns (2014); Foucault, Kozhan, and Tham (2015); Foucault, Hombert, and Roşu (2016); Menkveld and Zoican (2016))

Exchange of India (NSE) during April – June 2006 for one large representative stock. During this period high-frequency trading (and any algorithmic trading in general) was not allowed at the NSE and thus, any order submission, modification, and / or cancellation required a manual entry. In other words, high-frequency trading did not exist, while fast crashes did. Short-term traders who do not carry inventories overnight played an important role as liquidity providers and thus, it is the limited inventory capacity of financial intermediaries, rather than the speed advantage per se, and the slow moving nature of intermediation capital of institutional investors (see Mitchell, Pedersen, and Pulvino (2007) and Duffie (2010)) that enables fast crashes to take place.

We use a unique database of orders and transactions data for April – June 2006 for a large anonymous firm in the NIFTY index traded on the NSE which provides us with a unique identifier for each broker-trader combination on spot and futures markets.[3] During the sample period under consideration this stock experienced two fast crashes and recoveries in both spot and futures markets together with stock market indices such as NIFTY and SENSEX.[4] The first fast crash is characterized by a drop in the mid-quote by 6.09% (4.63%) and the second fast crash is characterized by a drop in the mid-quote of 11.10% (12.28%) on spot (futures) market within 15 minutes followed by sharp recovery. Thus, our data provide us with a unique laboratory to study the behavior of short-term endogenous liquidity providers in the open limit order book when algorithmic trading and designated market makers were not present. This helps us identify the limited inventory capacity of such

[3] We note that this anonymous firm is traded in a stock (spot) market but also in a single stock futures market, with trading volume in the single stock futures market being almost five times larger than the trading volume in the spot market.

[4] Analysts speculated that the reason for this drop was that the U.S. CPI number, released a day before the first crash, was above expectations. This, coupled with weaknesses observed in the London Metal Exchange, has led to losses in emerging markets like India, Mexico, and Brazil. As a result on May 18, 2006, the SENSEX (Indian stock market index) registered a fall of 826 points (6.76%) to close at 11,391, following heavy selling by foreign institutions and a weakness in global markets. This market meltdown was followed by a drop in SENSEX on May 19, 2006 by 452 points and the biggest intraday fall in the history of Indian stock market on May 22, 2006, when SENSEX dropped by 1,111 points triggering a market-wide circuit breaker. Market crashes on May 19, 2006 and May 22, 2006 are also identified as fast crash periods for the anonymous stock under consideration.

voluntarily liquidity providers, and the slow moving nature of longer term intermediation capital as the primary drivers of fast crashes.

NSE became the largest stock exchange in India in terms of volume traded overtaking the Bombay Stock Exchange (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. During the period under consideration, there were 139,275 distinct broker-trader combinations transacting a total of 231.5 million shares in the spot market and 1.4 million futures contracts (equivalent of 1 billion shares) in the futures market for the anonymous firm. The NSE classifies traders in terms of their legal affiliations. We find that these legal classifications of traders, like retail, institutions, etc. are not fully adequate for understanding liquidity provision in the market. Liquidity provision is an action, and as such is dynamic. Also, NSE does not have designated liquidity providers. Under some circumstances traders become liquidity providers, and under different scenarios, the same traders may become liquidity demanders. Several types of traders are short term liquidity providers, i.e., they tolerate deviations from their desired inventory positions only 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. Though, some legal classifications are useful as, for instance, Mutual Funds are natural long-term liquidity providers, while Foreign Institutions have a global view on the market and thus, their behavior might be affected by the shocks originated outside Indian market.

Our data permits us to track individual traders and their transactions over time, and identify liquidity providers based on their trading behavior and classify traders into short- (STT) and long-term traders (LTT) since traders with different investment horizons are likely to have differing liquidity provision characteristics, especially during market crashes, which is the main focus of this paper. We find that STT, who carry relatively small amounts of inventory intraday relative to their trading volume and carry little inventory overnight, are present on at least one side of the transaction for 85% (89%) of the daily trading volume in the spot (futures) market. Moreover, 37% (45%) of the daily trading volume in the spot (futures) market occurs among STT themselves. This pattern is similar to what has been observed in dealer markets, e.g., Lyons (1995), Hansch, Naik, and Viswanathan (1998) and Reiss and Werner (1998), and often referred to as "hot potato" trading which is used as an inventory management tool by market makers in dealer markets. Our evidence suggests that STT use "hot potato" trading in an open limit order book market as well.

We find that during normal price fluctuations, STT act as the main liquidity providers for LTT when the latter demand immediacy: in 52% (67%) of shares demanded by LTT on spot (futures) market on average per day. In cases when STT consume liquidity, they do so mainly from other STT in 59% (68%) of shares demanded by STT on spot (futures) market. We also document that larger the inventory of STT, more shares are needed to move the ask price (and vice versa for the bid price) on the spot market. Put differently, STT buy when the supply schedule is elastic and sell when demand schedule is elastic. Such behavior is in line with a patient inventory management as in Stoll (1978). In the same way, futures market is used to hedge STT's positions in the spot market.

In our sample, we observe two fast crashes and recoveries in the spot and futures market alike. The unusually large liquidity shocks in both cases were a result of a large selling pressure coming from foreign institutional investors (as defined by NSE). We document that STT increased their buying from LTT on the spot market by 5.5 basis points of the total daily volume at each one-minute interval during the fast crash (equivalent of an increase by 97% relative to the normal period). During the recovery period, STT unloaded the accumulated inventory back to LTT. As a result, STT increased their selling to LTT by 8.3 basis points of the total daily volume at each one-minute interval during the recovery period (equivalent of an increase by 143% relative to the normal period). Similar patterns hold for the futures market as well. Remarkably, STT trade against the rapid market movements both during the fast crash and recovery periods, however, their effort was not enough to stabilize the market.

Domestic mutual funds (as defined by NSE) and other long-term traders had to step in to provide support for price recovery to take hold: we observe an increase in trading activity between LTT themselves by 8.3 basis points at each one-minute interval during recovery period (equivalent of an increase by 203% relative to the normal period).

Additional support for the findings above is given by the analysis of inventory sensitivity to the price changes. As in Kirilenko, Kyle, Samadi, and Tuzun (2017), we document that overall activity of STT traders becomes either contrarian (their inventory increases when the spot and futures price goes down) or does not change during fast crash and recovery periods for spot and futures markets alike.

In sum, our evidence suggest that if the major intermediaries in the market are those relying on short-term inventory management, fast crashes might occur and in order to recover the market needs long-term traders to step in which takes some time.

The rest of the paper is organized as follows. Section I relates our work to the literature. Section II describes the data. Section III introduces methodology we use to identify short-term traders (STT). Section IV characterizes liquidity provision by STT during normal periods and during two fast crashes in our sample. We conclude in Section V.

I. Literature review

We contribute to two different streams of literature. First, we contribute to the literature on liquidity provision in the open limit order book markets. Second, we contribute to the literature on market fragility.

The literature on liquidity provision is vast and covers markets of different financial instruments (equities, bonds, derivatives, and foreign exchange) as well as markets with different trading mechanisms (dealer markets, limit order book markets, and hybrid markets), and therefore, we discuss only a few closely related papers. Conventional wisdom based on seminal work of Ho and Stoll (1983) 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. Lyons (1995) finds that inter-dealer trading accounts for about 95% of the total volume in foreign exchange markets highlighting the importance of inter-dealer trades. Hansch, 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. Overall, short-term traders, even though having limited capital individually, as a group are able to act as main liquidity providers on the market via "hot potato" trading.

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. Hendershott and Seasholes (2007) and Hendershott and Menkveld (2014) document inventory management by market makers and the price pressures that arise from it for NYSE. Venkataraman and Waisburd (2007) and Menkveld and Wang (2013) document liquidity benefits of the designated market makers especially for smaller firms. 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. Kahraman and Tookes (2017) find that the ability to trade on margin increases liquidity, however in crisis periods due to massive deleveraging liquidity deteriorates (downward liquidity spiral).

We contribute to this literature by providing supportive evidence for "hot potato" trading in the pure limit order book market. We show that this inventory management tool is a salient feature of short-term liquidity providers.

The emergence of algorithmic trading, especially high-frequency trading (HFT), has diminished the importance of traditional market makers, like NYSE specialists, and nowadays, the majority of the liquidity provision is voluntarily (see Menkveld (2013), O'Hara (2015), and Bongaerts and Van Achter (2016)). There is a plethora of studies investigating the effect of HFT on liquidity provision. Hendershott, Jones, and Menkveld (2011) show that increase in automation leads to increase in liquidity provision as well. Menkveld (2013) focuses on a single cross-venue high-frequency trader and documents that in four out of five trades that trader was providing liquidity. Malinova, Park, and Riordan (2013) show that retail traders enjoy better liquidity due to activity of high-frequency traders. Lyle and Naughton (2015) examine specific mechanisms through which this reduction in spreads may have occurred and why spreads did not continue to fall further with increased algorithmic trading. While there is consensus regarding the effect of HFT on spreads for small trades, examining welfare implications of HFT is difficult in part due to the difficulties associated with modelling the need for liquidity and the benefits to earlier resolution of uncertainties and the lack of comprehensive data. Budish, Cramton, and Shim (2015) argue in favor of frequent batch auctions and against continuous limit order book based trading that promotes HFT by rewarding speed.

The voluntarily nature of such liquidity provision raises concerns on whether endogenous market makers will be present in the market during turbulent periods, when they are most needed to provide liquidity. 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. Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and He and Krishnamurthy (2013) postulate that adverse shocks to the balance sheet of intermediaries, who act as liquidity providers, lowered their ability to commit capital for market making during those times.

The Flash Crash of May 6, 2010 has focused the attention of several researchers on understanding the determinants of market fragility. Bongaerts and Van Achter (2016) show that the presence of high-frequency market makers who have superior speed and superior information processing technology might lead to market freezes as slow liquidity providers are crowded out from the market. Interestingly, in the electronic order book market for stock that we examine here, during one of the two fast crashes trading was suspended. Easley, de Prado, and O'Hara (2012) develop a method for identifying order flow toxicity that adversely affects market makers resulting in market fragility. Kirilenko, Kyle, Samadi, and Tuzun (2017) study the role of HFT in the Flash Crash and document that their behavior did not change during the Flash Crash, while Menkveld and Yueshen (2016) argue that cross-market arbitrage (often conducted by high-frequency traders) broke down before the Flash Crash.

Inventory management by liquidity providers is closely linked to the market fragility. According to CFTC and SEC (2010), "...still lacking sufficient demand from fundamental buyers or cross-market arbitrageurs, HFT began to quickly buy and then resell contracts to each other – generating a "hot-potato" volume effect as the same positions were rapidly passed back and forth. Between 2:45:13 and 2:45:27, HFT traded over 27,000 contracts, which accounted for about 49 percent of the total trading volume, while buying only about 200 additional contracts net." (CFTC and SEC (2010), p. 3)

We contribute to this literature by examining the role of traders, who trade very frequently, during the two fast crashes in the market, where there was no algorithmic trading, and we find that they did not cause or amplify the fast crash. We show that speed differentials among traders is not the problem, but limited inventory capacity (capital constrains) of the short-term traders acting as main liquidity providers is. We also document that it is the slow-moving capital coming from domestic institutional investors that absorb the liquidity shocks and stabilize the market consistent with Mitchell, Pedersen, and Pulvino (2007) and Duffie (2010).

II. Data description

We use a unique database of orders and transactions for three months in 2006 (April – June) of a large anonymous firm traded on the National Stock Exchange (NSE) of India which provides us with a unique identifier for each broker-trader combination and legal classification on spot and futures markets. Our data includes detailed information on trades and quotes (the full history of the order: submission, modification, cancellation, execution). All of our subsequent analysis is conducted for this one representative NSE stock.[5]

During the sample period under consideration this stock has experienced two fast crashes and recoveries in the spot and futures market – 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 for both spot and futures markets. Figure 1 shows the spot and futures mid-quotes evolutions during the trading day together with NIFTY prices (median over one-minute interval) for the two days with fast crashes. We note that on May 19, 2006 there were two instances of market drawdowns, however, the second instance does not qualify as fast crash under our definition. In particular, on second-by-second basis during the first event on May 19 (trough at 10:39:14) the mid-quote in the spot (futures) market dropped by 6.09% (4.63%), while during the second event on May 19 (trough at 14:46:12) the mid-quote dropped by 2.74% (3.31%) within 15 minutes. Hence, only the first event with a trough at 10:39:14 is considered as fast crash. On May 22 (trough from 11:54:37 to 12:56:25), we observe a more severe drop in mid-quotes of 11.10% (12.28%) on spot (futures) market within 15 minutes. This last fast crash was also characterized by a trading halt before market recovery took place. We also note that the two fast crashes were accompanied by similar movement in NIFTY index though it was less pronounced.

INSERT FIGURE 1 HERE

INSERT TABLES I – II HERE

[5]We refer to Appendix A for detailed description of the NSE market.

Table I shows that there are 109,204 traders in the spot market, while in the futures market for this stock there are only 36,343 traders during the sample period. In total, there were 139,275 traders that traded either in the spot, futures, both in spot and futures, or submitted the orders which were not executed during this time period. The latter category includes 8.49% of traders (11,826 traders), therefore, the number of effective traders whose orders resulted in at least one trade during this time period is 127,449. The majority of the active traders on either spot (71.04%) or futures (86.47%) markets execute their orders on both sides of the market, i.e., both buy and sell. 67.46% of traders execute their orders on spot market only, 20.14% of traders execute their orders on futures market only. Only 3.91% of traders are active in both markets.

