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STOCK PRICE CRASHES:
ROLE OF SLOW-MOVING CAPITAL

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ABSTRACT

We study the role mutual funds play in the recovery from fast intraday crashes based on data from the National Stock Exchange of India for a single large stock. During normal times, trading activity and liquidity provision by mutual funds is negligible compared to other traders at around 4% of overall activity. Nevertheless, for the two intraday marketwide crashes in our sample, price recovery took place only after mutual funds moved in. Market stability may require the presence of well-capitalized standby liquidity providers for recovery from fast crashes.

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A liquid and stable stock market plays a critical role in the economy. It channels savings into long-term illiquid investments while at the same time providing liquidity to investors, thereby promoting economic growth (see Levine (2005)). The "Flash Crash" of May 6, 2010, focused exchanges' and regulators' attention on the need to better understand liquidity provision in the financial markets. In this paper, we focus on a particular role financial institutions play in the liquidity provision during intraday crashes and recoveries.

We show that when the demand for liquidity is unusually large leading to intraday fast crashes, mutual funds (MFs) acting as standby liquidity providers are able to step in to provide liquidity, thereby helping price recovery. By looking at micro-level data we are able to provide high-frequency evidence of MFs acting as liquidity providers during fast intraday crashes. MFs have a natural advantage in making a market for stocks they hold when the rewards are adequate (i.e., when price concessions are large enough). They move in only after prices have dropped sufficiently, highlighting the slow-moving feature of standby market-making capital.[1]

We use a unique database of orders and transactions data for the period April – June 2006 for one of the largest firms in the NIFTY and SENSEX indices traded on the National Stock Exchange of India (NSE).[2] Based on the number of trades, the NSE was the third-largest stock exchange after NYSE and NASDAQ in the world as of April 2006.[3] The NSE is organized as a limit order book market similarly to NYSE and NASDAQ, which has become the dominant market design.[4] Even though we use data for three months in 2006 for just one large stock from the NSE, we believe that our main conclusions carry over to the current

[1]Another potential reason for the slow-moving nature of MFs' intermediation capital could be that a sharp drop in a stock's price draws MFs' attention, after which MFs have to evaluate whether this drop is due to lack of liquidity or adverse information. And this evaluation may take time, slowing the deployment of market-making capital.

[2]NSE became the largest stock exchange in India in terms of volume traded, overtaking the Bombay Stock Exchange (BSE) at the end of 1995.

[3]According to the World Federation of Exchanges, the largest exchange in the world based on number of transaction was NASDAQ with more than 100,000 transactions per day, followed by the NYSE with around 91,000 transactions per day and the NSE with around 57,000 transactions per day as of April 2006.

[4]NASDAQ is a hybrid market, i.e., dealer market with a limit order book.

U.S. stock market and several other markets around the world, given the size of the NSE market and the similarities of the market structures between NSE and the stock markets worldwide.[5] We would like to be upfront about limitation of our data since we conduct our analyses on one stock. Even though it is one of the largest and representative stocks on the NSE, we would like to acknowledge this limitation and potential heterogeneity that exists among stocks. However, we believe that our emphasis on liquidity provision by different types of traders especially during fast intraday crashes should not be biased by the choice of a particular stock from the benchmark stock market index.[6]

Despite the above-mentioned limitation, our data have the following advantages. First, the data have a unique identifier for each broker-trader combination, which allows us to calculate the evolution of individual traders' inventory over time. Second, the data have the legal classification (Mutual Fund (MF), Foreign Institutional Investor (FII), and so on) for each trader in addition to the unique individual trader identity. Therefore, we are able to identify the types of legal entities who are standby liquidity providers. Some legal entities are natural liquidity providers and demanders: MFs can tolerate deviations from their desired holdings if prices become attractive; FIIs have a global view on the market, and thus their behavior might be affected by the shocks originated outside the Indian market. We concentrate our analysis on MFs and FIIs as these are the two largest well-known groups of institutional investors worldwide.

We show that during normal periods (i.e., not during intraday crashes), FIIs and MFs are of minor importance both in terms of their trading activity and liquidity provision as

[5] We acknowledge that no overnight short-selling is allowed in equity markets in India as opposed to U.S. However, given that we focus on intraday crashes and recoveries, any restrictions that apply overnight are of a minor concern in such context. Besides that overnight short-selling restriction could be overcome through single-stock futures (single stock-futures market is quite large in India as compared to U.S.). We also note that high-frequency traders and day traders (short-term traders) tend to end their day flat, hence they are unlikely to be influenced by any overnight restrictions. We show in the Internet Appendix that the trading behavior of short-term traders during intraday crashes was similar to that of high-frequency traders during the Flash Crash of May 6, 2010 in the U.S. market.

[6] We provide an external validity check by comparing our anonymous stock to the other stocks in NIFTY50 and to stocks in S&P500 in Section I.

measured by their contribution to the depth outstanding in the limit order book in the close proximity of the mid-quote (these two categories jointly are responsible for less than 10% of overall trading activity and liquidity provision). We also show that FIIs and MFs have considerably larger holding horizon than other traders present on the market. Nevertheless, the importance of FIIs and MFs for intraday price fluctuations should not be underestimated as the activity of these two categories becomes crucial in turbulent times.

There were two fast crashes and recoveries in the anonymous stock used in our analysis alongside crashes in stock market indices such as NIFTY and SENSEX, which suggests that analyzed fast crashes and recoveries were systematic in nature.[7] The first (second) crash was characterized by a drop in the spot market mid-quote by 7.9% (10.2%) within 30 minutes, followed by a sharp recovery of more than 60% within the 30 minutes after the crash's trough.

The unusually large liquidity shocks in both crashes were due to large selling pressure coming from FIIs (as defined by the NSE). We find that MFs were patient traders, buying and selling at better prices than other traders on average. Some MFs entered the market and bought only during the crash days. Moreover, net aggressive buying by MFs Granger-caused a rise in prices during the crash days; however, there was no observed causality during non-crash days. Further, spot returns did not Granger-cause net aggressive buying by MFs during crash and non-crash days. This is consistent with the hypothesis that buying by MFs helped price recovery; however, price recovery did not cause MFs to start buying.[8]

We contribute to two streams of literature: (1) role of financial institutions in liquidity provision and (2) causes of intraday fast crashes and recoveries.[9] From the first stream of

[7]We note that intraday fast crashes are not unique to emerging markets only. On contrary, such events also occur in developed markets as manifested by the Flash Crash of May 6, 2010 in the U.S. market during which both main stock-market index and its constituents experienced a fast crash and recovery as documented by, e.g., Kirilenko, Kyle, Samadi, and Tuzun (2017) and Menkveld and Yueshen (2019), and by the 121 fast stock-specific as well as 27 market-wide intraday crashes in France over 2013 as documented by Bellia, Christensen, Kolokolov, Pelizzon, and Renò (2018).

[8]Note that crash-day causality measures the average effect during the entire crash day. The market drawdown period is too short to estimate causality during that period alone.

[9]In Appendix A, we provide a summary of the findings with regard to liquidity provision in few-closely related papers.

literature, we know that (a subset of) mutual funds provide liquidity to the market during normal times. Keim (1999) conjectures that MFs are natural liquidity providers in the small-cap (and thus, illiquid) stocks they hold. Da, Gao, and Jagannathan (2011) come to similar conclusions by showing that the Dimensional Fund Advisors Micro Cap fund added 20.5 basis points per quarter to performance through liquidity provision. The degree to which institutions participate in the liquidity provision process depends on their characteristics such as, e.g., organizational structure (open-end versus closed-end funds) and holding horizon. Aragon (2007) and Agarwal, Daniel, and Naik (2009) find that hedge funds with large redemption restrictions have larger returns, presumably because they are able to invest in illiquid assets and obtain an illiquidity premium, though the authors do not provide a direct evidence on whether funds consume or supply liquidity. Çötelioğlu, Franzoni, and Plazzi (2020) identify leverage, age, asset illiquidity, and reputational capital as a relevant set of characteristics that explain the exposure of hedge funds' liquidity supply to funding conditions. Giannetti and Kahraman (2018) find that closed-end mutual funds and hedge funds with large share restrictions are more inclined to trade against long-term mispricing than open-end mutual funds and hedge funds with small share restrictions. Whilst previous studies focused on the equity markets, Anand, Jotikasthira, and Venkataraman (2020) provide similar evidence for bond markets and show that there is a subset of mutual funds which specialize in liquidity provision in corporate bonds.

Some institutions are in a better position to provide liquidity during turbulent market conditions than others. Cella, Ellul, and Giannetti (2013) show that 13F institutions that have long-term trading horizons tend to be liquidity providers, while short-term 13F institutions tend to demand liquidity from the market during turmoil periods (with the main focus on the period surrounding Lehman Brothers collapse). Anand, Irvine, Puckett, and Venkataraman (2013) emphasize the crucial role played by mutual funds specializing in long-term liquidity provision in the market recovery for the 2007-2009 financial crisis. In contrast, Manconi, Massa, and Yasuda (2012) provide evidence on the subset of institutions (those with large holdings of securitized products) enhancing shock propagation from securitized product markets to corporate bond markets during the 2007-2009 financial crisis.

We note that the above-mentioned papers describing liquidity provision by institutions during financial turmoil focus on market crashes that took longer to recover than the crashes we study in our paper. Specifically, we focus on *intraday* market crashes and recoveries, thus providing evidence that there exists a subset of institutions that specialize not on the long-term liquidity provision, but rather on the intraday liquidity supply. Intraday crash is a liquidity shock that makes a stock illiquid at a given point in time. We find that a subset of mutual funds who act as natural standby liquidity providers help market to recover from the intraday fast crashes which is consistent with earlier findings in the literature focused on long-term crashes (e.g., Anand, Irvine, Puckett, and Venkataraman (2013)).[10]

Our data allows us to track exact timing of transactions and order submissions coming from all mutual funds and foreign institutions without relying on the inferred capital flows coming from institutional investors and thus, sheds light on their role in intraday price dynamics. We note that most previous studies investigating the role of institutions in liquidity provision utilize quarterly data and thus, have to rely on inferred capital flows. Da, Gao, and Jagannathan (2011) using detailed data from Dimensional Fund Advisors note that usage of inferred flows from quarterly data leads to only 66% of transactions being correctly classified as liquidity demanding or liquidity providing (though such classification works significantly better than random assignment in the two groups). The two studies that use data on individual transactions by mutual funds and hedge funds provided by Abel Noser Solutions are Anand, Irvine, Puckett, and Venkataraman (2013) and Çötelioğlu, Franzoni, and Plazzi (2020), respectively. However, these data cover only the subset of population of mutual and hedge funds and are based on self-reporting by institutions. On the contrary, our data cover

[10]We note that out of 23 mutual funds present in our sample only 5 of them were active during the crash periods. In addition, inventory of those 5 mutual funds remained stable for the month before and after intraday crashes took place highlighting their specialization in intraday liquidity supply.

the *whole population* of not only institutional investors, but also other traders. The latter allows us to exploit trading network changes during intraday crashes and recoveries. Besides that it allows us to trace not only transactions, but also limit order submissions and thus, provide evidence on another dimension of liquidity provision which previous studies fail to uncover due to the absence of necessary data.

We also contribute to the literature investigating the causes of intraday fast crashes. The focus of the recent literature on crashes has been on whether high-frequency traders (HFTs) were instrumental in initiating and accentuating the crashes. Easley, Lopez de Prado, and O'Hara (2011) show that order-flow toxicity increased in the hours before the Flash Crash, making liquidity provision costly and eventually leading to the withdrawal from the market of many liquidity providers – most of whom were HFTs. In contrast, Kirilenko, Kyle, Samadi, and Tuzun (2017) show that HFTs were important market participants (jointly responsible for 34% of the trading volume in E-mini S&P 500 futures on the days surrounding the Flash Crash) and that their behavior did not change during the Flash Crash. Subsequently, Menkveld and Yueshen (2019) found that cross-market arbitrage typically conducted by HFTs broke down prior to the Flash Crash, consistent with arguments in Easley, Lopez de Prado, and O'Hara (2011). In addition to the studies on the role of HFTs in crashes, Kyle and Obizhaeva (2016) document five cases wherein large bets made by institutional investors led to price crashes, three of which occurred well before the rise of high-frequency trading.

The above-mentioned papers focus on identifying why crashes occurred and on understanding the role HFTs play in this process. In our paper, we find that large selling by FIIs initiated both crashes consistent with previous studies. We add to the literature by also investigating necessary condition for recovery from such fast intraday crashes and showing that buying by MFs stabilized the market and helped it recover from the crashes, despite MFs having been slow to move in. Mitchell, Pedersen, and Pulvino (2007) make a related observation regarding the slow-moving nature of market-making capital using data from the convertible debt market,[11] and Duffie (2010) examines the implications using a theoretical framework.

When the market crashes, mutual funds can pick the stock that is most attractive according to some "fair value" model they use. Only mutual funds that are well-capitalized (i.e., holding enough cash) could act quickly and take advantage of such opportunities, consistent with the evidence provided by Simutin (2014) who documents that mutual funds with excess cash holding outperform their peers by over 2% per annum.

To summarize, we provide a comprehensive analysis of the role of slow-moving standby liquidity providers during normal times, price crashes, and recoveries. The rest of the paper is organized as follows. Section I describes the data and introduces trader classification used in the paper. Sections II and III provide descriptive analysis of the trading patterns of different traders during whole sample period and during intraday fast crashes and recoveries, respectively. Section IV zooms into behavior of standby liquidity providers during the two crashes in our sample and describes potential channel through which standby liquidity providers inject a stabilizing force into the market. We conclude in Section V.

I. Data description and trader classification

We use a unique database of orders and transactions for three months in 2006 (April – June) of a large anonymous firm traded on the NSE that is part of SENSEX and NIFTY indices, which provides us with a unique identifier for each broker-trader combination and

[11] Mitchell, Pedersen, and Pulvino (2007) document that during the 2005-2006 period convertible bond arbitrage hedge funds faced massive redemptions forcing them to liquidate their holdings of convertible bonds, leading to sharply depressed prices. Multistrategy hedge funds supplied liquidity, although it took some time to move their capital in place. In the two fast crashes we study in our paper, liquidity shocks originated from liquidations by foreign institutional investors. Some mutual funds in our sample were able to provide liquidity; however, it took some time for them to move in – corresponding to multistrategy hedge funds in Mitchell, Pedersen, and Pulvino (2007). Many other mutual funds did not provide liquidity during fast crashes and recoveries – corresponding to convertible bond mutual funds in Mitchell, Pedersen, and Pulvino (2007) who were not in a position to provide liquidity.

legal classification in the spot market.[12] Our data includes detailed information on trades and quotes (the full history of the order: submission, modification, cancellation, and execution).[13] All our subsequent analysis is conducted for this one representative NSE stock that was part of SENSEX and NIFTY indices.[14] We exclude three days with half-day trading sessions from our sample (April 29, May 23, and June 25, 2006).

A. *External validity: anonymous stock*

We would like to note that conducting the analysis on one single stock is an important limitation of our study. Therefore, we compare the anonymous stock used in this study to stocks that were part of NIFTY50 index to ensure representativeness for the Indian market and also to the smallest stocks that were part of S&P500 index (bottom 20% in terms of market capitalization) to ensure that our results could be generalized to other markets as well. In particular, we collect daily data on market capitalization (in bln USD), annualized turnover, Amihud illiquidity, and market-to-book ratio as of March 2006 (before the start of our sample period) for all stocks in NIFTY50 and the smallest stocks in S&P500 from Datastream.[15]

INSERT TABLE I HERE

Panel A of Table I reports quintile breakpoints, minimum, and maximum for the NIFTY50 index constituents of the monthly average of daily market capitalization (in bln USD), daily annualized turnover, daily Amihud illiquidity measure ($\times 10^8$) and daily market-to-book ratio. For the anonymous stock we report a corresponding quintile for each of the variables. In particular, we note that anonymous stock belongs to the second market capitalization

[12] Kahraman and Tookes (2017) and Murphy and Thirumalai (2017) also use data provided by the NSE.

[13] We refer to Internet Appendix Section IA.1 for summary statistics on trader and order types for spot and single futures market.

[14] We refer to Appendix B for a detailed description of the NSE market.

[15] Data on index constituents come from Bloomberg.

quintile (between 2.51 bln USD and 3.37 bln USD), to the fifth annualized turnover quintile (from 1.53 to 2.86), to the first Amihud illiqudity quintile (from 0.01 to 0.06) and to the third market-to-book ratio quintile (from 3.16 to 4.96). Put differently, anonymous stock is among the most liquid (both in terms of turnover and Amihud illiquidity), but not among the largest of NIFTY50 index constituents.

In order to measure the similarity between our anonymous stock and other NIFTY50 index constituents in the four-dimensional space of the above-mentioned stocks' characteristics, for each stock i in NIFTY50 we construct a matching error with respect to stock $j \neq i$:

$$Matching\ Error_{ij} = \frac{|\frac{Mcap_j}{Mcap_i} - 1| + |\frac{Turnover_j}{Turnover_i} - 1| + |\frac{ILLIQ_j}{ILLIQ_i} - 1| + |\frac{MTBV_j}{MTBV_i} - 1|}{4} \quad (1)$$

For each stock i, we select five stocks $j \neq i$ from NIFTY50 with the smallest matching error and compute the average matching error across these five stocks. The distribution of the average matching errors for NIFTY50 index constituents is reported in Panel A of Table I. We note that our anonymous stocks belongs to the third quintile of the matching error distribution suggesting that in the space spanned by the four above-mentioned stocks' characteristics our anonymous stock is not an outlier and thus, is representative for the Indian market.[16]

Panel B of Table I reports similar analysis for the smallest stocks in the S&P500 (bottom 20% in terms of market capitalization). We show that our anonymous stock belongs to the second quintile in terms of market capitalization, the fourth quintile in terms of turnover and Amihud illiqudity, and to the fifth quintile in terms of the market-to-book ratio. We

[16]We note that NIFTY50 covers around 60% to 70% of the total market capitalization. We acknowledge that our results might not hold for small and extremely illiquid stocks. However, we would like to emphasize that regulators are mainly concerned with fast intraday crashes and recoveries in the main stock-market indices like S&P500 in U.S. which accounts for 70% to 80% of the total market capitalization.

also construct matching error for each of the smallest stocks in S&P500 and our anonymous stock and select five stocks from the S&P500 universe with the smallest matching error. We document that anonymous stock belongs to the third quintile of the matching error distribution. In conclusion, our anonymous stock can be considered as a representative stock in the four-dimensional space of the above-mentioned characteristics for the bottom 20% of the S&P500 and thus, the results of this study could be generalizable for other markets as well.

B. Trader classification

The NSE classifies all traders in terms of their legal affiliations. There are three primary categories: individuals, corporations, and financial institutions; and 13 subcategories: 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, nonresident Indians, foreign institutional investors, and overseas corporate bodies. For the purpose of our analysis, investigating the role of institutions in the recoveries from the fast crashes, we divide traders into three categories based on their legal classification (see Figure 1): foreign institutional investors (FIIs), mutual funds (MFs), and other traders (Other). In addition, a trader to be classified as FII or MF has to trade at least 750 shares (the size of a single-stock futures contract) on a median day when the trader is active. Traders that trade less than 750 shares per day do not have an opportunity to use the futures market for hedging purposes.[17] Each trader belongs only to one category during our sample period (i.e., traders do not switch categories from one day to another).[18]

INSERT FIGURE 1 HERE

[17] We note that several MFs and FIIs (based on legal classification only) do not satisfy this requirement. However, their activity during the period considered is negligible. These traders are active on average during 5 days only and transact on average 109 shares per day.

[18] We refer to the Internet Appendix Section IA.2 for fine-tuned classification where we expand the Other traders category.

II. Summary statistics

In this section, we provide summary statistics of the trading activity of FIIs and MFs (see Section II.A) and liquidity provision of FIIs and MFs as measured by their contribution to the depth of the limit order book (see Section II.B) during our sample period.

A. *Trading activity*

We start by documenting trading activity of the different trader categories. Table II shows that during our sample period there are 127 (0.1% of the total number of traders) FIIs and 268 (0.3% of the total number of traders) MFs present in the market. FIIs as a group are responsible for 4.64% of the total (buying + selling) trading volume, while MFs as a group are responsible for 3.78% of the total (buying + selling) trading volume. We also note that trading activity of both FIIs and MFs is not concentrated on one side of the market but rather is split between buy and sell sides.