Table II shows that the majority of the order flow in the spot market is represented by new order submissions (around 71% for both buy and sell sides of the market), followed by cancellations (around 17% for buy side and 15% for sell side of the market) and modifications (around 12% for buy side and 14% for sell side of the market). Similar patterns also hold for the futures market.[6]

III. Traders' classification

The NSE classifies all 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. However, legal classifications of traders are not adequate for

[6]Cancellation proportions are comparable to the one of e.g., Numeric Investors (investment management company, currently known as Man Numeric (after acquisition by Man Group) with assets under management around 30 billion USD) whose trading strategy typically leaves around 10-15% of orders unexecuted / cancelled (see Perold and Tierney (1997)).

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 (see Figure 2). 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. We do this based on the conjecture that STT are continuously present in the market and observant of events, whereas LTT are present in the market only at periodic intervals and when trigger events happen.

INSERT FIGURE 2 HERE

On a given day, we classify traders into Small and Other Traders. Small traders are traders whose trading volume is less than or equal to 750 shares (equivalent of one contract) on a given day.[7] Other traders are classified as traders whose trading volume exceeds 750 shares on a given day. We further classify other traders by their end-of-day inventory. Short-term traders (STT) are traders whose end-of-day inventory is less than 10% of traded volume. Long-term traders (LTT) are traders whose end-of-day inventory is more than 10% of traded volume. We further split long-term traders into mutual funds (MF) and foreign institutional investors (FII) and other long-term traders. Mutual funds and FII are legally classified by the National Stock Exchange of India.[8] To determine the final category of a trader, we look at the modal classification of the trader across days and select it as the trader's category unless the mode equals "Small" trader. If a mode classification is equal to "Small" trader then we assign it as a trader category if and only if a trader is classified as Small trader on more than 67% of days, otherwise we use the next most frequent classification as the trader's category.[9]

[7]The size of futures contract is 750 shares in our sample.

[8]We note that several MF and FII end up in Small or STT groups. However, their activity during the period considered is negligible. These traders are active on average 5 (2) days on spot (futures) market and transact on average 109 (2,375) shares per day on spot (futures) market.

[9]We also document that the categorization of STT is persistent over time. Please see Appendix B for details.

INSERT TABLE III HERE

Table III shows buy and sell trading volume for each of the three trader categories. In particular, we find that STT are responsible for 61.36% (67.21%) of the total (buy+sell) trading volume for spot (futures) market. LTT are responsible for 22.11% (31.41%) of the total trading volume for spot (futures) market. Small traders are responsible for 16.53% (1.38%) of the total trading volume for spot (futures) market. Besides that, considerable portion of trading activity stems from STT who are active in spot and futures market alike: 35.94% and 28.42% for spot and futures markets, respectively. We also note that the size of the futures market is five times larger than the size of the spot market. Although the spot market is smaller than the futures market, it is more diverse in terms of market participants. For example, Small traders essentially do not trade in the futures market and hence, despite the lower traded volume, the spot market is an important venue of price discovery.

The difference in size of the spot and futures markets is caused by a security transaction tax that is much larger for the spot market (around 10 bps) than for the futures market (around 1 bps). Moreover, it is easier to take short positions on the futures market than in the spot market. Overnight short positions in the spot market was not allowed during our sample period with the exception of participatory notes, but this way of borrowing shares was available to very few investors, mainly FIIs.

IV. Empirical results

In this section, we discuss our empirical results. First, we show that STT are the main intermediaries in the market. Given that STT have limited inventory capacity, the only way for them to be the hub for the majority of the transactions is to manage inventory risks by passing inventories among themselves as "hot potatoes" as Ho and Stoll (1983) and Viswanathan and Wang (2004) argue. Hence, we start by showing that STT indeed are involved heavily in "hot potato" trading (see Section IV.A). We then document that during normal times STT act as the main liquidity providers (see Section IV.B). Finally, we find that buying by STT is not enough to stop prices from crashing, and price recovery started only when MF stepped in and started buying in sufficient quantities (see Section IV.C).

A. "Hot potato" trading

HYPOTHESIS 1: *STT are "hot potato" traders.*

Lyons (1997) refers to hot potato trading as "repeated passing of inventory imbalances between dealers." (Lyons (1997), p. 275) However, the NSE is not a dealer market, hence we modify this definition to suit open limit order book market design. In particular, we would call STT "hot potato" traders if they satisfy the following two conditions. First, the majority of the transactions involve such traders as a counterparty. Second, the amount of transactions between STT themselves is larger than between STT and any other market participant.

Table IV shows average daily trading volume between each possible trader-pair (i, j) and the results of the trading activity regression estimation. In particular, for each one-minute interval t on day k we compute the trading volume (in number of shares) coming from each possible trader-pair (i, j) relative to the total trading volume on day k and regress it on trader-pair dummies (D_{ij} where $j \leq i$), day fixed effects (FE_k) and half-hour time dummies (TD_b)[10]:

$$\frac{Vol_{ijkt}}{\sum_{(i,j)} Vol_{ijk}} = \sum_k \alpha_k FE_k + \sum_b d_b TD_b + \sum_{(i,j)} \beta_{ij} D_{ij} + \epsilon_{ijkt} \quad where \;\; j \leq i \tag{1}$$

INSERT TABLE IV HERE

[10] As a robustness check, we also perform the analysis where we use total one-minute trading volume instead of total daily trading volume in the denominator. Please see Appendix C for details.

We document that STT are the most frequent counterparty for LTT and Small traders, for spot and futures market alike. Roughly 8.47 (13.82) basis points of the average daily volume for spot (futures) market is between STT and LTT at each one-minute interval, which corresponds to 26% (42%) per day. Roughly 7.71 (2.35) basis points of the total daily trading volume at each one-minute intervals for spot (futures) market is between STT and Small traders, with Small traders being not that active in futures market. This translates into 22% (2%) of daily trading volume per day. The volume traded between STT themselves in each one-minute interval is 11.43 and 14.51 basis points of the daily trading volume respectively for spot and futures market. This translates into 37% (45%) of the total trading volume per day for spot (futures) market. Overall, STT are involved at around 27.62 (30.67) basis points of the daily trading volume for spot (futures) market at each one-minute interval or 85% (89%) of the daily trading volume per day. The trading activity among STT themselves constitutes around 2/5 and 1/2 of their overall trading activity for spot and futures markets, respectively.

We also report results of the F-tests for "hot potato" trading hypothesis. In particular, we test whether STT exhibit "hot potato" traders' characteristics. We reject at 5% significance level the null hypothesis that the trading activity among STT themselves is equal to the trading activity between STT and LTT or between STT and Small in spot and futures markets alike. We reject at 1% significance level that the trading activity between STT and LTT (Small) is equal to the trading activity between LTT (Small) and other market participants on spot and futures markets alike. To sum up, STT exhibit the properties of "hot potato" traders.

The proportion of trading activity among STT themselves is in line with Reiss and Werner (1998) who report that inter-dealer trading in 1991 on London Stock Exchange accounts for on average 24% and can be as high as 65% of all trades, when dealer inventories are high. However, if we consider high-frequency traders (HFT) as a natural evolution of STT once algorithmic trading is allowed, we document twice as high total trading activity of such traders as reported by Brogaard, Hendershott, and Riordan (2014) who documents that in 2009 on NASDAQ (dealer market with elements of the limit order book) HFT overall were responsible for 42% (18%) of volume for large (small) stocks. Moreover, Johnson, Van Ness, and Van Ness (2017) documents (using the same dataset but for NASDAQ-listed stocks only) that HFT are responsible for 47% of trading volume, however, only 8% of it is among HFT themselves as compared to our estimate of 37% among STT for the spot market. Interestingly, according to CFTC and SEC (2010), HFT exhibited "hot potato" trader characteristics during the Flash Crash of May 6, 2010.

B. Liquidity provision

HYPOTHESIS 2: *STT are main liquidity providers.*

Liquidity is "a broad and elusive concept that generally denotes the ability to trade large quantities quickly, at low cost, and without moving the price." (Pástor and Stambaugh (2003), p. 644) Clearly, there are multiple ways to define liquidity provision in the literature.

We start our analysis by focusing on the immediacy aspect of liquidity. In particular, we adopt definition of liquidity provision similar to Brogaard, Hendershott, and Riordan (2014) who define market and marketable orders (i.e., orders that initiate the trade and demand immediacy) as liquidity consuming orders and non-marketable orders (i.e., orders that do not initiate the trade and provide immediacy) as liquidity providing orders. In order to determine which order initiates the transaction, we match trades with respective quotes and compare the timestamps of the two sides of the transaction. The order with the latest timestamp is the one that initiates the transaction and thus, consumes liquidity.[11]

Table V shows summary statistics for liquidity provision by different trader categories. We document that in the spot market, only LTT are strong net liquidity providers: 18.45%

[11]In case orders on the two sides of the transaction have the same timestamp, we cannot determine which order is consuming liquidity and which order is providing liquidity. However, there are very few such unclassified cases: 0.76% and 1.22% of trading volume for spot and futures markets, respectively.

of their trading volume. Both STT and Small traders consume more liquidity than they provide. Remarkably, STT are weak net liquidity consumers: only 3.49% of their trading volume is dedicated to net liquidity consumption, while for Small traders the net liquidity consumption captures 11.79% of the trading volume. For the futures market, both STT (0.06% relative to their trading volume) and LTT (0.26% of their trading volume) are weak net liquidity providers, while Small traders remain net liquidity consumers (8.96% of their trading volume). In summary, STT consume approximately the same amount of liquidity they provide. This finding is in line with Brogaard, Hendershott, and Riordan (2014) who document that HFT liquidity consumption is equal to HFT liquidity provision for large stocks.

INSERT TABLE V HERE

Table VI shows average daily trading volume between each possible trader-pair (i, j) and the results of the liquidity regression estimation. In particular, for each one-minute interval t on day k we compute the trading volume (in number of shares) coming from each possible trader-pair (i, j) relative to the total trading volume on day k and regress it on trader-pair dummies (D_{ij} where i refers to category that consumes liquidity and j to category that provides liquidity), day fixed effects (FE_k) and half-hour time dummies (TD_b):

$$\frac{Vol_{ijkt}}{\sum_{(i,j)} Vol_{ijk}} = \sum_k \alpha_k FE_k + \sum_b d_b TD_b + \sum_{(i,j)} \beta_{ij} D_{ij} + \epsilon_{ijkt} \quad for \;\; all \;\; (i, j) \tag{2}$$

INSERT TABLE VI HERE

When a trader initiates a trade through a market (marketable limit) order, we say the trader "consumes" liquidity. The trader taking the other side of the trade "provides" liquidity. β_{ij} shows the one-minute average proportion of the daily trading volume (in basis points) that trader category i consumes from trader category j (all β_{ij} are positive). Overall liquidity consumption (demand for immediacy) of trader category i is $\sum_j \beta_{ij}$. Overall liquidity provision (supply of immediacy) of trader category i is $\sum_i \beta_{ji}$. Net liquidity provision by trader category as in Table V is a difference between overall liquidity provision and overall liquidity consumption.

Although, STT are weak net liquidity consumers for spot market, Table VI shows that in the majority of cases STT consume liquidity from another STT (7.656 / (3.451 + 7.656 + 1.911) = 58.81%), followed by liquidity consumption from LTT (3.451 / (3.451 + 7.656 + 1.911) = 26.51%), with the remainder of liquidity consumed from Small traders. When LTT or Small traders demand liquidity, STT provide the majority of it. In particular, in the spot market STT provide 52.23% of the total liquidity demanded by LTT (1.935 / (1.373 + 1.935 + 0.397)). In the spot market STT provide 67.28% of the total liquidity demanded by Small traders (2.550 / (0.558 +2.550 + 0.682)). Similar pattern holds for the liquidity provided by STT in the futures market: 66.76% of the total liquidity demanded by LTT, 67.65% of the total liquidity demanded by STT, and 71.42% of the total liquidity demanded by Small traders. We also perform F-tests on whether STT are the most likely liquidity providers when market participants demand immediacy. With 1% significance level we reject that the amount of liquidity provided by STT is equal to the amount of liquidity provided by other market participants. In other words, we show that STT are the main providers of immediacy aspect of liquidity on the NSE.

We now turn to another aspect of liquidity which is related to the price impact of the trades. More specifically, we run a panel regression with elasticity of ask and bid sides of the limit order book on the amount of the inventory accumulated by STT. Naturally, the more elastic is the limit order book, the larger orders could be executed without moving the price. We aim to investigate whether STT increase (decrease) their inventory when there is a lot of depth available on the ask (bid) side of the book. In other words, we are testing whether STT put pressure on the market while managing their inventory. This is also consistent with Stoll (1978) who suggests that a market maker who wishes to unload a large positive inventory position will put a quote at a competitive ask price to encourage other market participants to buy from her and put a less competitive quote at the bid price thereby discouraging other market participants from selling to her – or refrain from posting quotes at the bid. Hendershott and Menkveld (2014) develop a dynamic model for such inventory management and verify its predictions for NYSE specialists.