INSERT TABLE II HERE

On average across trader-days, we show that FIIs and MFs tend to have larger trading volume than other traders. In particular, average daily trading volume of individual FII (MF) is 51,150 (12,187) shares as compared to 669 shares of individual trader from Other category. Noteworthy, end-of-day inventory position ($\frac{\#\ of\ shares\ bought - \#\ of\ shares\ sold}{\#\ of\ shares\ bought + \#\ of\ shares\ sold}$) of FIIs (MFs) is 99.3% (96.7%), while end-of-day inventory of other traders is 30.5% only. This suggest that individual FII (MF) build up their positions on a particular day (either buying or selling during the same day), while individual Other traders tend to engage in intraday trading strategies (both buying and selling during the same day).

B. Contribution to the limit order book depth

We now move to examining liquidity provision by FIIs and MFs as measured by their contribution to the limit order book depth. In particular, we look at the proportion of the total depth supplied by FIIs and MFs respectively at the close proximity (in basis points) to the mid-quote.

INSERT TABLE III HERE

Table III reports an average of one-minute median depth in thousands of shares 10, 25, 50, 75, and 100 basis points away from the mid-quote, together with the proportion of shares coming from FIIs and MFs. Both FIIs and MFs supply liquidity on both sides of the limit order book. At the bid side of the limit order book, FIIs (MFs) supply between 3.41% and 4.46% (between 1.61% and 2.42%) of the total depth outstanding. At the ask side of the limit order book, FIIs (MFs) supply between 4.84% and 6.00% (between 3.00% and 4.10%) of the total depth outstanding. We note that proportion of the depth supplied by FIIs (MFs) remains relatively constant while moving further away from the mid-quote (from 10 basis points to 100 basis points).

To sum up, we document that FIIs and MFs are different from Other traders as they have a longer holding horizon of a stock. We also show that FIIs and MFs jointly are responsible for less than 10% of the total trading volume and less than 10% of the liquidity provision as measured by their contribution to the depth of the limit order book during our sample period.[19] Despite that, the role of FIIs (MFs) is crucial during the fast crashes (recoveries).

[19]We refer to Internet Appendix Section IA.3 for the summary statistics on the alternative measures of liquidity provision during our sample period.

III. Fast crashes

In this section, we identify stock price crashes and describe the behavior of FIIs and MFs during crashes. We identify crashes using two methods, both of which identify essentially the same crashes. First, we use the drift-burst statistics developed by Christensen, Oomen, and Renò (2016) and also used by Bellia, Christensen, Kolokolov, Pelizzon, and Renò (2018):

$$
\begin{aligned}
T_t &= \sqrt{\frac{h_\mu}{K_2}}\frac{\mu_t}{\sigma_t} \\
\mu_t &= \frac{1}{h_\mu}\sum_{i=1}^{n}\left(K\left(\frac{t_{i-1}-t}{h_\mu}\right)r_{t_{i-1}}\right) \\
\sigma_t &= \sqrt{\frac{1}{h_\sigma}\sum_{i=1}^{n}\left(K\left(\frac{t_{i-1}-t}{h_\sigma}\right)r^2_{t_{i-1}}\right)} \\
K(x) &= \exp(-|x|)1(x \leq 0) \\
K_2 &= \int_R K^2(x)dx
\end{aligned}
\tag{2}
$$

Intuitively, the drift-burst statistic compares the average one-minute mid-quote returns, r_t, computed over the rolling window before time t (with the length of the window determined by the bandwidth, h_μ) to the volatility of the returns computed over the rolling window before time t (with the length of the window determined by the bandwidth, h_σ), with the most recent observations receiving the highest weight. A crash trough is the time t when the average returns become too large with respect to their volatility. Under the null of no drift burst, T_t follows standard normal distribution; however, when there is a drift burst, $|T_t|$ goes to infinity. We estimate drift-burst statistics for the mean bandwidth (h_μ) of 15 minutes and the volatility bandwidth (h_σ) of 45 minutes. This implies that we are interested in the crashes that develop, on average, within 15 minutes, similar to the Flash Crash of May 6, 2010. In the end of each one-minute interval, we compute the drift-burst statistics based on the one-second mid-quote returns. Given that we are interested in the crashes, we focus our attention on negative drift-burst statistics. We mark one-minute intervals when the absolute value of the drift-burst statistics exceeds its critical value at 95% confidence level as crash troughs. The critical value used in the paper accounts for the multiple tests, as in Christensen, Oomen, and Renò (2016).[20] In our sample, we detect eight such troughs. The drift-burst statistic by itself does not tell us whether the crash is reverted. Therefore, we look at the cumulative returns 30 minutes before and after the trough. We select only those crashes that recover by at least 50%. After applying the recovery condition, only two crashes remain: those that took place on May 19, 2006, and May 22, 2006. On May 19, 2006, the trough of the crash is at 10:38 a.m. On May 22, 2006, the trough of the crash is at 11:52 a.m.

Second, we use the more intuitive crash identification rule: a 3% drop in one-minute mid-quotes over 15 minutes, followed by a recovery in one-minute mid-quotes of 3% over 15 minutes. We obtain the same two crashes with the trough point of May 19 being exactly the same as identified by the drift-burst statistic, and the trough point for May 22 being two minutes later than the one identified by the drift-burst statistic. Since the two crashes' troughs that the two methods identified are essentially the same, we use the troughs identified by the first method (the drift-burst statistic) for the analysis that follows.

For further analysis, we focus our attention on the four days surrounding the crash days from May 16 through May 25.[21] We compare the behavior of FIIs and MFs during the crash days with their behavior during the two days before and two days after the crash instead of comparing with all other days in the sample.

INSERT FIGURE 2 HERE

Figure 2 shows the mid-quotes evolutions during the trading day together with NIFTY

[20] We thank the authors for sharing the code for the estimation procedure as well as the dataset containing the critical values of the drift-burst statistic that account for multiple testing problems.

[21] We note that May 18 and May 23 are either missing from our data or only include trades for the first 30 minutes of the trading day.

prices (median over a one-minute interval) for the two days on which the crashes happened. On May 19, we observe two events that look like a crash followed by a fast recovery. Indeed, on May 19, we identify two troughs based on the drift-burst statistic. However, only during the first event did the crashes develop and revert quickly enough. During the 30 minutes before the first crash's trough, prices fell by 7.9% and recovered by only 5.1% (reversal of 64.5%) in the 30 minutes that followed. However, during the 30 minutes before the second crash's trough, prices fell by 6.1% and recovered in the next 30 minutes by only 0.6% (9.1% reversal). Put differently, during the second event on May 19, prices did not fall and recover fast enough to be classified as a fast crash. On May 22, during the 30 minutes before the trough, prices fell by 10.2% and recovered in the next 30 minutes by 7.0% (a 68.4% reversal). This crash was also characterized by a trading halt (from 11:56 a.m. to 12:56 p.m.) before market recovery took place. We also note that the two crashes were accompanied by similar movement in the NIFTY index, though it was less pronounced. Therefore, despite the fact that we focus on one anonymous stock, the two crashes that we analyze in the paper are not idiosyncratic, but rather systematic in nature similar to the Flash Crash of May 6, 2010 in the U.S.

We provide graphical representation of MFs' and FIIs' trading behavior (see Figure 3). Figure 3 shows that selling by FIIs coincides with the crashes, while buying by MFs is followed by the market recovery. We also note that inventory position of Other traders remains rather flat during the crash period and decreases during recovery periods, therefore trading activity of Other traders is unlikely to have stabilizing and/or destabilizing role on the market. Figure 3 provides suggestive evidence that the crashes were driven by selling pressure from FIIs, while recoveries happen due to buying pressure from of MFs. Although, out of 23 MFs present in our sample only 5 were active during the crash periods, those active MFs were able to inject enough liquidity to stabilize the market. These graphs are consistent with the stabilizing role of the slow-moving capital (see Duffie (2010)).[22]

[22]We refer to the Internet Appendix Section IA.4 for inventory sensitivity analysis in the spirit of Kirilenko,

INSERT FIGURE 3 HERE

In addition, we examine the contribution of the FIIs and MFs to the depth outstanding in the limit order book 10, 25, 50, 75, and 100 basis points away from the mid-quote during crash and recovery periods.

INSERT TABLES IV and V HERE

Tables IV and V show that FIIs supply liquidity on the ask side of the limit order book, while MFs supply liquidity on the bid side of the limit order book during crash and recovery periods. This finding is in contrast to the whole sample summary statistics reported in Table III where presence of FIIs and MFs was symmetric on both sides of the limit order book. Moreover, presence of FIIs (MFs) on the ask (bid) side of the book reaches more than 20% in some cases, while for the whole sample period joint contribution of FIIs and MFs to the depth on the each side of the limit order book does not go above 10%. We also show that the presence of FIIs and MFs is persistent throughout the crash and recovery period on the ask and bid side of the limit order book, respectively.[23]

Overall, our results show that though during normal periods trading activity and liquidity provision of the FIIs and MFs is relatively small, during fast crashes and recoveries their activity becomes much more prevalent.

IV. Role of FIIs and MFs during fast crashes and recoveries

In this section, we analyze Granger-causality between activity of FIIs and MFs and the mid-quote returns (see Section IV.A) and discuss one of the potential channel that allows

Kyle, Samadi, and Tuzun (2017).

[23]We refer to Internet Appendix Section IA.5 for the summary statistics on the alternative measures of liquidity provision during crash periods.

MFs to stabilize the market during the fast crashes (see Section IV.B).[24]

A. Granger-causality

So far, we have provided suggestive evidence for the cause of crashes – selling by FIIs – as well as for the cause of recoveries – buying by MFs. In this section, we investigate whether FIIs (MFs) Granger-cause crashes (recoveries) versus whether crashes (recoveries) Granger-cause FIIs (MFs) activity.

First, we compute marketable order imbalance ($MOIB$) for each trader category i as buy volume initiated by trader category i minus sell volume initiated by this trader category i, and scale it with overall (buyer- plus seller-initiated) volume in the market during a one-minute time interval t (see equation (3)). 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.[25]

$$MOIB_{i,t} = \frac{Buyer\ initiated\ volume_{i,t} - Seller\ inititated\ volume_{i,t}}{Buyer\ initiated\ volume_{t} + Seller\ inititated\ volume_{t}} \tag{3}$$

Second, we compute limit order book imbalance ($LOIB$) for each trader category i as median depth outstanding at the bid side of the limit order book within 100 basis points from the mid-quote for trader category i minus median depth outstanding at the ask side of the limit order book within 100 basis points from the mid-quote for trader category i and scale it with overall (bid plus ask side of the limit order book) median depth outstanding within 100 basis points from the mid-quote during one-minute time interval t (see equation (4)).