Table VII presents the results of the elasticity regression estimation. In particular, for STT we run the following regression:

$$\pi_{kt} = \beta_0 + \sum_k \alpha_k FE_k + \sum_b d_b TD_b + \beta_1 Inv_{STTkt} + \epsilon_{kt} \tag{3}$$

where π_{kt} is price elasticity of the limit order book (measured as number of shares it takes to move prices by 100, 50, 25, or 10 basis points on either the bid or ask side) on day k during one-minute interval t, FE_k is a day fixed effect, TD_b is half-hourly time dummies (proxying for the intraday patterns in liquidity), and Inv_{STTkt} is the median inventory of STT on date k and one-minute interval t.

INSERT TABLE VII HERE

Panel A of Table VII shows that high spot inventory (large and positive inventory) of all STT is associated with an increase in the elasticity of the ask side of the limit order book and a decrease in the elasticity of the bid side of the limit order book in the spot market, consistent with patient inventory management. STT traders that are active on both futures and spot markets are the dominant players of the STT. We therefore look separately at the effect of such STT and at the effect of the inventory of STT that are active on only one market on the elasticity of the spot market. We observe that inventory of STT active on only spot market is not associated with changes in price elasticity, while STT active on both markets drive overall results. The net effect of STT active on both markets (spot+futures) is associated with a decrease in ask side elasticity measured as number of shares it takes to move prices by 100 basis points and is not associated with changes in the depth of the limit order book closer to the best bid-offer level. We note that the net effect is dominated by futures market inventory. (Table III shows that in number of shares spot market trading activity of STT active in both markets is only 1/5 of the aggregate trading activity (spot + futures) of STT active in both markets.)

Panel B of Table VII shows that futures inventory of all STT as well as inventory of STT active on only futures market is not associated with changes in the elasticity of the futures market. Inventory of STT active on both markets is associated with a strong decrease in ask side elasticity and with a marginal decrease in bid side elasticity as well. Net inventory of STT active in both markets is associated with a decrease (increase) in futures market elasticity on ask (bid) side. Different signs of the coefficients in spot and futures markets for STT active on both markets could be explained by the fact that STT use futures market to hedge their positions on spot market and in this way transfer liquidity from futures market to spot market.

To sum up, we document that although in the net terms STT do not provide liquidity, they are the main providers of immediacy to any other trader category. In addition, the majority of STT's liquidity consumption is concentrated among themselves. STT are also patient in managing their inventories in the spot market and hence, STT provide better liquidity for large orders. Finally, STT use futures market for hedging purposes.

C. Liquidity provision during fast crashes

HYPOTHESIS 3: *STT do not change their behavior during fast crashes.*

We start our analysis by defining extreme market conditions in the following way: the price for the stock declines by more than 3% and then sharply recovers by more than 3% within 15-minute time span (both before and after the trough) on a second-by-second basis in both spot and futures markets. We find two such fast crashes in our sample: one crash on May 19, 2006 and one crash on May 22, 2006.

Brogaard, Riordan, Shkilko, and Sokolov (2014) study behavior of HFT in case of extreme price movements, and hence, their definition of liquidity provision is suitable for the purpose of our study. Specifically, liquidity provider should trade against the market movement: buy when the market drops and sell when the market recovers. Table VIII shows the results of the trading activity regression estimation around two fast crashes in our sample (one crash on May 19, 2006 and one crash on May 22, 2006) for spot and futures markets. In particular, for each one-minute interval t on day k we compute the trading volume (in number of shares) coming from each possible trader-pair (i, j) relative to the total trading volume on day k and regress it on trader-pair dummies (D_{ij} where i refers to selling category and j to buying category) and their interaction with dummy variables for market drawdowns ($Down_{kt}$) and recovery (Up_{kt}) periods, day fixed effects (FE_k), and half-hour time dummies (TD_b):

$$\begin{aligned}\frac{Vol_{ijkt}}{\sum_{(i,j)} Vol_{ijk}} &= \sum_k \alpha_k FE_k + \sum_b d_b TD_b + \sum_{(i,j)} \beta_{ij} D_{ij} + \\ &+ \sum_{(i,j)} \gamma_{ij} Down_{kt} D_{ij} + \sum_{(i,j)} \delta_{ij} Up_{kt} D_{ij} + \epsilon_{ijkt} \quad for \;\; all \;\; (i,j)\end{aligned} \tag{4}$$

$Down_{kt}$ (Up_{kt}) is equal to one for – (+) 30 minutes from the trough of the fast crash and zero otherwise.

INSERT TABLE VIII HERE

Panel A of Table VIII shows that during the market drawdown period, we observe that STT significantly increase their buying from LTT by 5.55 basis points for spot market (i.e., their buying from LTT almost doubled relative to the normal period), while LTT do not increase trading activity among themselves. We acknowledge that we cannot statistically confirm that STT buying from LTT during fast crash was different than their buying from

LTT during recovery period. In summary, STT tried to accommodate the volume sold by LTT, however STT are not able to stop market drawdown.

Panel A of Table VIII shows that during market recovery after the fast crash, there is a significant increase in trading activity between LTT by 8.33 basis points in the spot market, i.e., trading activity between LTT tripled relative to normal period. STT unload their inventory accumulated during market drawdown to LTT (significant increase of selling volume by 8.32 basis points). Panel B of Table VIII repeats the analysis discussed above for the futures market. During drawdown periods STT increase their buying from LTT. STT also use recovery period to unload inventory bought from LTT.

Remarkably, during both drawdown and recovery STT increase their trading activity in the opposite direction to the market movement and, therefore, provide liquidity to the market when it is necessary. Moreover, the trading among STT does not increase during both drawdown and recovery, hence, within STT category trading does not amplify market movements during such time periods. Our findings are in line with Brogaard, Riordan, Shkilko, and Sokolov (2014) who document that HFT provide liquidity in case of a single stock experiencing an extreme price movement by absorbing order flow from NON-HFT.

We acknowledge that the current specification does not allow us to test separately for the behavior of mutual funds and foreign institutional investors (part of LTT category) due to multicollinearity problem: foreign institutions activity is concentrated during the down period and mutual funds activity is concentrated during the recovery period. Instead, we group FII, MF, and other LTT in one group. We provide the graphical representation of the behavior of mutual funds and foreign institutions (see Figure 3). Figure 3 shows that selling by FII in the spot market coincides with the fast crashes (see Panels A and C), while buying by Mutual Funds in the spot market is followed by the market recovery (Panels B and D). These graphs are consistent with the stabilizing role of the slow-moving capital (see Duffie (2010)). Note that futures market mimics the spot market; however, behavior of the FII and MF in the futures market is not related to it. We also emphasize that FII take opposite positions in spot and futures markets, however, this positions are established by different traders within the FII group.

INSERT FIGURE 3 HERE

These two fast crashes resembles the Flash Crash of May 6, 2010 in the U.S. According to CFTC and SEC (2010), the Flash Crash was generated by large institutional trader who entered an order to sell 75,000 E-mini S&P 500 futures which corresponds to more than 4 billion USD. Our two fast crashes are also characterized by large selling pressure from institutions. Normally, such large orders are executed over prolonged period of time, however before the Flash Crash, the trading algorithm executed the order in a very rapid fashion which lead to an extreme price drop. Van Kervel and Menkveld (2016) and Korajczyk and Murphy (2016) document how HFT behave during prolonged execution of the institutional orders. Namely, they show that initially HFT "lean against the wind" and "go with the wind" as time passes. The switch of their behavior is attributable both to inventory management concerns and order anticipation.

We provide evidence in line with STT "leaning against the wind." Table IX shows the results of the cash flow regression estimation around two fast crashes in our sample (one crash on May 19, 2006 and one crash on May 22, 2006) for spot and futures markets. Given that STT tend to end each day with flat positions, we make a simplifying assumption that in the end of the day they do not have any positions to liquidate and hence, each day they start with zero inventory position. We note that we compute aggregate cash flows for STT category. Hence, we do not exclude the possibility for vast heterogeneity within the STT category. In particular, for each one-minute interval t on day k with at least one transaction we compute cumulative cash flow for STT (+ (−) price times number of shares traded in case of sell (buy) transaction) and regress it on dummy variables for market drawdowns ($Down_{kt}$) and recovery (Up_{kt}) periods, day fixed effects (FE_k), and half-hour time dummies (TD_b):

$$Cash\ Flow_{STTkt} = \sum_k \alpha_k FE_k + \sum_b d_b TD_b + \gamma Down_{kt} + \delta Up_{kt} + \epsilon_{kt} \tag{5}$$

where $Down_{kt}$ (Up_{kt}) is equal to one for – (+) 30 minutes from the trough of the fast crash and zero otherwise.

INSERT TABLE IX HERE

Panels A and B of Table IX show cash flow analysis (in million rupees) for spot and futures markets, respectively. We observe that cash flows decrease during market drawdown and increase during market recovery period on both markets alike. Although, we lack statistical power for this test. To further support our hypothesis, we depict the cumulative cash flows of STT during the two fast crash days (Figure 4). We document that cumulative cash flows for STT decrease during market drawdowns and increase during recovery periods.

INSERT FIGURE 4 HERE

Another way to support our hypothesis is to look at whether STT demand immediacy during the market drawdown or trade with passive orders. In particular, for each one-minute interval t on day k we compute the trading volume (in number of shares) coming from each possible trader-pair (i, j) relative to the total trading volume on day k and regress it on trader-pair dummies (D_{ij} here i refers to liquidity providing category and j to liquidity consuming category) and their interaction with dummy variables for market drawdowns ($Down_{kt}$) and recovery (Up_{kt}) periods, day fixed effects (FE_k), and half-hour time dummies (TD_b):

$$\begin{aligned} \frac{Vol_{ijkt}}{\sum_{(i,j)} Vol_{ijk}} &= \sum_k \alpha_k FE_k + \sum_b d_b TD_b + \sum_{(i,j)} \beta_{ij} D_{ij} + \\ &+ \sum_{(i,j)} \gamma_{ij} Down_{kt} D_{ij} + \sum_{(i,j)} \delta_{ij} Up_{kt} D_{ij} + \epsilon_{ijkt} \quad for\ \ all\ \ (i,j) \end{aligned} \tag{6}$$

$Down_{kt}$ (Up_{kt}) is equal to one for – (+) 30 minutes from the trough of the fast crash and zero otherwise.

INSERT TABLE X HERE

Panel A of Table X shows that for the spot market, STT demand more liquidity from LTT during both fast crash and recovery periods, however, during the recovery periods STT are more aggressive than during the crash periods. STT increase their liquidity provision to LTT during the recovery, although to a lesser extent than they increase their demand for liquidity. In summary, our results are in line with the desire of STT to unload inventory accumulated during the crash as fast as possible.

Panel B of Table X shows that on the futures market, STT exhibit increase in both demand for immediacy from LTT and supply of immediacy to LTT during fast crash and recovery periods alike, which is in line with the fact that relatively more volume is transacted between STT and LTT during turmoil periods than during normal periods.

To provide further evidence that STT provide liquidity during fast crash periods, we present the number of shares quoted within 100 basis points of the mid-quote (see Figures 5 – 6). We observe that STT are still present during the fast crash period within 100 basis points from the mid-quote, although their presence is less profound than during normal periods (which is in line with quoted spread widening during the turmoil periods). On contrary, behavior of FII and MF on spot market is in line with FII causing a fast crash and MF helping markets to recover.

INSERT FIGURES 5 – 6 HERE

Table XI presents the analysis similar to Kirilenko, Kyle, Samadi, and Tuzun (2017). In particular, we estimate regression on the sensitivity of the inventory changes of STT during time interval t on day k to the contemporaneous mid-quote return (Ret_{kt}) during market drawdown ($Down_{kt}$) and recovery (Up_{kt}) periods controlling for lagged spot/futures inventory ($Inv_{ik,t-1}$) and lagged changes in the spot /futures inventory ($\triangle Inv_{ik,t-1}$) and day fixed effects (FE_k):

$$\begin{aligned}\triangle Inv_{ikt} = &\sum_k \alpha_k FE_k + \sum_b d_b TD_b + \beta_1 Ret_{kt} + \beta_2 Down_{kt} Ret_{kt} + \beta_3 Up_{kt} Ret_{kt} + \\ &+ \beta_4 Down_{kt} + \beta_5 Up_{kt} + \beta_6 \triangle Inv_{ik,t-1} + \beta_7 Inv_{ik,t-1} + \\ &+ \beta_8 Down_{kt} \triangle Inv_{ik,t-1} + \beta_9 Down_{kt} Inv_{ik,t-1} + \\ &+ \beta_{10} Up_{kt} \triangle Inv_{ik,t-1} + \beta_{11} Up_{kt} Inv_{ik,t-1} + \epsilon_{ikt}\end{aligned} \tag{7}$$

where $Down_{kt}$ (Up_{kt}) is equal to one for – (+) 30 minutes from the trough of the fast crash and zero otherwise.

INSERT TABLE XI HERE

We present the results for 15-seconds and one-minute frequency. In Panel A of Table XI, we document that at 15-seconds and one-minute frequency all STT are trading in the direction of the price movement during normal times, but they become more contrarian during the fast crashes for both market drawdown and recovery periods and this effect is solely driven by STT active on both markets. At 15-seconds and one-minute frequency STT active on only spot market are contrarian during normal times and move with the market during turbulent periods. The sensitivity of net inventory (spot+futures) of STT active on both markets to price movements depends on the frequency under consideration: they either become contrarian (15-seconds) or do not change their behavior (one-minute) during market drawdown and recovery periods.