[24] We refer to Internet Appendix Section IA.6 for the role of short-term traders (a subset of Other traders category from the extended classification scheme, see Internet Appendix Section IA.2) in causing intraday fast crashes and recoveries.

[25] In case orders on the two sides of the transaction have the same timestamp, we cannot determine which order is initiating the trade. However, there are very few such unclassified cases (0.76% of trading volume).

$$LOIB_{i,t} = \frac{Bid\ Depth_{i,t} - Ask\ Depth_{i,t}}{Bid\ Depth_t + Ask\ Depth_t} \tag{4}$$

In order to do that, we estimate the vector-autoregression model on one-minute mid-quote returns, marketable order imbalance ($MOIB$) and limit order book imbalance ($LOIB$) from different trader categories. We use BIC criterion to decide on the number of lags, n.

$$\begin{aligned}
Ret_t &= \alpha + \sum_{lag=1}^{n} \beta_{lag} Ret_{t-lag} + \sum_{lag=1}^{n} \sum_{i} \delta_{i,lag} MOIB_{i,t-lag} + \sum_{lag=1}^{n} \sum_{i} \gamma_{i,lag} LOIB_{i,t-lag} + \epsilon_t \\
MOIB_{i,t} &= \alpha + \sum_{lag=1}^{n} \beta_{lag} Ret_{t-lag} + \sum_{lag=1}^{n} \sum_{i} \delta_{i,lag} MOIB_{i,t-lag} + \sum_{lag=1}^{n} \sum_{i} \gamma_{i,lag} LOIB_{i,t-lag} + \epsilon_t \\
LOIB_{i,t} &= \alpha + \sum_{lag=1}^{n} \beta_{lag} Ret_{t-lag} + \sum_{lag=1}^{n} \sum_{i} \delta_{i,lag} MOIB_{i,t-lag} + \sum_{lag=1}^{n} \sum_{i} \gamma_{i,lag} LOIB_{i,t-lag} + \epsilon_t
\end{aligned} \tag{5}$$

INSERT TABLE VI HERE

Table VI presents the results of Granger-causality tests (for brevity, we report only results that are relevant for our analysis). We show that both marketable order imbalance ($MOIB$) and limit order book imbalance ($LOIB$) from FIIs and MFs Granger-cause mid-quote returns on the crash days. In particular, p-values of the Granger-causality test from $MOIB$ to mid-quote returns are 2.70% and 0.00% and p-values of the Granger-causality test from $LOIB$ to mid-quote returns are 1.40% and 3.70% for FIIs and MFs, respectively. At the same time, mid-quote returns do not Granger-cause marketable order imbalance ($MOIB$) with the p-values of 94.00% and 25.50% and limit order book imbalance ($LOIB$) with the p-values of 49.00% and 84.20% of FIIs and MFs, respectively. On the contrary, during non-crash days, the marketable order imbalance ($MOIB$) of MFs and FIIs and limit order book imbalance ($LOIB$) of MFs do not Granger-cause mid-quote returns, nor vice versa. This is consistent with FIIs in causing a crash and MFs in causing the recovery.

INSERT FIGURES 4 – 7 HERE

Figures 4 and 5 plot orthogonalized impulse response functions from marketable order imbalance ($MOIB$) and limit order book imbalance ($LOIB$) to mid-quote returns for both crash and non-crash days. Decomposition order is as follows: mid-quote returns, marketable order imbalance from FIIs, MFs, and Other traders, and limit order book imbalance from FIIs, MFs, and Other traders. One standard deviation shock to FIIs' $MOIB$ or MFs' $MOIB$ results in a larger effect on the mid-quote returns on the crash days (around 2-5 bps at one-minute horizon) than on the non-crash days (around 0 bps at one-minute horizon). One standard deviation shock to FIIs' $LOIB$ or MFs' $LOIB$ also results in a larger effect on the mid-quote returns on the crash days (around 2-3 bps at one-minute horizon) than on the non-crash days (around 0-1 bps at one-minute horizon).

Figures 6 and 7 plot orthogonalized impulse response functions from mid-quote returns to marketable order imbalance ($MOIB$) and limit order book imbalance ($LOIB$), respectively. Decomposition order is as follows: mid-quote returns, marketable order imbalance from FIIs, MFs, and Other traders, and limit order book imbalance from FIIs, MFs, and Other traders. We note that in all cases the effect is marginal for both crash and non-crash days.

We find that MFs induce the recovery process in the spot market; however, it takes a while for them to step in. They act as standby liquidity providers who are slow in deploying their market-making capital. Our statistical tests confirm that buying by MFs leads to recovery, but recovery does not lead MFs to buy. Our findings are consistent with Keim (1999), who expresses the view that MFs are natural liquidity providers in the stocks they hold, and Da, Gao, and Jagannathan (2011), who find that the Dimensional Fund Advisors Micro Cap fund added 20.5 basis points per quarter to performance through liquidity provision.

B. *Execution quality of FIIs and MFs*

In this section, we uncover one potential channel that allows MFs to insert a stabilization force into the market. We first examine whether MFs and FIIs in our sample are opportunistic buyers and sellers, thus systematically providing liquidity throughout our sample period. For that purpose, we plot MFs' and FIIs' cumulative end-of-day inventory position since the beginning of our sample period and the minimum and maximum trading price observed during the day. We note that overnight short selling was not allowed, and therefore negative inventories should be interpreted as a decrease of the starting inventory position.

INSERT FIGURE 8 HERE

Panels A and B Figure 8 show that FIIs move with the price, while MFs in our sample are indeed opportunistic traders: they buy when the price goes down and sell when the price goes up.[26] Panels C and D of Figure 8 show the end-of-day cumulative inventory position for FIIs and MFs that were active on the crash days, respectively. We observe that these MFs were not active before the crash; they bought during the crash and held their inventory position until the end of our sample period. This behavior suggests that mutual funds were standby liquidity providers and that it took some time for them to deploy their market-making capital to provide liquidity.

In Figure 8, we show that MFs systematically act as opportunistic traders. Multiple reasons could give rise to such trading patterns, and in the following analysis, we test one possible explanation. If MFs trade as if they had limit prices for buying and selling based on some notion of "fair value", then it should naturally lead to opportunistic trading through patient buying (selling) at the volume-weighted average price below (above) Other traders' volume-weighted price (i.e., there should be a better quality of trade execution).

[26] Perold and Tierney (1997) document that Numeric Investors behaved in this way when taking positions based on their fair-value model.

To evaluate the quality of trade execution, for each trader l on day k, we compute the volume-weighted average price of its transactions relative to the daily volume-weighted average price of all transactions for the buy and sell side separately and regress it on dummy variables that equal one if a trader belongs to either FIIs or MFs; on a dummy variable that equals one for traders active the crash days, the interaction between them, and day fixed effects (FE_k):[27]

$$\begin{aligned}\frac{VWAP_{lk}}{VWAP_k} = \sum_k \alpha_k FE_k + \beta_1 FII_{lk} + \beta_2 MF_{lk} + \beta_3 FII_{lk} * Active_l + \\ + \beta_4 MF_{lk} * Active_l + \beta_5 Active_l + \epsilon_{lk}\end{aligned} \tag{6}$$

INSERT TABLE VII HERE

Table VII shows that, for the specification, including interaction variables, MFs buy a stock at a price relative to the daily VWAP of all transactions that is 0.22% lower than the volume-weighted average price of Other traders, while FIIs active on the crash days buy at a price 0.27% higher than the volume-weighted average price of Other traders. FIIs also sell stock at a price relative to the daily VWAP of all transactions that is 0.31% lower than the volume-weighted average price of Other traders. In other words, MFs are patient buyers, while FIIs are impatient sellers, and this effect is not solely driven by those MFs and FIIs active during the crash days; rather, it is a general characteristic of the traders that belong to these categories during our sample period. MFs move slowly not because they are slow to react to the market signal, but because they wait until the price hits their buying limit estimate from the "fair-value" model.

[27]We do not use aggregation for trader categories because within each category, there might be traders with different strategies.

V. Conclusion

Stock price crashes, though infrequent, do occur with adverse consequences. The Flash Crash of May 6, 2010, has drawn regulators' and exchanges' attention to the need to understand the role of different types of traders during crashes and their recoveries as opposed to normal periods.

Based on a dataset with unique identifiers for each broker-dealer-trader combination, along with their legal entity type, we provide a comprehensive analysis of the interactions among mutual funds (MFs), who hold a large inventory of stocks and can tolerate deviations from their desired inventory positions for a longer period of time; foreign institutional investors (FIIs), who trade based on their global perspective; and other traders, who are characterized by shorter trading horizons. We acknowledge the limitation of our data as we only concentrate on one large representative stock in the NSE. However, we believe that given very granular nature of our data and the fact that we concentrate on one of the largest stocks on NSE, which was the third-largest stock exchange after NYSE and NASDAQ, our results of liquidity provision during fast intraday crashes can be generally applicable to other major limit order book markets.

Both MFs and FIIs trade much less than other traders, nevertheless, their importance during fast intraday crashes should not be neglected. In line with the previous literature indicating that large sell orders initiate crashes, we find that large sell orders by FIIs put a downward pressure on the stock price. During the first crash, MFs, though slow to move in, started buying in sufficient quantities to help stop the crash and initiate price recovery. In the second crash, trading was halted. When trading resumed, MFs once again started buying in sufficient quantities to promote the subsequent price recovery. We also shed light on the potential channel that allows MFs to inject stabilizing force in the market, in particular, we show MFs are patient traders that trade with better execution quality than other traders. We add to the previous literature by concentrating on micro-level high-frequency analysis of liquidity provision by MFs.