In Panel B of Table XI, we report similar analysis for the futures market. STT either become more contrarian during the turbulent periods or do not change their behavior depending on the frequency under consideration during fast crashes and recoveries, with one exception for STT active on both markets. By comparing 15-seconds and one-minute frequency results we note the difference that is attributable to the more complicated lag structure of the data, however due to the limited number of observations we do not include lagged returns and their interactions with drawdown / recovery dummies.

Kirilenko, Kyle, Samadi, and Tuzun (2017) distinguish between two types of endogenous market makers: HFT versus other market makers, with HFT being 16 most active traders out of all endogenous market makers. Our analysis is similar in spirit as we distinguish between STT active solely on one market and STT active on both markets, with the latter category being closer to modern HFT who are known for their cross-market activity. Interestingly, behavior of STT active solely in the spot market resembles the behavior of other market makers: being contrarian during normal periods and starting to move with the market during the fast crash and recovery periods at the 15-seconds frequency. Comparing the behavior of HFT and STT active in both markets, we observe similar effects at the 15-seconds frequency for the spot market: moving with the market during normal times they become more contrarian or do not change their behavior during fast crash and recovery periods.

V. Conclusion

The Flash Crash of May 6, 2010 focused the attention of exchanges and regulators on the need to understand what causes market fragility. There is an ongoing debate in the literature on the role of high frequency trading (HFT), which is a recent development. We contribute to the literature by showing that there may be other forces that affect intraday liquidity and influence market fragility, and play an important role in stock price crashes and recoveries.

We use a unique dataset containing order book and transactions data for a large firm traded on the National Stock Exchange (NSE) of India for April-June in 2006. The data have a unique identifier for each broker-dealer combinations across spot and futures markets. By using orders and cancellations in addition to transactions, we are able to provide a more complete picture of market liquidity. We use data for both spot and futures on the same underlying whereas most studies examine the spot or the futures market in isolation, as in Kirilenko, Kyle, Samadi, and Tuzun (2017). We are therefore able to examine the role of "diversity" of participation (spot is more diverse in terms of participants characteristics) separately from the role of volume/size (futures market has larger volume) as well as the role of short sale restrictions (shorting is harder in the spot market).

We find that large sell orders by foreign institutional investors put a downward pressure on the stock price. Short term traders with limited inventory carrying capacity relative to their trading volume were the major intermediaries providing intraday liquidity. Their buying was not enough to prevent the fast crashes. It took some time before mutual funds moved in and started buying which helped stop the fast crash and initiated price recovery. Both fast crashes and recoveries began in the spot market.

Limited inventory carrying capacity and individually prudent inventory risk management rather than speed of trading appears to be the root cause of market fragility manifesting itself in market crashes. Our findings emphasize the stabilizing role of slow-moving capital that steps in when liquidity provision by short term traders is insufficient.

References

Andersen, T. G. and O. Bondarenko (2014). Reflecting on the vpin dispute. *Journal of Financial Markets 17*, 53–64.

Bongaerts, D. and M. Van Achter (2016). High-frequency trading and market stability. *Working paper*.

Brogaard, J., T. Hendershott, and R. Riordan (2014). High-frequency trading and price discovery. *Review of Financial Studies 27*(8), 2267–2306.

Brogaard, J., R. Riordan, A. Shkilko, and K. Sokolov (2014). High-frequency trading and extreme price movements. *Available at SSRN*.

Brunnermeier, M. K. and L. H. Pedersen (2009). Funding liquidity and market liquidity. *Review of Financial Studies 22*(2201-2238), 6.

Budish, E. B., P. Cramton, and J. J. Shim (2015). The high-frequency trading arms race: Frequent batch auctions as a market design response. *Quarterly Journal of Economics 130*(4), 1547–1621.

Cespa, G. and T. Foucault (2011). Learning from prices, liquidity spillovers, and market segmentation. *CEPR Discussion Paper No. DP8350*.

CFTC and SEC (2010). Findings regarding the market events of May 6, 2010. *Report of the Staffs of the CFTC and SEC to the Joint Advisory Committee on Emerging Regulatory Issues*.

Comerton-Forde, C., T. Hendershott, C. M. Jones, P. C. Moulton, and M. S. Seasholes (2010). Time variation in liquidity: The role of market-maker inventories and revenues. *The Journal of Finance 65*(1), 295–331.

Duffie, D. (2010). Presidential address: Asset price dynamics with slow-moving capital. *The Journal of finance 65*(4), 1237–1267.

Easley, D., M. M. L. de Prado, and M. O'Hara (2012). Flow toxicity and liquidity in a high-frequency world. *Review of Financial Studies 25*(5), 1457–1493.

Easley, D., M. Lopez de Prado, and M. O'Hara (2011). The microstructure of the flash crash: Flow toxicity, liquidity crashes and the probability of informed trading. *Journal of Portfolio Management 37*(2), 118–128.

Foucault, T., J. Hombert, and I. Roşu (2016). News trading and speed. *Journal of Finance 71*(1), 335–382.

Foucault, T., R. Kozhan, and W. W. Tham (2015). Toxic arbitrage. *HEC Paris Research Paper No. FIN-2014-1040*.

Gromb, D. and D. Vayanos (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of financial Economics 66*(2), 361–407.

Hansch, O., N. Y. Naik, and S. Viswanathan (1998). Do inventories matter in dealership markets? Evidence from the London Stock Exchange. *The Journal of Finance 53*(5), 1623–1656.

He, Z. and A. Krishnamurthy (2013). Intermediary asset pricing. *The American Economic Review 103*(2), 732–770.

Hendershott, T., C. M. Jones, and A. J. Menkveld (2011). Does algorithmic trading improve liquidity? *Journal of Finance 66*(1), 1–33.

Hendershott, T. and A. J. Menkveld (2014). Price pressures. *Journal of Financial Economics 114*(3), 405–423.

Hendershott, T. and M. S. Seasholes (2007). Market maker inventories and stock prices. *The American Economic Review 97*(2), 210–214.

Ho, T. S. and H. R. Stoll (1983). The dynamics of dealer markets under competition. *The Journal of Finance 38*(4), 1053–1074.

Johnson, H., B. F. Van Ness, and R. A. Van Ness (2017). Are all odd-lots the same? Odd-lot transactions by order submission and trader type. *Journal of Banking and Finance 79*, 1–11.

Kahraman, C. and H. E. Tookes (2017). Trader leverage and liquidity. *Journal of Finance*.

Kirilenko, A. A., A. S. Kyle, M. Samadi, and T. Tuzun (2017). The Flash Crash: The impact of high frequency trading on an electronic market. *Journal of Finance 72*.

Korajczyk, R. A. and D. Murphy (2016). High frequency market making to large institutional trades. *Working paper*.

Lyle, M. R. and J. P. Naughton (2015). How does algorithmic trading improve market quality? *Working paper*.

Lyons, R. K. (1995). Tests of microstructural hypotheses in the foreign exchange market. *Journal of Financial Economics 39*(2), 321–351.

Lyons, R. K. (1997). A simultaneous trade model of the foreign exchange hot potato. *Journal of International Economics 42*(3), 275–298.

Malinova, K., A. Park, and R. Riordan (2013). Do retail traders suffer from high frequency traders? *Working paper*.

Menkveld, A. J. (2013). High frequency trading and the new market makers. *Journal of Financial Markets 16*(4), 712–740.

Menkveld, A. J. and T. Wang (2013). How do designated market makers create value for small-caps? *Journal of Financial Markets 16*(3), 571–603.

Menkveld, A. J. and B. Z. Yueshen (2016). The Flash Crash: A cautionary tale about highly fragmented markets. *Working paper*.

Menkveld, A. J. and M. A. Zoican (2016). Need for speed? Exchange latency and liquidity. *Forthcoming in the Review of Financial Studies*.

Mitchell, M., L. H. Pedersen, and T. Pulvino (2007). Slow moving capital. *Working paper*.

Naik, N. Y. and P. K. Yadav (2003). Do dealer firms manage inventory on a stock-by-stock or a portfolio basis? *Journal of Financial Economics 69*(2), 325–353.

O'Hara, M. (2015). High frequency market microstructure. *Journal of Financial Economics 116*(2), 257–270.

Pástor, L. and R. F. Stambaugh (2003). Liquidity risk and expected stock returns. *Journal of Political Economy 111*(3), 642–685.

Perold, A. F. and B. J. Tierney (1997). numeric investors lp. *Harvard Business Case 9-298-012*.

Raman, V. and P. Yadav (2013). The who, why, and how well of order revisions: An analysis of limit order trading. *Working paper*.

Reiss, P. C. and I. M. Werner (1998). Does risk sharing motivate interdealer trading? *The Journal of Finance 53*(5), 1657–1703.

Scholtus, M., D. van Dijk, and B. Frijns (2014). Speed, algorithmic trading, and market quality around macroeconomic news announcements. *Journal of Banking and Finance 38*, 89–105.

SEC (2010). Concept release on equity market structure. *Release No. 34-61358, File No. S7-02-10*.

Stoll, H. R. (1978). The supply of dealer services in securities markets. *The Journal of Finance 33*(4), 1133–1151.

Van Kervel, V. and A. J. Menkveld (2016). High-frequency trading around large institutional orders. *Working paper*.

Venkataraman, K. and A. C. Waisburd (2007). The value of the designated market maker. *Journal of Financial and Quantitative Analysis 3*(42), 735–758.

Viswanathan, S. and J. J. Wang (2004). Inter-dealer trading in financial markets. *The Journal of Business 77*(4), 987–1040.

Table I Number of traders

This table shows the number and proportion of traders who are active on spot and futures markets. We divide traders into those who execute trades on both sides of the market, or on only one side of the market, or do not execute trades at all, separately for spot and futures markets. We also divide traders into those who execute trades on both spot and futures markets, only on spot market, only on futures market, and do not execute trades at all. For futures market, we include only those traders who submit orders and / or execute trades for the contracts with maturity date within the same month when the transaction occurs. Data on trader IDs, orders, and trades for anonymous stock for the period from April till June 2006 are provided by the NSE.

	Panel A: Spot Market		**Panel B: Futures Market**		**Panel C: Spot and Futures Market**		
Buy & Sell	77,578	71.04%	31,427	86.47%	Spot & Futures	5,444	3.91%
Only Buy	15,011	13.75%	825	2.27%	Only Spot	93,952	67.46%
Only Sell	6,807	6.23%	1,245	3.43%	Only Futures	28,053	20.14%
No Execution	9,808	8.98%	2,846	7.83%	No Execution	11,826	8.49%
Total	109,204	100.00%	36,343	100.00%	Total	139,275	100.00%

Table II Order types

This table shows the number and proportion of new order, cancellation and modifications for spot and futures markets and for buy and sell sides respectively. Only regular book orders are included in the sample (i.e., we exclude stop loss orders). For futures market we include only those orders for the contracts with maturity date within the same month when the order is submitted / modified / cancelled.

	Panel A: Spot Market				**Panel B: Futures Market**			
	Buy		Sell		Buy		Sell	
New	1,189,726	70.94%	1,203,863	70.68%	671,454	62.50%	664,458	63.19%
Cancel	277,881	16.57%	259,193	15.22%	251,998	23.46%	212,621	20.22%
Modify	209,408	12.49%	240,293	14.11%	150,832	14.04%	174,472	16.59%

Table III Trading volume per trader group

This table shows the number of traders in each trader group, the number of shares bought and sold by each trader group as well as the total trading volume and proportion of trading volume attributable to each trader group (for traders active on one market only and on both markets). For futures market we include only transactions for the contracts with maturity date within the same month when the transaction occurs. We include both regular and stop loss orders. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small).

Panel A: Spot market

	Active on spot market only					Active on both markets					Grand Total	
	# of traders	Buy	Sell	Total (Buy+Sell)		# of traders	Buy	Sell	Total (Buy+Sell)		(Buy+Sell)	
LTT	1,471	17,714,563	17,995,962	35,710,525	15.44%	219	7,906,414	7,576,263	15,482,677	6.69%	51,193,202	22.11%
STT	5,597	29,353,683	29,489,364	58,843,047	25.42%	950	41,531,164	41,673,644	83,204,808	35.94%	142,047,855	61.36%
Small	90,646	19,016,930	18,790,857	37,807,787	16.32%	513	230,741	227,405	458,146	0.20%	38,265,933	16.53%
											231,506,990	100.00%

Panel B: Futures market

	Active on futures market only					Active on both markets					Grand Total	
	# of traders	Buy	Sell	Total (Buy+Sell)		# of traders	Buy	Sell	Total (Buy+Sell)		(Buy+Sell)	
LTT	6,613	138,145,500	143,008,500	281,154,000	27.58%	219	22,530,000	16,506,750	39,036,750	3.83%	320,190,750	31.41%
STT	19,574	197,282,250	198,171,000	395,453,250	38.79%	950	145,077,000	144,619,500	289,696,500	28.42%	685,149,750	67.21%
Small	5,628	6,033,750	6,691,500	12,725,250	1.25%	513	653,250	724,500	1,377,750	0.14%	14,103,000	1.38%
											1,019,443,500	100.00%

Table IV Trading activity regression

This table shows the average of daily trading volume between different trader categories and the results of the trading regression estimation based on one-minute intervals. We regress one-minute trading volume relative to the total daily volume between different trader categories on a set of all possible trader-pair dummy variables (see equation (1)). We estimate regression without a constant. We use day and intraday fixed effects. We cluster standard errors by day. ***, **, * denotes significance level at 1%, 5%, and 10% respectively. t-stats are reported in parentheses. For futures market we include only transactions for the contracts with maturity date within the same month when the transaction occurs. We include both regular and stop loss orders. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small). Daily averages are reported in 100,000 shares. Regression coefficients are reported in basis points.