Our findings emphasize the role of well-capitalized standby liquidity providers like MFs, which can redeploy capital into the market when the rewards are sufficient, thereby providing much-needed liquidity. This process takes some time, since such liquidity providers have to understand the reasons for the crash and may also require a large price concession. Circuit breakers, while providing the needed time for standby liquidity providers to move in, may not provide the necessary incentives. To the extent that there are no alternative mechanisms to provide the necessary incentives for attracting standby liquidity providers, rare crashes may be inevitable in markets where competitive forces have resulted in thinly capitalized intermediaries (such as high-frequency traders, HFTs) being the de facto liquidity providers.

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Table I External validity: anonymous stock

This table shows the summary statistics for NIFTY50 index constituents, the smallest S&P500 index constituents (bottom 20% in terms of market capitalization), and anonymous stock. Panel A (Panel B) reports quintile breakpoints, minimum, and maximum for NIFTY50 (S&P500) of the monthly average of daily market capitalization (in bln USD), daily annualized turnover, daily Amihud illiquidity measure ($\times 10^8$), daily market-to-book ratio as of March 2006. In addition, we report quintile breakpoints, minimum, and maximum of the matching error (averaged across five most similar stocks) that was constructed for each index constituent on the basis of the four above-mentioned characteristics. For the anonymous stock we report a corresponding quintile for each of the variables. Before computing average monthly values for each of the variables, we winsorize daily values at 2.5% and 97.5%. Daily data for market capitalization, return, trading volume, and market-to-book ratio comes from Datastream. The lists of index constituents come from Bloomberg.

	Mcap	*Turnover*	*ILLIQ*	*MTBV*	*Matching Error*
Panel A: Quintile breakpoints of NIFTY50					
Min	0.99	0.13	0.01	1.05	0.22
Q20	2.51	0.27	0.06	2.10	0.28
Q40	3.37	0.50	0.10	3.16	0.35
Q60	5.42	0.90	0.14	4.96	0.42
Q80	11.41	1.53	0.23	8.94	0.51
Max	24.87	2.86	0.82	20.76	1.16
# of stocks	48	48	48	48	48
Anonymous stock	Quintile 2	Quintile 5	Quintile 1	Quintile 3	Quintile 3
Panel B: Quintile breakpoints of S&P500 (bottom 20%)					
Min	2.08	0.60	0.01	0.98	0.09
Q20	2.52	1.31	0.02	1.59	0.14
Q40	3.36	1.70	0.03	2.08	0.16
Q60	4.06	2.15	0.04	2.85	0.18
Q80	4.69	2.99	0.05	3.94	0.22
Max	5.21	7.20	0.08	15.51	0.30
# of stocks	93	93	93	93	93
Anonymous stock	Quintile 2	Quintile 4	Quintile 4	Quintile 5	Quintile 3

Table II Trading volume per trader category

This table shows the number of traders in each trader group, number of shares bought and sold by each trader group and proportion of trading volume attributable to each trader group. In addition, we report the trading volume and end-of-day inventory position averaged by trader-day within each trader group. We include both transaction of the regular book orders and stop loss orders. We classify traders into three categories: foreign institutions (FII), mutual funds (MF), and other traders (Other). Data on trader IDs, orders, and trades for anonymous stock for the period from April till June 2006 are provided by the NSE.

	# of traders	Total buying volume		Total selling volume		Total volume (buying + selling)		Average by trader-day	
		# of shares	% of shares	# of shares	% of shares	# of shares	% of shares	Inventory	Trading volume
FII	127	7,019,742	6.36%	8,825,689	7.99%	9,967,471.00	4.64%	99.3%	51,150
MF	268	2,947,729	2.67%	5,183,524	4.69%	8,131,253.00	3.78%	96.7%	12,187
Other	99,001	100,476,999	90.98%	96,435,257	87.32%	196,912,256.00	91.58%	30.5%	669

Table III Contribution to the limit order book depth

This table shows average contribution to the limit order book by foreign institutions (FII) and mutual funds (MF) in the proximity of the midpoint. Average depth is reported in thousands shares. Data on trader IDs, orders, and trades for anonymous stock for the period from April till June 2006 are provided by the NSE.

# of bps from the midpoint	Bid side			Ask side		
	Average depth	FII	MF	Average depth	FII	MF
10	1.92	4.46%	1.61%	1.82	4.86%	3.00%
25	5.08	4.41%	1.90%	5.03	6.00%	3.75%
50	9.89	3.91%	2.42%	10.55	5.97%	4.00%
75	14.15	3.58%	2.39%	16.52	5.24%	4.10%
100	17.90	3.41%	2.40%	16.52	4.84%	3.86%

Table IV Contribution to limit order book depth: Crashes

This table shows average contribution to the limit order book by foreign institutions (FII) and mutual funds (MF) in the proximity of the midpoint for the periods from 30 to 20 minutes before the trough of the crash (Panel A), from 20 to 10 minutes before the trough of the crash (Panel B), and from 10 minutes before the trough of the crash to the trough of the crash (Panel C). Average depth is reported in thousands shares. Data on trader IDs, orders, and trades for anonymous stock for the period from April till June 2006 are provided by the NSE.

# of bps from the midpoint	Bid side			Ask side		
	Average depth	FII	MF	Average depth	FII	MF
Panel A: [-30 -20]						
10	0.30	0.00%	0.00%	0.40	0.00%	0.00%
25	2.11	0.00%	7.39%	1.49	0.00%	0.00%
50	4.80	0.00%	18.31%	4.13	8.58%	0.00%
75	6.87	0.00%	20.29%	5.41	9.08%	0.00%
100	8.15	0.00%	18.89%	6.67	10.42%	0.00%
Panel B: [-20 -10]						
10	0.22	0.00%	0.25%	0.41	0.00%	0.00%
25	1.08	0.00%	4.30%	1.79	0.00%	1.68%
50	2.23	0.00%	4.06%	4.14	3.09%	10.57%
75	3.72	0.00%	2.50%	5.58	2.20%	12.19%
100	5.65	0.00%	1.89%	6.42	2.11%	11.15%
Panel C: [-10 0]						
10	0.58	0.00%	9.30%	0.39	2.52%	0.00%
25	1.53	0.00%	6.69%	1.37	11.82%	0.00%
50	3.54	0.00%	8.41%	3.16	15.68%	0.00%
75	4.97	0.00%	6.69%	4.70	18.03%	0.00%
100	6.03	0.00%	5.98%	5.70	19.16%	0.00%

Table V Contribution to limit order book depth: Recoveries

This table shows average contribution to the limit order book by foreign institutions (FII) and mutual funds (MF) in the proximity of the midpoint for the periods from the trough of the crash to 10 minutes after the trough of the crash (Panel A), from 10 to 20 minutes after the trough of the crash (Panel B), and from 20 to 30 minutes after the trough of the crash (Panel C). Average depth is reported in thousands shares. Data on trader IDs, orders, and trades for anonymous stock for the period from April till June 2006 are provided by the NSE.

# of bps from the midpoint	Bid side			Ask side		
	Average depth	FII	MF	Average depth	FII	MF
Panel A: [0 +10]						
10	0.89	0.00%	9.04%	0.35	0.00%	0.00%
25	3.82	0.00%	14.94%	1.51	6.32%	0.00%
50	8.52	0.00%	20.40%	2.58	4.85%	0.00%
75	10.08	0.00%	17.93%	3.66	3.89%	0.00%
100	11.08	0.00%	16.99%	4.47	3.56%	0.00%
Panel B: [+10 +20]						
10	0.48	0.00%	0.00%	0.51	9.52%	0.00%
25	1.40	0.00%	9.54%	2.49	8.48%	0.00%
50	2.80	0.00%	15.20%	4.25	10.87%	0.00%
75	4.85	0.00%	18.27%	5.60	16.06%	0.00%
100	6.02	0.00%	17.74%	7.86	22.13%	0.00%
Panel C: [+20 +30]						
10	2.64	0.00%	2.57%	0.16	0.00%	0.00%
25	6.12	0.00%	0.80%	0.96	0.00%	0.00%
50	14.81	0.00%	4.16%	3.41	13.10%	0.00%
75	18.43	0.00%	4.43%	5.11	14.67%	0.00%
100	19.79	0.00%	6.53%	6.19	13.64%	0.00%

Table VI Granger causality

This table shows the results of the Granger-causality tests for a vector-autoregression for one-minute returns, marketable and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregressions for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MF), and other traders (Other). For brevity, we report only those Granger-causality tests that are relevant for our analysis. ***, **, and * denote significance level at 1%, 5%, and 10%, respectively.

	19-22 of May		16-25 of May, excl crash days		
Equation	Excluded	p-value	Equation	Excluded	p-value
Return	MOIB FII	2.70%**	Return	MOIB FII	12.00%
Return	MOIB MF	0.00%***	Return	MOIB MF	95.40%
Return	LOIB FII	1.40%**	Return	LOIB FII	0.20%***
Return	LOIB MF	3.70%**	Return	LOIB MF	54.90%
MOIB FII	Return	94.00%	MOIB FII	Return	33.20%
MOIB MF	Return	25.50%	MOIB MF	Return	42.00%
LOIB FII	Return	49.00%	LOIB FII	Return	8.20%*
LOIB MF	Return	84.20%	LOIB MF	Return	24.60%

Table VII Quality of trade execution

This table shows the regression for the terms of execution FIIs and MFs face as compared to Other traders (see equation (6)) separately for buy and sell volume. As a dependent variable, we use the volume-weighted average price for each trader relative to the volume-weighted average price for all traders during the day. Active is a dummy variable that equals one if a trader was active during May 19 and/or May 22, 2006. We use day fixed effects. We cluster standard errors by day and trader. ***, **, and * denote significance level at 1%, 5%, and 10%, respectively. *t*-stats are reported in parentheses.

	Buy		Sell	
	(1)	(2)	(3)	(4)
FII	0.11	0.06	-0.34***	-0.31***
	(0.97)	(0.44)	(-3.60)	(-2.77)
MF	-0.26**	-0.22*	-0.12	-0.07
	(-1.98)	(-1.81)	(-1.18)	(-0.71)
$FII \times Active$		0.27**		-0.23
		(2.06)		(-0.88)
$MF \times Active$		-0.16		-0.34
		(-0.30)		(-1.28)
Active		-0.09***		-0.02
		(-4.67)		(-1.51)
Constant	99.99***	100.01***	100.05***	100.05***
	(726,744.29)	(25,934.47)	(458,248.17)	(40,866.56)
Observations	265,362	265,362	254,224	254,224
Adjusted R^2	0.018	0.019	0.031	0.031
Day FE	Yes	Yes	Yes	Yes
Clustered SE	By Trader and Day	By Trader and Day	By Trader and Day	By Trader and Day

Figure 1. Trader Classification

This figure shows the trader classification scheme used in this paper.