	Panel A: Spot Market		**Panel B: Futures Market**	
	Mean	Coef	Mean	Coef
LTT_LTT	1.381	2.938***	8.391	4.913***
		(6.75)		(11.83)
LTT_STT	5.419	8.471***	34.194	13.815***
		(18.42)		(34.51)
LTT_Small	0.961	2.605***	0.666	2.030***
		(6.54)		(4.99)
STT_STT	7.724	11.433***	37.365	14.507***
		(25.57)		(30.30)
STT_Small	4.498	7.713***	1.583	2.345***
		(19.56)		(5.70)
Small_Small	0.687	2.236***	0.013	1.784***
		(5.51)		(4.40)
Day FE		Yes		Yes
Time FE		Yes		Yes
Cluster SE		By Day		By Day
Normalize		By Day		By Day
Observations		110,880		122,760
Adjusted R2		0.322		0.382

Panel C: F-tests

	Spot	Futures
H0: STT_STT=LTT_STT		
F-stat	37.87	4.81
p-value	[0.00]	[0.03]
H0: STT_STT=STT_Small		
F-stat	269.8	2132
p-value	[0.00]	[0.00]
H0: LTT_STT=LTT_LTT+LTT_Small		
F-stat	39.54	253.7
p-value	[0.00]	[0.00]
H0: STT_Small=LTT_Small+Small_Small		
F-stat	35.59	13.35
p-value	[0.00]	[0.00]

Table V Liquidity provision

This table shows liquidity provision measured by number of shares “demanded” (if a trader initiates the trade) versus number of shares “provided” (if trader does not initiate the trade) by each trader group (for traders active on one market only and on both markets). When a trader initiates a trade through a market order, we say the trader “demanded” liquidity. The trader taking the other side of the trade “provided” liquidity. Both Demand and Provide are positive numbers. We could not identify which side of the transaction consumes / provides liquidity in 0.76% (1.22%) of total trading volume for spot (futures) market. For futures market we include only transactions for the contracts with maturity date within the same month when the transaction occurs. We include both regular and stop loss orders. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small).

Panel A: Spot market

	Active on spot market only			Active on both markets			Total	
	Demand	Provide	Provide-Demand	Demand	Provide	Provide-Demand	Provide-Demand	$\frac{Provide-Demand}{Provide+Demand}$
LTT	12,508,585	23,021,359	10,512,774	8,243,518	7,122,445	-1,121,073	9,391,701	18.45%
STT	28,936,116	29,458,846	522,730	43,968,156	3,8,530,036	-5,438,120	-4,915,390	-3.49%
Small	20,979,642	16,533,987	-4,445,655	242,854	212,198	-30,656	-4,476,311	-11.79%

Panel B: Futures market

	Active on futures market only			Active on both markets			Total	
	Demand	Provide	Provide-Demand	Demand	Provide	Provide-Demand	Provide-Demand	$\frac{Provide-Demand}{Provide+Demand}$
LTT	137,909,250	138,543,000	633,750	18,918,750	19,098,000	179,250	813,000	0.26%
STT	202,005,750	189,651,000	-12,354,750	137,083,500	149,877,000	12,793,500	438,750	0.06%
Small	6,922,500	5,684,250	-1,238,250	687,000	673,500	-13,500	-1,251,750	-8.96%

Table VI Liquidity provision regression

This table shows the average of daily trading volume between different trader categories and the results of the liquidity provision regression estimation based on one-minute intervals. We regress one-minute trading volume relative to the total daily volume between different trader categories in a particular interval on a set of all possible trader-pair dummy variables. We differentiate between liquidity provision and liquidity consumption (see equation (2)). We estimate regression without a constant. We use day and intraday fixed effects. We cluster standard errors by day. ***, **, * denotes significance level at 1%, 5%, and 10% respectively. t-stats are reported in parentheses. For futures market we include only transactions for the contracts with maturity date within the same month when the transaction occurs. We include both regular and stop loss orders. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small). Daily averages are reported in 100,000 shares. Regression coefficients are reported in basis points.

		Panel A: Spot Market		**Panel B: Futures Market**	
Consume	Provide	Mean	Coef	Mean	Coef
LTT	LTT	1.373	2.452***	8.087	4.184***
			(7.96)		(14.85)
LTT	STT	1.935	3.379***	16.888	7.078***
			(11.88)		(26.62)
LTT	Small	0.397	1.294***	0.320	1.263***
			(4.83)		(4.80)
STT	LTT	3.451	5.353***	17.001	7.382***
			(17.71)		(28.79)
STT	STT	7.656	10.773***	36.998	13.540***
			(30.74)		(36.33)
STT	Small	1.911	3.543***	0.693	1.390***
			(13.69)		(5.29)
Small	LTT	0.558	1.547***	0.338	1.263***
			(5.93)		(4.80)
Small	STT	2.550	4.427***	0.877	1.453***
			(17.10)		(5.42)
Small	Small	0.682	1.787***	0.013	1.142***
			(6.70)		(4.35)
Day FE			Yes		Yes
Time FE			Yes		Yes
Cluster SE			By Day		By Day
Normalize			By Day		By Day
Observations			166,320		184,140
Adjusted R2			0.305		0.381

Panel C: F-tests

	Spot	Futures
H0: STT_STT=STT_LTT+STT_Small		
F-stat	19.37	156.6
p-value	[0.00]	[0.00]
H0: LTT_STT=LTT_LTT+LTT_Small		
F-stat	1.63	33.12
p-value	[0.21]	[0.00]
H0: Small_STT=Small_LTT+Small_Small		
F-stat	14.14	13.55
p-value	[0.00]	[0.00]

Table VII Price elasticity and inventories

This table reports results of the elasticity regressions for each of the four different left-hand side variables (see equation (3)). For brevity, we report only coefficients in front of the inventories of STT (β_1). We use day and intraday fixed effects. We cluster standard errors by day. ***, **, * denotes significance level at 1%, 5%, and 10% respectively. t-stats are reported in parentheses. For futures market, we include in inventory computation only transactions for the contracts with maturity date within the same month when the transaction occurs. We include both regular and stop loss orders. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small).

Panel A: Spot market

	Ask side				Bid side			
	100bps	50bps	25bps	10bps	100bps	50bps	25bps	10bps
STT Spot Inventory (all)	0.034***	0.030***	0.019***	0.007***	-0.009	-0.013	-0.011*	-0.006**
	(2.78)	(3.53)	(3.54)	(2.94)	(-0.59)	(-1.47)	(-1.91)	(-2.19)
STT Spot Inventory (one market)	-0.017	0.003	0.012	0.006	0.022	0.005	-0.003	-0.002
	(-0.66)	(0.21)	(1.33)	(1.57)	(0.90)	(0.33)	(-0.32)	(-0.46)
STT Spot Inventory (both markets)	0.088***	0.065***	0.035***	0.013***	-0.034	-0.033*	-0.022*	-0.013**
	(4.21)	(4.80)	(4.78)	(3.84)	(-1.05)	(-1.75)	(-1.99)	(-2.19)
STT Net Inventory (both markets)	-0.055**	-0.014	0.003	0.004	-0.010	-0.002	0.000	-0.000
	(-2.56)	(-1.15)	(0.46)	(1.16)	(-0.41)	(-0.14)	(0.00)	(-0.14)

Panel B: Futures market

	Ask side				Bid side			
	100bps	50bps	25bps	10bps	100bps	50bps	25bps	10bps
STT Fut Inventory (all)	-0.017	-0.006	0.001	0.000	-0.002	-0.003	-0.005*	-0.001
	(-0.46)	(-0.38)	(0.11)	(0.07)	(-0.17)	(-0.51)	(-1.86)	(-0.65)
STT Fut Inventory (one market)	0.100	0.033	0.012	0.003	-0.002	-0.004	-0.005	0.000
	(1.62)	(1.32)	(1.08)	(0.99)	(-0.17)	(-0.60)	(-1.33)	(0.04)
STT Fut Inventory (both markets)	-0.262***	-0.087***	-0.021**	-0.005**	-0.001	0.000	-0.006*	-0.003*
	(-3.31)	(-3.44)	(-2.40)	(-2.13)	(-0.03)	(0.01)	(-1.79)	(-1.79)
STT Net Inventory (both markets)	-0.253*	-0.036	0.008	0.005	0.049*	0.028**	0.006	0.004*
	(-1.96)	(-1.00)	(0.65)	(1.47)	(1.78)	(2.10)	(1.19)	(1.82)

Table VIII Trading activity regression during fast crashes

This table shows the average of daily trading volume between different trader categories and the results of the trading activity regression estimation based on one-minute intervals from 16-May-2006 till 24-May-2006 for spot (Panel A) and futures (Panel B) markets. We regress one-minute trading volume relative to the total daily volume between different trader categories in a particular interval on a set of all possible trader-pair dummy variables. We differentiate between buying and selling volumes (see equation (4)). We also include interaction with down/up dummy variables defined as -/+ 30 minutes from the trough of the crash. We estimate regression without a constant. We use day and time fixed effects. We cluster standard errors by day. ***, **, * denotes significance level at 1%, 5%, and 10% respectively. t-stats are reported in parentheses. "Down=Up" column contains F-stats and respective p-values for the test of equality of the coefficients during drawdown and recovery periods. We include both regular and stop loss orders. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small). Daily averages are reported in 100,000 shares. Regression coefficients are reported in basis points.

		Panel A: Spot market					**Panel B: Futures market**				
Sell	Buy	Mean	Normal	Down	Up	Down=Up	Mean	Normal	Down	Up	Down=Up
LTT	LTT	1.292	4.087**	-0.092	8.328***	65.99	11.215	5.310***	-1.060	2.990	8.66
			(2.85)	(-0.10)	(14.03)	[0.00]		(11.17)	(-1.76)	(1.64)	[0.03]
LTT	STT	2.601	5.682***	5.550**	5.671	0.00	16.070	6.993***	4.366***	1.727	18.37
			(4.61)	(2.93)	(1.53)	[0.98]		(23.99)	(5.83)	(1.32)	[0.01]
LTT	Small	0.499	3.456*	0.598	1.096	1.59	0.223	1.124***	-0.047	0.778	12.51
			(2.32)	(0.48)	(1.16)	[0.26]		(4.40)	(-0.08)	(1.22)	[0.01]
STT	LTT	2.684	5.809***	0.402	8.315**	14.92	18.431	7.859***	1.053	6.071**	1.66
			(5.21)	(0.77)	(3.63)	[0.01]		(25.44)	(0.60)	(2.80)	[0.25]
STT	STT	8.019	12.024***	6.479	3.047	0.62	28.873	11.368***	4.655	1.823	0.28
			(15.35)	(1.78)	(1.70)	[0.47]		(26.24)	(1.37)	(0.89)	[0.62]
STT	Small	2.184	5.647***	1.586	1.336	0.27	0.511	1.224***	0.038	0.842	11.48
			(4.46)	(1.00)	(1.09)	[0.63]		(4.70)	(0.06)	(1.29)	[0.01]
Small	LTT	0.454	3.382*	-0.823	2.301	8.43	0.483	1.227***	0.208	0.803	5.91
			(2.31)	(-0.79)	(1.26)	[0.03]		(4.87)	(0.34)	(1.21)	[0.05]
Small	STT	2.144	5.672***	0.407	0.329	0.01	0.962	1.385***	0.988	0.938	0.03
			(4.58)	(0.24)	(0.44)	[0.94]		(5.65)	(1.10)	(1.38)	[0.88]
Small	Small	0.641	3.765*	-0.167	0.541	2.26	0.008	1.045***	-0.127	0.672	11.24
			(2.49)	(-0.12)	(0.59)	[0.19]		(4.28)	(-0.23)	(1.16)	[0.02]
Day FE				Yes					Yes		
Time FE				Yes					Yes		
Yes				By Day					By Day		
Normalize				By Day					By Day		
Observations				17,820					20,790		
Adjusted R2				0.311					0.450		

Table IX Cash flow regression for STT during fast crashes

This table shows the results of the cash flow regression estimation based on one-minute intervals from 16-May-2006 till 24-May-2006 for spot (Panel A) and futures (Panel B) market. We regress cumulative one-minute cash flows for STT on crash and recovery dummy variables defined as -/+ 30 minutes from the trough of the crash (see equation (5)). We use day and time fixed effects. We cluster standard errors by day. ***, **, * denotes significance level at 1%, 5%, and 10% respectively. *t*-stats are reported in parentheses. We include both regular and stop loss orders. For futures market, we use only transactions for the contracts with maturity date within the same month when the transaction occurs. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small).

	Panel A: Spot market		**Panel B: Futures market**	
	(1)	(2)	(1)	(2)
Down	-0.330	-0.188	-2.360	-2.443
	(-1.20)	(-0.51)	(-1.99)	(-1.81)
Up	0.247	0.309	2.752	2.961
	(1.13)	(1.58)	(1.33)	(1.30)
Constant	0.014	-0.203	0.445**	0.434
	(0.69)	(-1.43)	(3.21)	(0.73)
Day FE	No	Yes	No	Yes
Time FE	No	Yes	No	Yes
Cluster SE	By Day	By Day	By Day	By Day
Observations	1,562	1,562	1,562	1,562
Adjusted R2	0.002	-0.000	0.015	0.016

Table X Liquidity provision regression during fast crashes

This table shows the average of daily trading volume between different trader categories and the results of the liquidity provision regression estimation based on one-minute intervals from 16-May-2006 till 24-May-2006 for spot (Panel A) and futures (Panel B) markets. We regress one-minute trading volume relative to the total daily volume between different trader categories in a particular interval on a set of all possible trader-pair dummy variables. We differentiate between liquidity provision and liquidity consumption (see equation (6)). We also include interaction with down/up dummy variables defined as -/+ 30 minutes from the trough of the crash. We estimate regression without a constant. We use day and time fixed effects. We cluster standard errors by day. ***, **, * denotes significance level at 1%, 5%, and 10% respectively. t-stats are reported in parentheses. "Down=Up" column contains F-stats and respective p-values for the test of equality of the coefficients during drawdown and recovery periods. We include both regular and stop loss orders. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small). Daily averages are reported in 100,000 shares. Regression coefficients are reported in basis points.

		Panel A: Spot market					**Panel B: Futures market**				
Consume	Provide	Mean	Normal	Down	Up	Down=Up	Mean	Normal	Down	Up	Down=Up
LTT	LTT	1.289	4.083**	-0.102	8.308***	61.52	10.585	5.189***	-0.860	2.809	11.03
			(2.86)	(-0.11)	(13.46)	[0.00]		(11.60)	(-1.49)	(1.79)	[0.02]
LTT	STT	1.954	5.063***	1.727	4.029***	1.71	15.806	6.990***	2.505*	2.339**	0.01
			(4.07)	(1.05)	(10.25)	[0.25]		(17.22)	(2.23)	(3.54)	[0.93]
LTT	Small	0.399	3.348*	0.035	0.928	4.43	0.295	1.188***	-0.028	0.684	10.07
			(2.24)	(0.03)	(0.91)	[0.09]		(4.57)	(-0.05)	(1.15)	[0.02]
STT	LTT	3.300	6.472***	4.172***	9.707***	12.68	18.372	8.012***	2.932*	5.363***	2.09
			(5.73)	(6.03)	(7.99)	[0.02]		(35.16)	(1.95)	(13.64)	[0.2]
STT	STT	7.953	12.003***	6.442	3.036	0.63	28.604	11.441***	4.618	1.693	0.31
			(15.23)	(1.81)	(1.69)	[0.46]		(24.19)	(1.38)	(0.84)	[0.6]
STT	Small	1.739	5.114***	0.757	0.106	0.57	0.572	1.290***	0.207	0.760	5.84
			(4.05)	(0.48)	(0.14)	[0.49]		(4.93)	(0.30)	(1.21)	[0.05]
Small	LTT	0.549	3.505*	-0.294	2.460	5.82	0.398	1.222***	0.182	0.848	7.83
			(2.37)	(-0.32)	(1.41)	[0.06]		(4.70)	(0.28)	(1.21)	[0.03]
Small	STT	2.554	6.137***	1.212	1.611	0.59	0.896	1.387***	0.841	0.957	0.18
			(5.18)	(0.76)	(1.34)	[0.48]		(5.40)	(0.96)	(1.35)	[0.69]
Small	Small	0.637	3.760*	-0.172	0.538	2.33	0.008	1.075***	-0.124	0.643	11.44
			(2.50)	(-0.13)	(0.59)	[0.19]		(4.29)	(-0.22)	(1.12)	[0.01]
Day FE				Yes					Yes		
Time FE				Yes					Yes		
Cluster SE				By Day					By Day		
Normalize				By Day					By Day		
Observations				17,820					20,790		
Adjusted R2				0.326					0.478		

Table XI Inventory sensitivity to price movements during fast crashes

This table shows the results of the inventory sensitivity regression estimation based on 15-seconds and one-minute intervals from 16-May-2006 till 24-May-2006 for spot (Panel A) and futures (Panel B) markets (see equation (7)). We regress changes in inventory in spot market for STT on concurrent return and control variables omitted for brevity (lagged spot/futures inventory, lagged changes in spot/futures inventory). We also include interaction with down/up dummy variables defined as -/+ 30 minutes from the trough of the crash. For futures inventory computation we use only transactions for the contracts with expiry date within the same month when the transaction occurs. We use day fixed effects. We use robust standard errors. ***, **, * denotes significance level at 1%, 5%, and 10% respectively. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small).

Panel A: Spot market

	15 sec				One min			
	STT All	STT Spot Only	STT Both	Net STT	STT All	STT Spot Only	STT Both	Net STT
Spot Return	125.35***	-82.17***	210.60***	189.43***	80.65***	-89.48***	161.39***	-131.60**
	(7.13)	(-6.55)	(11.56)	(5.38)	(2.62)	(-3.27)	(4.75)	(-2.11)
Down*Spot Return	-110.70*	52.50*	-170.21***	-130.70	-202.93**	78.39*	-267.00***	-37.36
	(-1.78)	(1.88)	(-2.89)	(-1.47)	(-2.10)	(1.81)	(-2.79)	(-0.39)
Up*Spot Return	-168.58***	75.03***	-251.54***	-193.90***	-147.15***	139.49***	-251.65***	97.04
	(-5.25)	(3.13)	(-7.52)	(-3.38)	(-2.95)	(3.46)	(-5.26)	(0.91)
Down	0.87	-0.18	0.73***	0.66	2.64*	-0.50	2.19***	2.05
	(1.55)	(-0.61)	(2.94)	(1.37)	(1.68)	(-0.42)	(2.62)	(1.48)
Up	-0.53**	-0.13	-0.14	-1.27***	-0.86	-0.07	-0.21	-2.68
	(-2.33)	(-0.67)	(-0.81)	(-2.99)	(-0.99)	(-0.10)	(-0.36)	(-1.55)
Constant	0.15	0.17***	-0.00	0.10	0.64*	0.68***	-0.08	0.31
	(1.43)	(3.04)	(-0.05)	(0.72)	(1.74)	(2.93)	(-0.31)	(0.68)
Observations	6,365	6,365	6,365	6,365	1,582	1,582	1,582	1,582
Adjusted R2	0.058	0.040	0.068	0.018	0.142	0.094	0.115	0.053

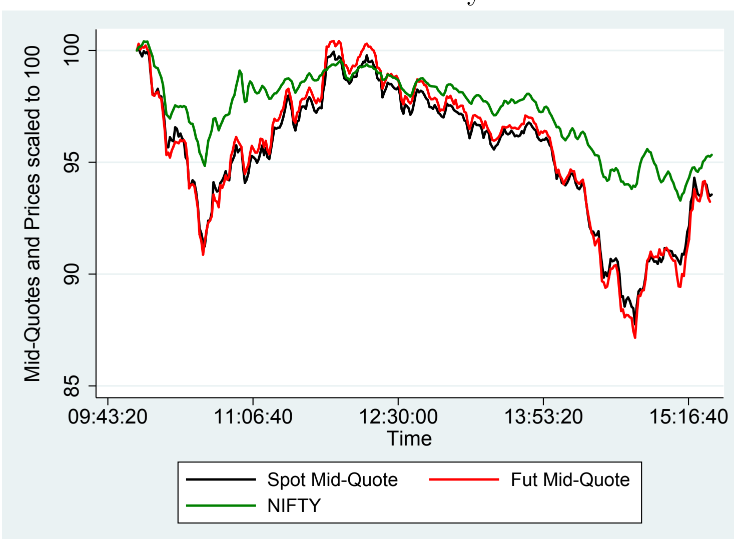
Panel B: Futures market

	15 sec				One min			
	STT All	STT Futures Only	STT Both	Net STT	STT All	STT Futures Only	STT Both	Net STT
Futures Return	225.72***	160.13***	62.15**	121.55***	-227.07**	56.78	-320.97***	-111.96**
	(4.90)	(4.41)	(2.29)	(4.22)	(-2.16)	(0.73)	(-5.51)	(-1.98)
Down*Futures Return	-342.53***	-227.06**	-124.98**	-202.39***	-67.36	-189.67	174.21	11.24
	(-3.10)	(-2.52)	(-2.17)	(-2.89)	(-0.33)	(-1.25)	(1.60)	(0.11)
Up*Futures Return	-282.97***	-171.98***	-96.01**	-186.74***	9.82	-148.70	254.75***	31.68
	(-3.82)	(-3.03)	(-2.19)	(-4.01)	(0.07)	(-1.51)	(3.22)	(0.41)
Down	1.18	0.65*	0.76**	0.60	6.91**	2.63**	3.21**	2.26
	(1.59)	(1.95)	(2.04)	(1.23)	(2.53)	(2.14)	(2.06)	(1.58)
Up	-1.19***	0.18	-0.99***	-1.27***	-2.78	1.06	-2.39*	-2.73
	(-3.07)	(0.83)	(-3.10)	(-2.97)	(-1.60)	(1.00)	(-1.91)	(-1.58)
Constant	-0.24	-0.36**	0.06	0.10	-1.26	-1.46**	0.26	0.31
	(-1.11)	(-2.01)	(0.47)	(0.73)	(-1.39)	(-2.28)	(0.48)	(0.66)
Observations	6,365	6,365	6,365	6,365	1,582	1,582	1,582	1,582
Adjusted R2	0.046	0.029	0.028	0.015	0.102	0.082	0.119	0.052
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1. Fast crashes

This figure shows dynamics of the mid-quote on spot and futures markets together with NIFTY prices at one-minute frequency for two fast crash days: May 19 and May 22, 2006. Mid-quotes and prices are scaled to 100 at the beginning of the trading day.

Panel A: 19th of May 2006



Panel B: 22nd of May 2006

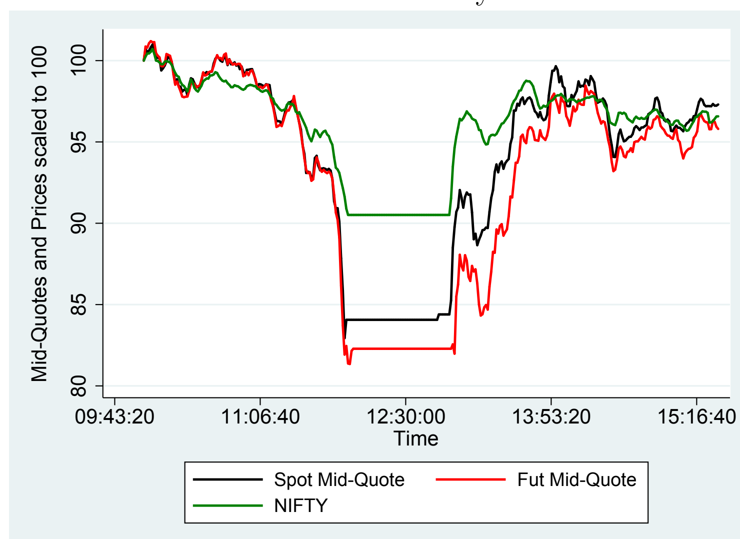


Figure 2. Traders' classification

This figure shows the algorithm we use to classify traders into short-term, long-term, and small traders.