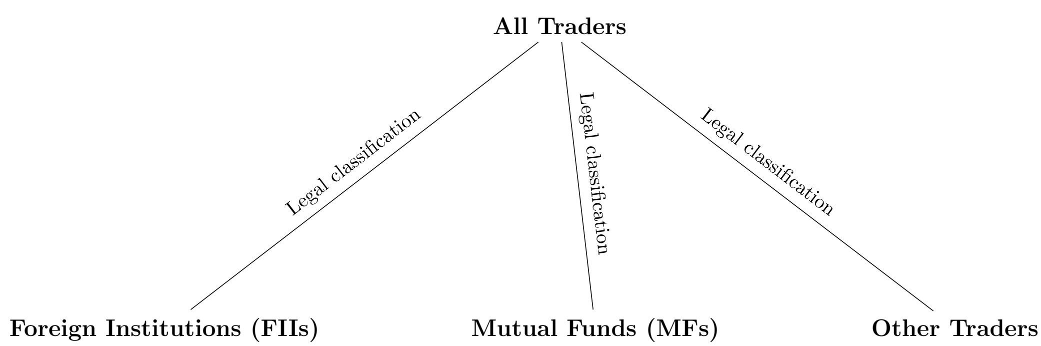
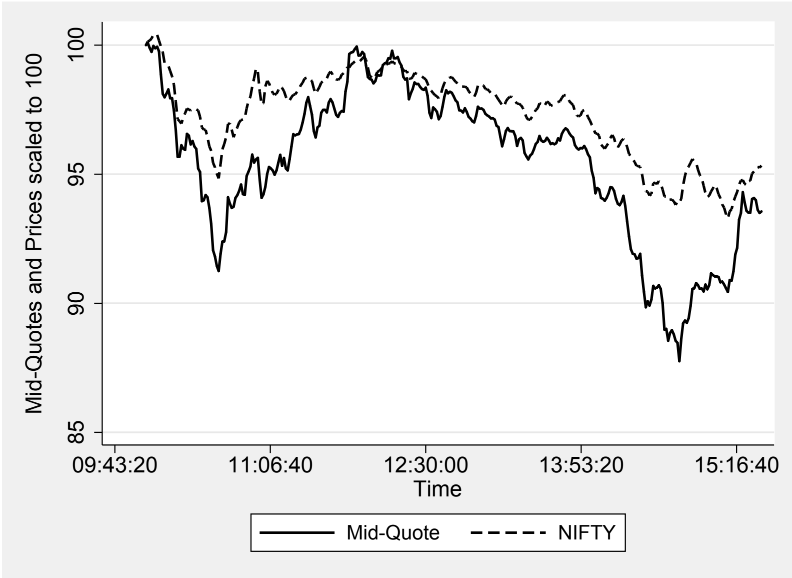


Figure 2. Crashes

This figure shows the dynamics of the mid-quote in the spot and futures markets, together with NIFTY prices at a one-minute frequency for the two 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: 19 of May 2006



Panel B: 22 of May 2006

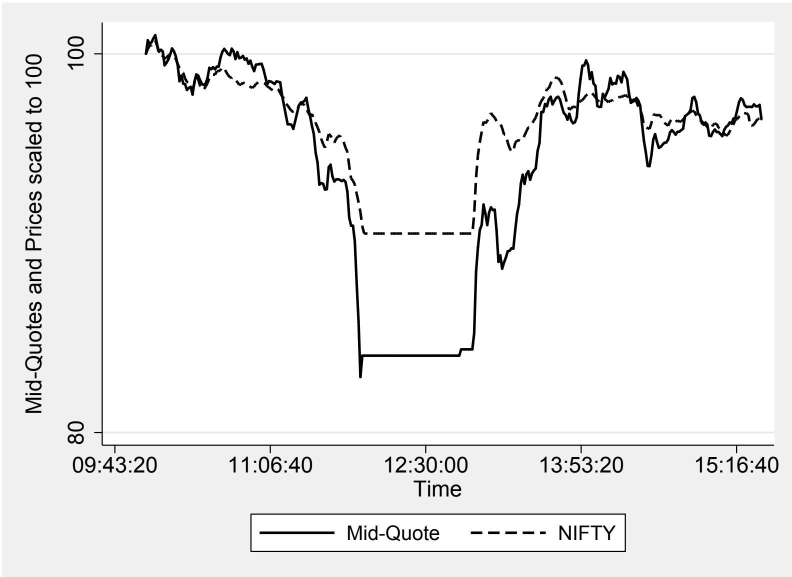
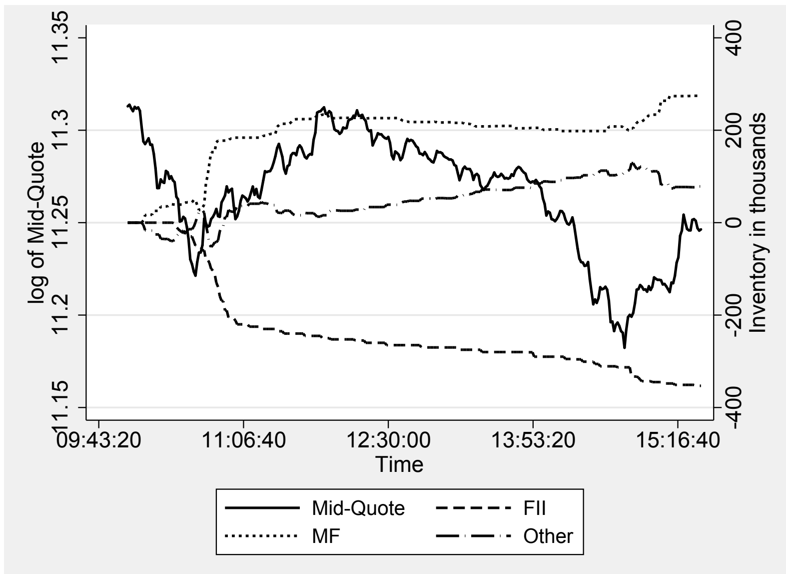


Figure 3. Inventory dynamics during the fast crashes and recoveries

This figure shows dynamics of the mid-quote and inventory of FIIs, MFs, and other traders (Other) at a one-minute frequency during the two crash days: May 19 and May 22, 2006.

Panel A: 19th of May 2006



Panel B: 22nd of May 2006

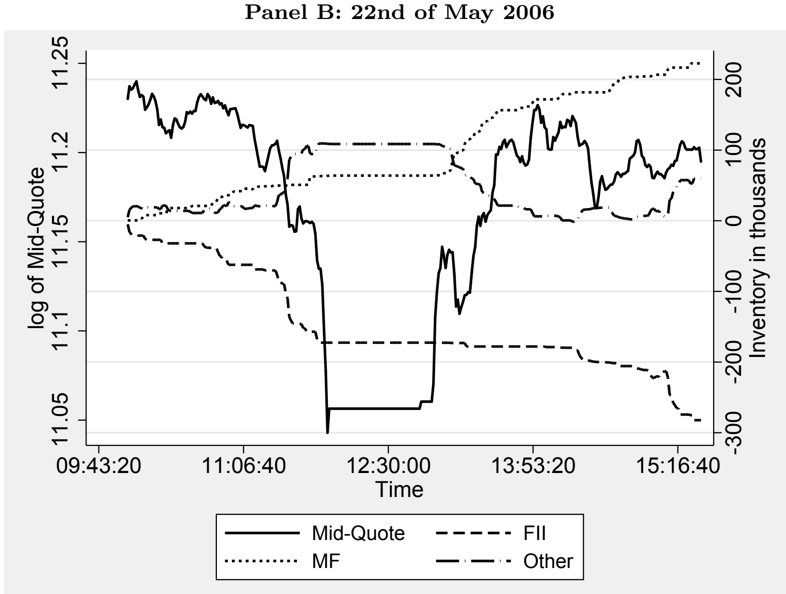
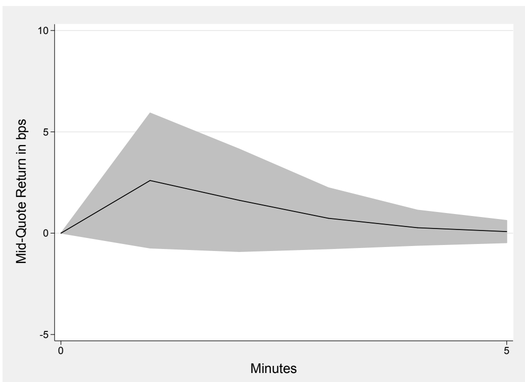


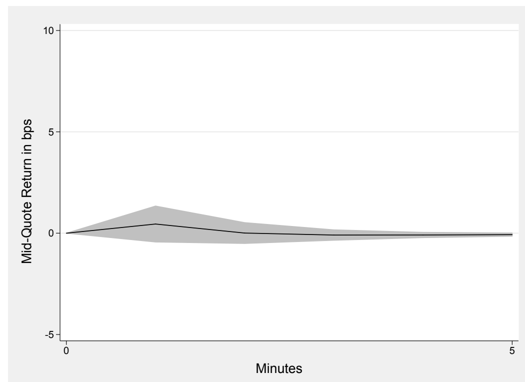
Figure 4. Orthogonalized impulse response functions for mid-quote return from *MOIB*

This figure shows orthogonalized impulse response functions for mid-quote return from marketable order imbalance (*MOIB*) based on vector-autoregression for one-minute returns, marketable and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregression for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MFs), and other traders (Other).

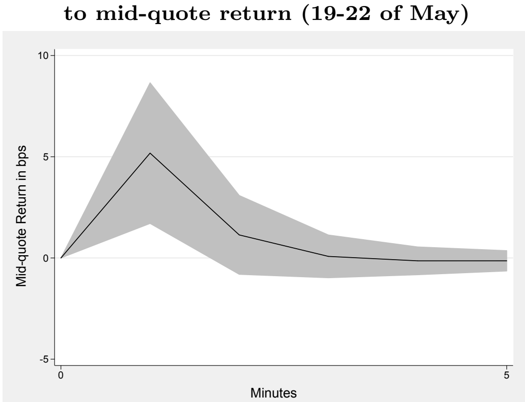
Panel A: Shock from *MOIB* of FIIs to mid-quote return (19-22 of May)



Panel B: Shock from *MOIB* of FIIs to mid-quote return (16-25 of May, excl crash days)



Panel C: Shock from *MOIB* of MFs to mid-quote return (19-22 of May)



Panel D: Shock from *MOIB* of MFs to mid-quote return (16-25 of May, excl crash days)

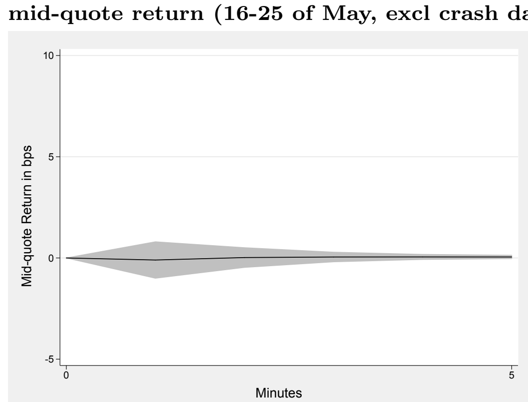
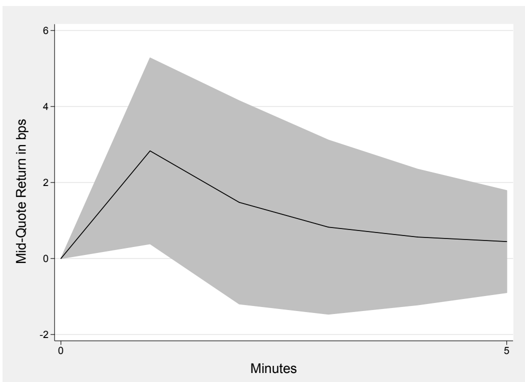


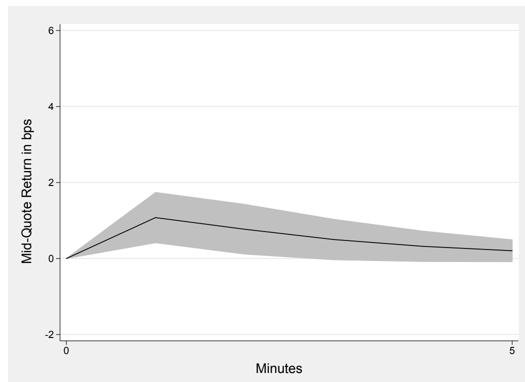
Figure 5. Orthogonalized impulse response functions for mid-quote return from $LOIB$

This figure shows orthogonalized impulse response functions for mid-quote return from limit order book imbalance ($LOIB$) based on vector-autoregression for one-minute returns, marketable and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregression for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MFs), and other traders (Other).

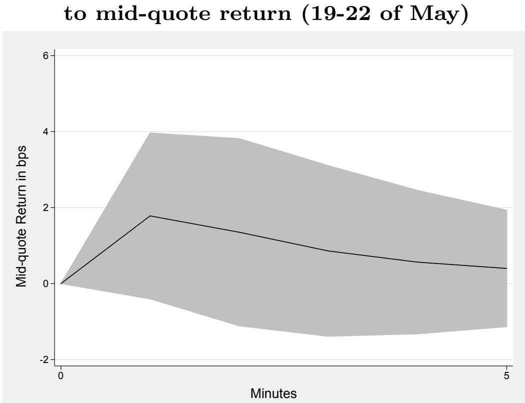
Panel A: Shock from $LOIB$ of FIIs to mid-quote return (19-22 of May)



Panel B: Shock from $LOIB$ of FIIs to mid-quote return (16-25 of May, excl crash days)



Panel C: Shock from $LOIB$ of MFs to mid-quote return (19-22 of May)



Panel D: Shock from $LOIB$ of MFs to mid-quote return (16-25 of May, excl crash days)

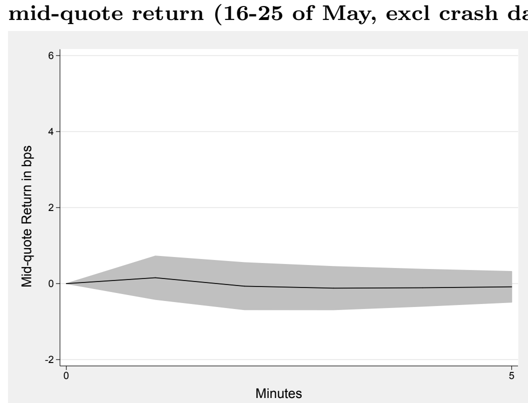
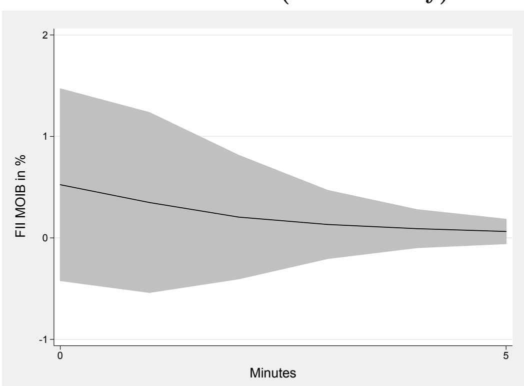


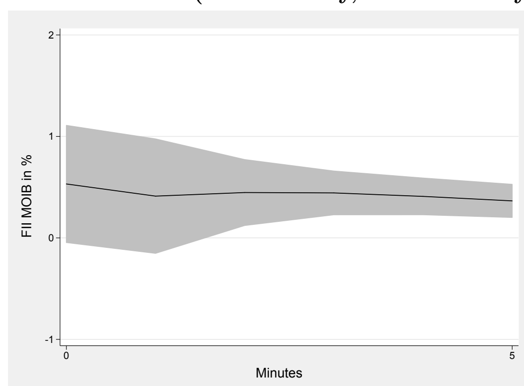
Figure 6. Orthogonalized impulse response functions for $MOIB$ from mid-quote returns

This figure shows orthogonalized impulse response functions for marketable order imbalance ($MOIB$) from mid-quote return based on vector-autoregression for one-minute returns, marketable and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregressions for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MF), and other traders (Other). For brevity, we report only those impulse response functions that are relevant for our analysis.

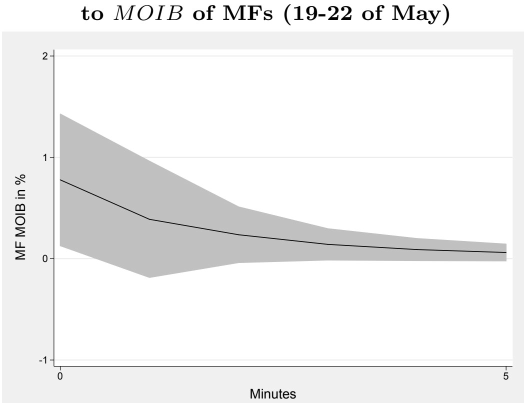
Panel A: Shock from mid-quote return to $MOIB$ of FIIs (19-22 of May)



Panel B: Shock from mid-quote return to $MOIB$ of FIIs (16-25 of May, excl crash days)



Panel C: Shock from mid-quote return to $MOIB$ of MFs (19-22 of May)



Panel D: Shock from mid-quote return to $MOIB$ of MFs (16-25 of May, excl crash days)

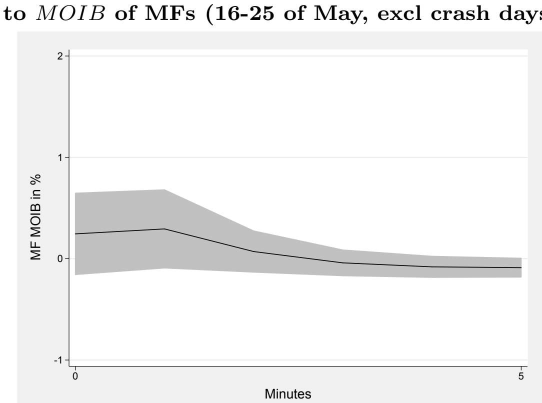
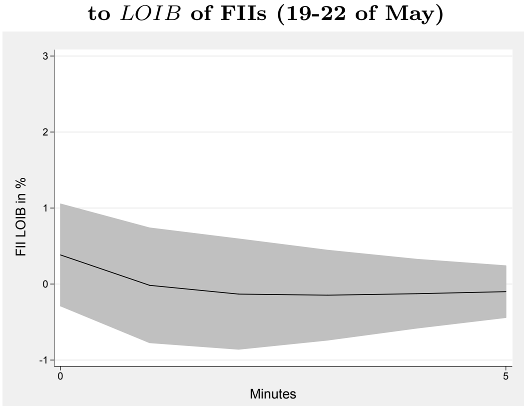


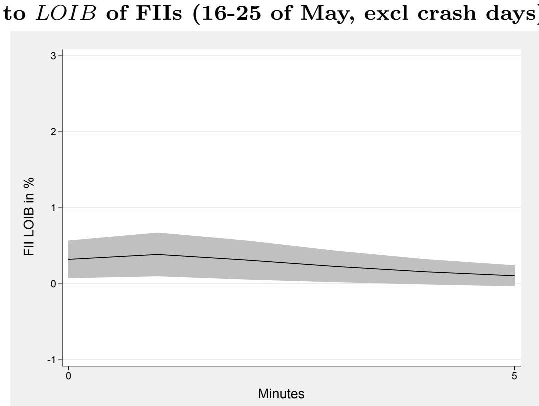
Figure 7. Orthogonalized impulse response functions for $LOIB$ from mid-quote returns

This figure shows orthogonalized impulse response functions for limit order book imbalance ($LOIB$) from mid-quote return based on vector-autoregression for one-minute returns, marketable and limit order imbalances from different trader categories (see equation (5)). We estimate vector-autoregressions for the crash days and for the four non-crash days. We classify traders into three categories: foreign institutions (FIIs), mutual funds (MF), and other traders (Other). For brevity, we report only those impulse response functions that are relevant for our analysis.