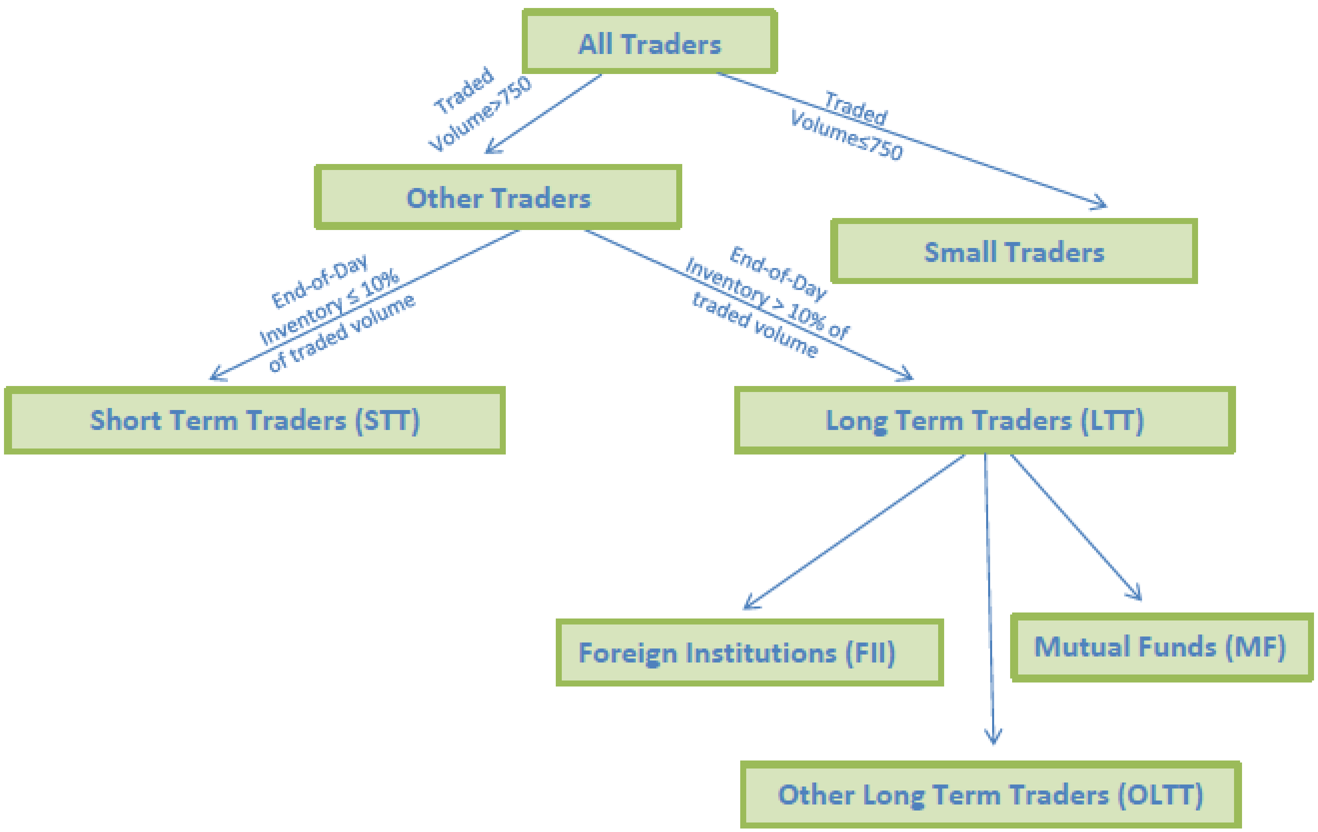
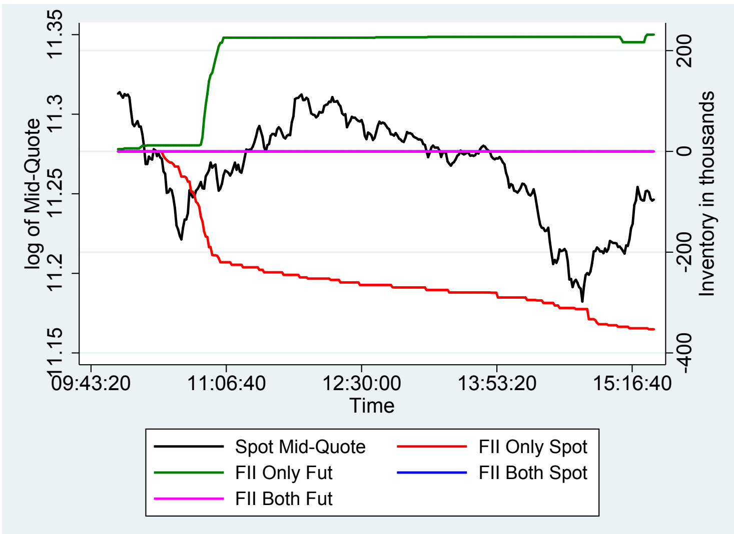


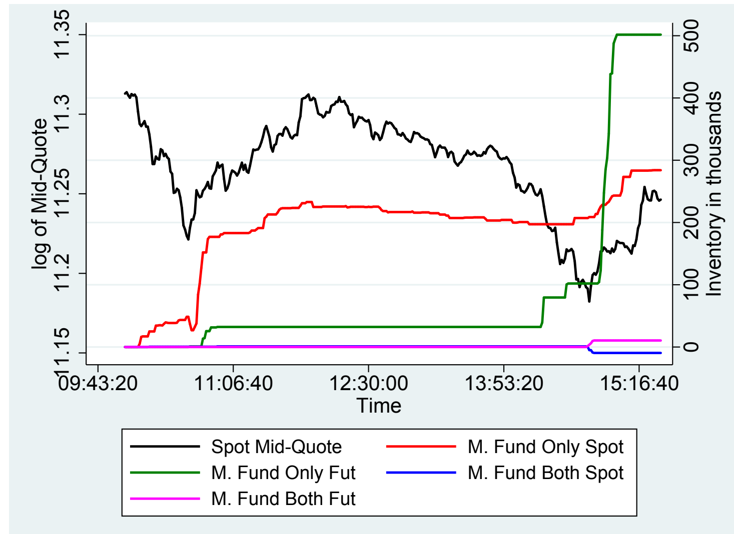
Figure 3. Inventories of FII and MF during the fast crashes

This figure shows dynamics of the mid-quote and inventory of foreign institutional investors and mutual funds at one-minute frequency for the spot and futures markets during the two fast crash days: May 19 and May 22, 2006.

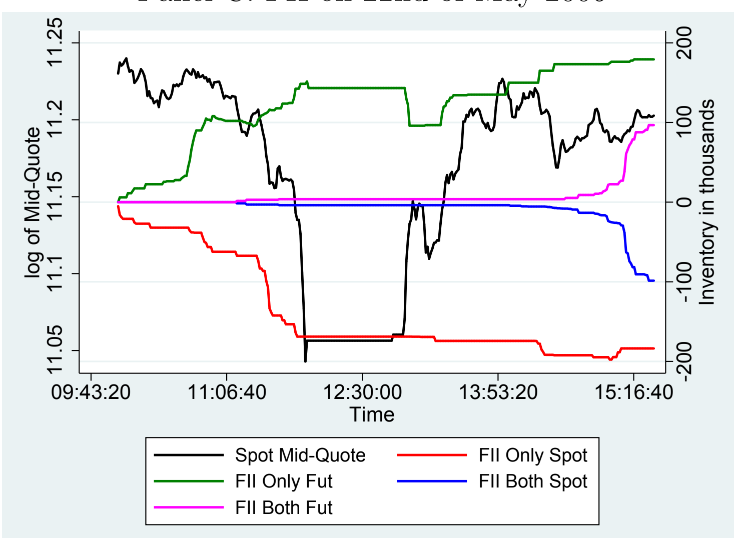
Panel A: FII on 19th of May 2006



Panel B: MF on 19th of May 2006



Panel C: FII on 22nd of May 2006



Panel D: MF on 22nd of May 2006

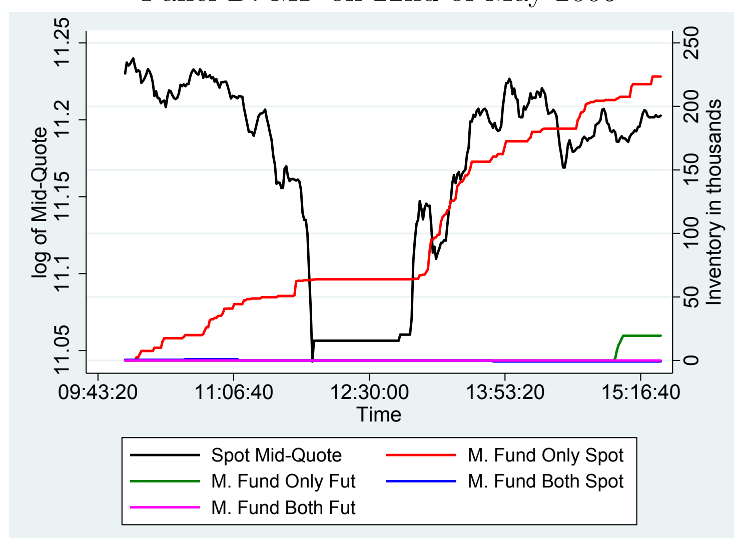


Figure 4. Cumulative cash flows of STT during fast crashes

This figure shows cumulative cash flows of STT at one-minute frequency for spot and futures market during the two fast crash days: May 19 and May 22, 2006. Cumulative cash flows are computed as cumulative sum of + (−) price times number of shares traded in case of sell (buy) transaction.

Panel A: 19th of May 2006

Panel B: 22nd of May 2006

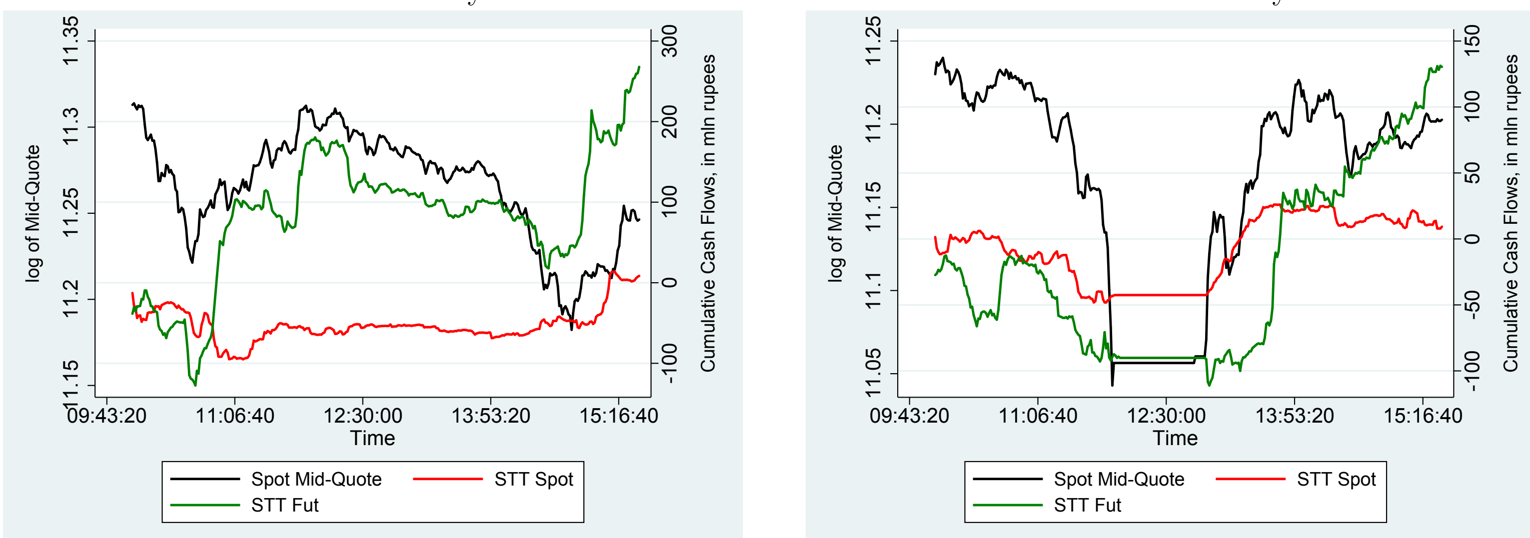


Figure 5. Depth of the limit order book during the fast crashes: Spot market

This figure shows median number of shares outstanding within 100 bps from the midpoint for STT, FII, and MF, respectively, at one-minute frequency for spot market during the two fast crash days: May 19 and May 22, 2006.

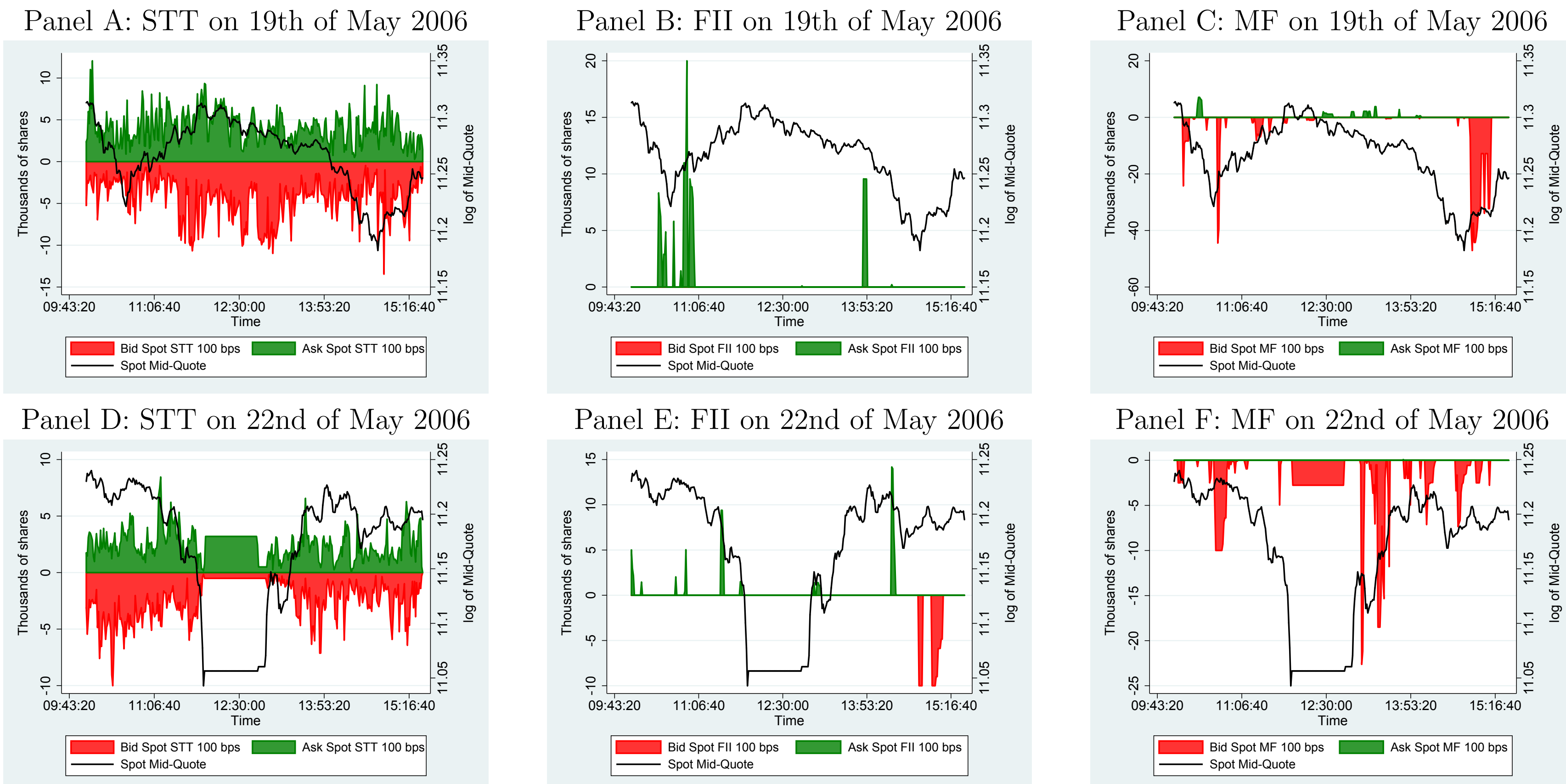
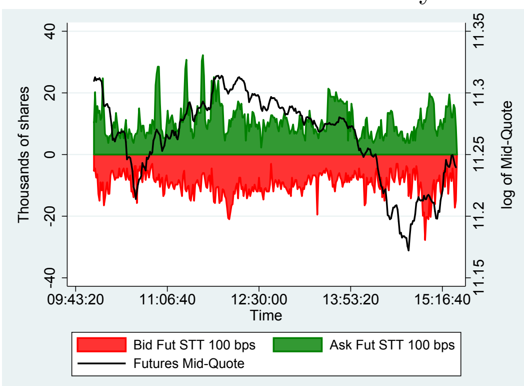


Figure 6. Depth of the limit order book during the fast crashes: Futures market

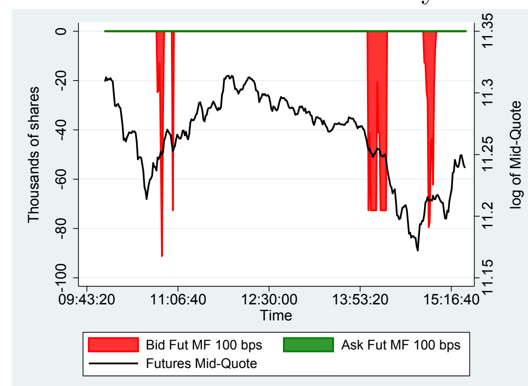
This figure shows median number of shares outstanding within 100 bps from the midpoint for STT, FII, and MF, respectively, at one-minute frequency for futures market during the two fast crash days: May 19 and May 22, 2006.

Panel A: STT on 19th of May 2006

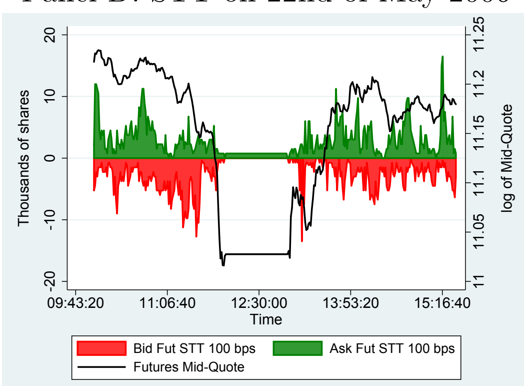


Panel B: FII on 19th of May 2006

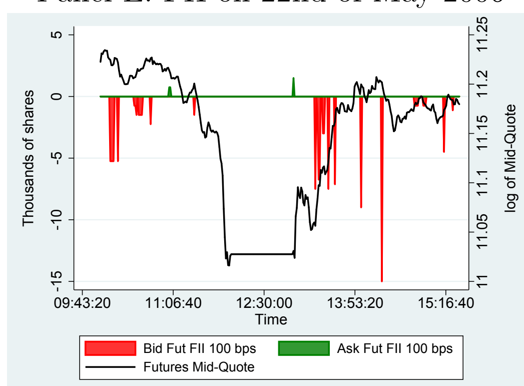
Panel C: MF on 19th of May 2006



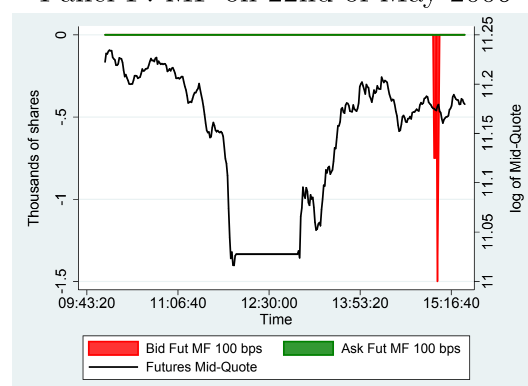
Panel D: STT on 22nd of May 2006



Panel E: FII on 22nd of May 2006



Panel F: MF on 22nd of May 2006



Appendix A Description of the National Stock Exchange (NSE)

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. 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.

INSERT FIGURE A1 HERE

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. Figure A1 show the trading day timeline in more details.

Appendix B Persistence of STT

On a given day, we classify traders into Small, long-term traders (LTT), and short-term traders (STT). To determine the final category of a trader, we look at the mode of the classification of traders across days and select it as a trader category if the mode is not equal to "Small" trader. If a mode classification is equal to "Small" trader then we assign it as a trader category if and only if a trade is classified as Small trader on more than 67% of days, otherwise we use the next most frequent classification as trader's category. The main focus of our analysis are STT. Hence, we look at how persistent is this trader category. Table B1 shows the proportion of active days on which STT was classified as STT. We look separately at the STT that represent jointly 75% and 50% of the trading volume of this category (i.e., most active STT).

INSERT TABLE B1 HERE

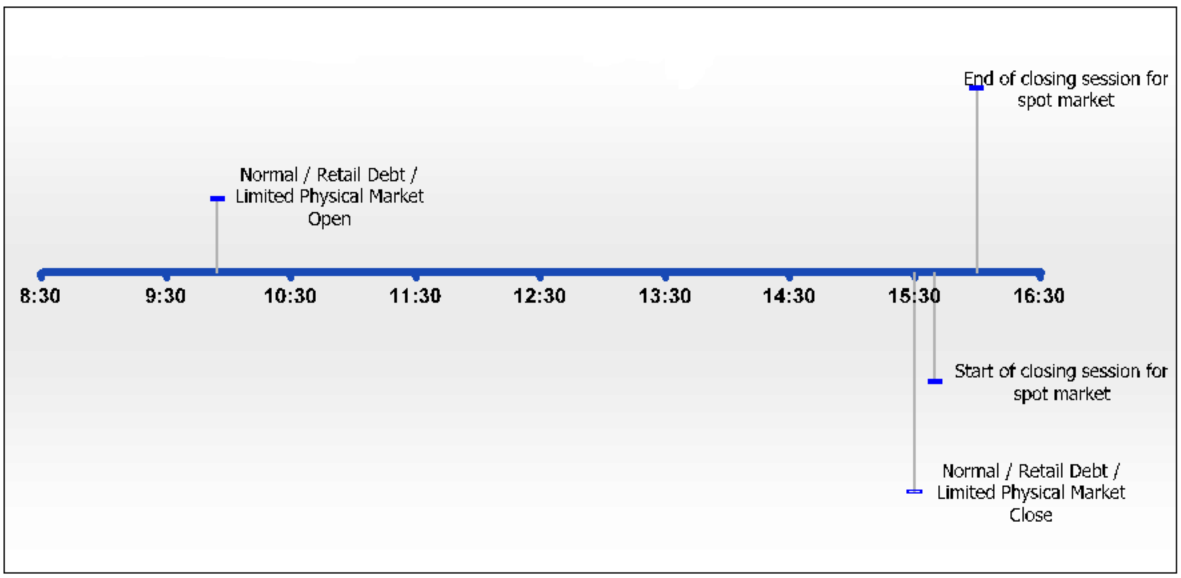
Appendix C Trading activity and liquidity provision normalized by one-minute

We re-run trading activity and liquidity provision regressions normalized by one-minute volume as opposed to normalized by daily volume in the paper (see Tables IV – VI in the paper). Tables C1 – C2 present the results.

INSERT TABLES C1 – C2 HERE

Figure A1. Trading day timeline

This figure shows the trading day timeline of National Stock Exchange of India (NSE) as of 2006.



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

Table B1 STT persistence

This table shows summary statistics (number of traders, average number of active days, 5%, 50%, and 95% percentile of persistence ratio) for STT in spot and futures markets. We define persistence ratio as a proportion of all active days when a trader is classified as STT. We present these statistics for all STT, top STT responsible jointly for 75% of STT trading volume, and top STT responsible jointly for 50% of STT trading volume.

	Panel A: Spot market					**Panel B: Futures market**				
	# of traders	# of active days	P5	P50	P95	# of traders	# of active days	P5	P50	P95
All STT	6,547	5.31	33%	71%	100%	20,524	4.38	33%	100%	100%
75% STT	289	26.44	44%	79%	100%	596	27.61	52%	86%	100%
50% STT	27	46.56	60%	81%	100%	64	50.06	65%	92%	100%

Table C1 Trading activity regression (normalized by one-minute volume)

This table shows the average of one-minute trading volume between different categories and the results of the trading activity regression estimation based on one-minute intervals. We regress one-minute trading volume relative to the total one-minute volume between different trader categories on a set of all possible trader-pair dummy variables. Regression coefficients are reported in basis points. We estimate regression without a constant. We use day and intraday fixed effects. We cluster standard errors by day. ***, **, * denotes significance level at 1%, 5%, and 10% respectively. t-stats are reported in parentheses. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small). One-minute volume averages are reported in 1,000 of shares. Regression coefficients are reported in percentage points.

	Panel A: Spot Market		**Panel B: Futures Market**	
	Mean	Coef	Mean	Coef
LTT_LTT	0.432	4.372***	2.508	9.797***
		(11.32)		(21.17)
LTT_STT	1.678	21.871***	10.359	40.960***
		(29.46)		(102.95)
LTT_Small	0.295	5.724***	0.195	1.020***
		(23.39)		(12.61)
STT_STT	2.382	35.080***	11.446	45.843***
		(43.35)		(50.36)
STT_Small	1.387	26.837***	0.473	2.357***
		(46.95)		(17.57)
Small_Small	0.212	5.484***	0.004	0.023***
		(23.24)		(3.94)
Day FE		Yes		Yes
Time FE		Yes		Yes
Cluster SE		By Day		By Day
Normalize		By Minute		By Minute
Observations		106,104		119,124
Adjusted R2		0.630		0.778
Panel C: F-tests				
H0: STT_STT=LTT_STT				
F-stat		89.79		14.61
p-value		[0.00]		[0.00]
H0: STT_STT=STT_Small				
F-stat		99.07		1,980.00
p-value		[0.00]		[0.00]
H0: LTT_STT=LTT_LTT+LTT_Small				
F-stat		593.30		7,818.00
p-value		[0.00]		[0.00]
H0: STT_Small=LTT_Small+Small_Small				
F-stat		764.90		282.90
p-value		[0.00]		[0.00]

Table C2 Liquidity provision regression (normalized by one-minute volume)

This table shows the average of one-minute trading volume between different categories and the results of the liquidity provision regression estimation based on one-minute intervals. We regress one-minute trading volume relative to the total one-minute volume between different trader categories in a particular interval on a set of all possible trader-pair dummy variables. We differentiate between liquidity provision and liquidity consumption. We estimate regression without a constant. We use day and intraday fixed effects. We cluster standard errors by day. ***, **, * denotes significance level at 1%, 5%, and 10% respectively. t-stats are reported in parentheses. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small). One-minute volume averages are reported in 1,000 of shares. Regression coefficients are reported in percentage points.

		Panel A: Spot Market		**Panel B: Futures Market**	
Consume	Provide	Mean	Coef	Mean	Coef
LTT	LTT	0.429	4.353***	2.414	9.659***
			(11.30)		(21.12)
LTT	STT	0.595	8.355***	5.110	20.094***
			(25.61)		(78.16)
LTT	Small	0.123	2.026***	0.095	0.416***
			(21.45)		(11.80)
STT	LTT	1.073	13.398***	5.157	20.950***
			(25.76)		(80.21)
STT	STT	2.361	35.018***	11.334	45.897***
			(43.29)		(50.45)
STT	Small	0.595	10.309***	0.208	0.904***
			(37.68)		(17.09)
Small	LTT	0.170	3.578***	0.097	0.601***
			(19.31)		(11.74)
Small	STT	0.781	16.413***	0.261	1.458***
			(47.97)		(16.39)
Small	Small	0.211	5.479***	0.004	0.022***
			(23.27)		(3.89)
Day FE			Yes		Yes
Time FE			Yes		Yes
Cluster SE			By Day		By Day
Normalize			By Minute		By Minute
Observations			159,156		178,686
Adjusted R2			0.565		0.712

Panel C: F-tests

	Spot Market	Futures Market
H0: STT_STT=STT_LTT+STT_Small		
F-stat	131.9	452.7
p-value	[0.00]	[0.00]
H0: LTT_STT=LTT_LTT+LTT_Small		
F-stat	62.52	601.6
p-value	[0.00]	[0.00]
H0: Small_STT=Small_LTT+Small_Small		
F-stat	531.7	223.9
p-value	[0.00]	[0.00]