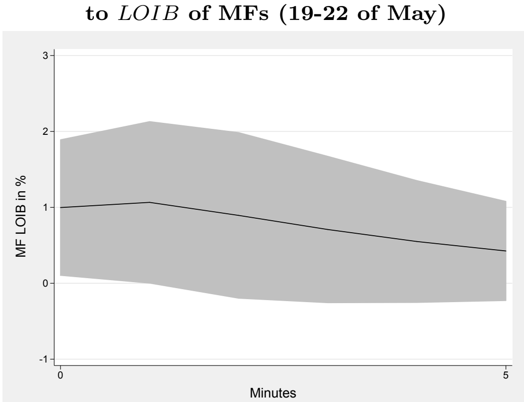
Panel A: Shock from mid-quote return to $LOIB$ of FIIs (19-22 of May)



Panel B: Shock from mid-quote return to $LOIB$ of FIIs (16-25 of May, excl crash days)



Panel C: Shock from mid-quote return to $LOIB$ of MFs (19-22 of May)



Panel D: Shock from mid-quote return to $LOIB$ of MFs (16-25 of May, excl crash days)

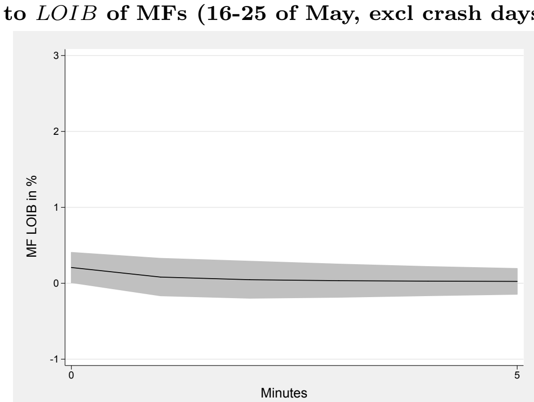
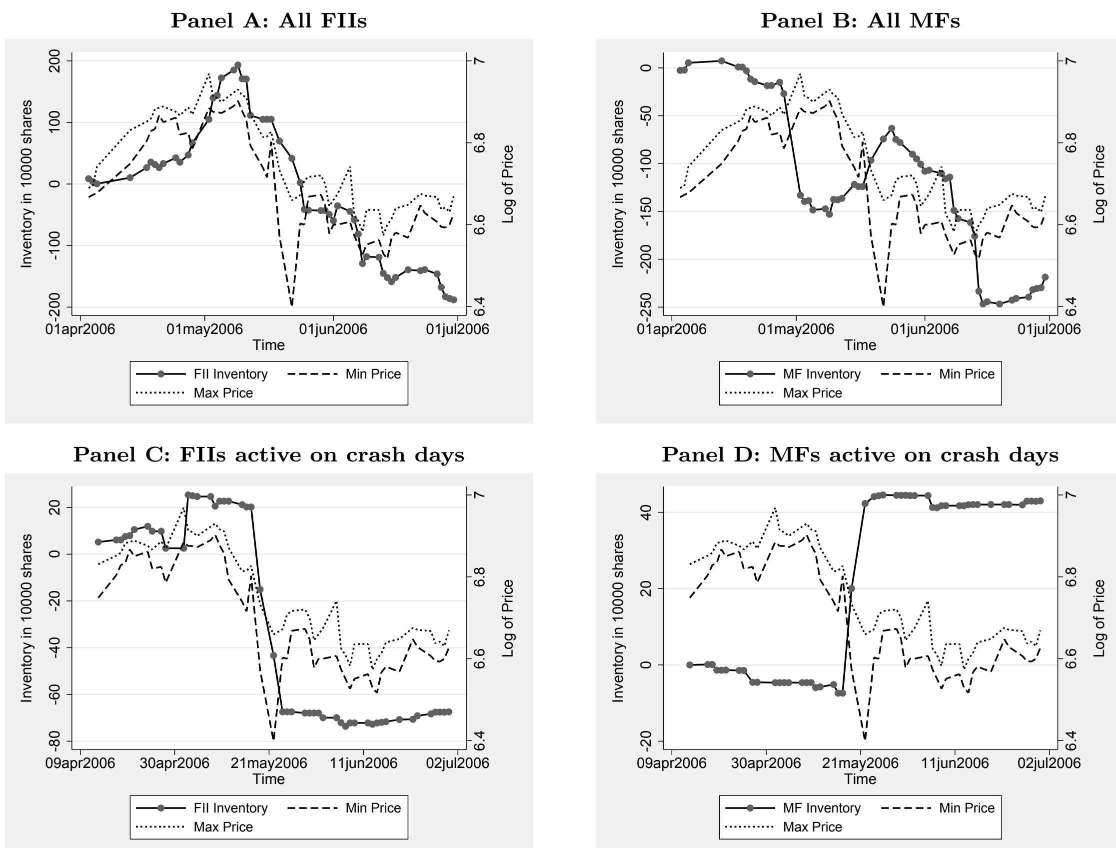


Figure 8. Cumulative inventories of FII and MF

This figure shows FIIs' and MFs' cumulative end-of-day inventory position in the spot and futures markets. Panel A (Panel B) shows the cumulative end-of-day inventory position of all FIIs (All MFs) in our sample, while Panel C (Panel D) show the cumulative end-of-day inventory position of FIIs (MFs) that were active on the two crash days: May 19 and May 22, 2006. Negative values of cumulative inventories should be interpreted as a decrease in the starting position as of the beginning of April 2006.



Appendix A Data, markets, and liquidity provision findings in a few closely-related studies

The Table A1 provides the summary of the findings in a few closely related studies with a particular focus of the data used, market under investigations, type of crisis (if any) and the findings in terms of liquidity provision.

Table A1 Data, Markets, and Liquidity Provision Findings in a Few Closely-Related Studies

Author (year)	Data	Market	Liquidity Provision Findings	Crisis period	Duration of crisis
Panel A: Equities					
Keim (1999)	Case study: DFA's "9-10" fund	Equities	DFA's "9-10" fund provided liquidity for small cap stocks during 1982-1995		
Da, Gao, and Jagannathan (2011)	Quarterly holdings of mutual funds and data from Dimensional Fund Advisors	Equities	DFA's Micro Cap fund earned 20.5 bps per quarter from liquidity provision		
Anand, Irvine, Puckett, and Venkataraman (2013)	Data from Abel Noser Solutions at the transaction level including institution and broker ids, date and time of execution	Equities	There was a subset of institutions that engaged in long-term liquidity supply that was crucial for market recovery from the 2007-2009 financial crisis	2007-2009 financial crisis	Several years
Cella, Ellul, and Giannetti (2013)	Quarterly holdings of mutual funds	Equities	Mutual funds with short investment horizon demand liquidity during market turmoil therefore amplifying the initial shock	Main focus on the collapse of Lehman Brothers	Several years
Giannetti and Kahraman (2018)	Quarterly holdings of mutual funds and hedge funds	Equities	Open-end funds are less likely to engage in long-term arbitrage due to high risk of fund outflows. Focus on fire sales and shifts in noise trader demand		

Table A1 (continued)

Author (year)	Data	Market	Liquidity Provision Findings	Crisis period	Duration of crisis
Çötelioğlu, Franzoni, and Plazzi (2020)	Data from Abel Noser Solutions at the transaction level including institution and broker ids, date and time of execution	Equities	Leverage, age, asset illiquidity, and reputational capital are relevant characteristics that explain the exposure of hedge funds' liquidity supply to funding conditions		
Panel B: E-mini S&P500 futures					
Easley, Lopez de Prado, and O'Hara (2011)	Intraday transactions data	E-mini S&P500 stock index futures	Flow toxicity increased prior to the Flash Crash making liquidity provision costly which in turn might lead to non-designated liquidity providers withdrawing from the market	Flash Crash of May 6, 2010	Intraday
Kirilenko, Kyle, Samadi, and Tuzun (2017)	Intraday audit trial transaction-level data with trader ids from CFTC	E-mini S&P500 stock index futures	Most active non-designated liquidity providers do not change their behavior during the Flash Crash and thus, are not the ones to be blamed for its occurrence and / or exacerbation	Flash Crash of May 6, 2010	Intraday
Menkveld and Yueshen (2019)	Intraday trade and quote data	E-mini S&P500 stock index futures, SPY, and 50 most crashed stocks	During Flash Crash cross-market arbitrage broke down, making it costly for the large seller trading on one market venue only since she has to rely on local liquidity supply	Flash Crash of May 6, 2010	Intraday

Table A1 (continued)

Author (year)	Data	Market	Liquidity Provision Findings	Crisis period	Duration of crisis
			Panel C: Bonds		
Mitchell, Pedersen, and Pulvino (2007)	Quarterly fund holdings	Convertible bonds (over-the-counter market)	Convertible bond arbitrage hedge funds which experienced large redemptions were the main liquidity demanders, while multistrategy hedge funds supplied liquidity	2005-2006	Several years
Manconi, Massa, and Yasuda (2012)	Quarterly fund holdings	Corporate bonds (over-the-counter market)	Funds retained illiquid securitized bonds and sold more liquid corporate bonds contributing to the propagation of crisis from securitized product market to corporate bond market	2007-2009 financial crisis	Several years
Anand, Jotikasthira, and Venkataraman (2020)	Monthly inferred flows of mutual funds	Corporate bonds (over-the-counter market)	Subset of funds earn positive alpha from liquidity provision, they are quite persistent in their trading style even during market turmoil and in the presence of large redemptions		
			Panel D: Various instruments (hedge funds)		
Aragon (2007)	Monthly hedge fund returns from TASS database	Various financial instruments	Hedge funds with more share restrictions invest in less liquid assets		
Agarwal, Daniel, and Naik (2009)	Combination of TASS, CISDM, HFR and MSCI hedge funds databases (analysis is conducted at annual frequency)	Various financial instruments	Hedge funds with longer lock-up periods earn higher returns consistent with the ability of manager to invest in illiquid assets		

Appendix B Description of the National Stock Exchange (NSE)

The National Stock Exchange of India Ltd. (NSE) was incorporated in November 1992, following the liberalization of the Indian financial market and the official establishment of the 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. The NSE and the Bombay Stock Exchange (BSE) are the largest stock exchanges in the country based on market capitalization and traded volume, though there are a total of 21 exchanges that actively operate in India. 97.71% (55.99%) of stocks are traded daily on the NSE (BSE). In 2011, the market capitalization of stocks traded on the NSE was Rs. 67 trillion (USD 1.5 trillion) while the total market capitalization of stocks traded on the BSE was Rs. 68 trillion (USD 1.5 trillion).

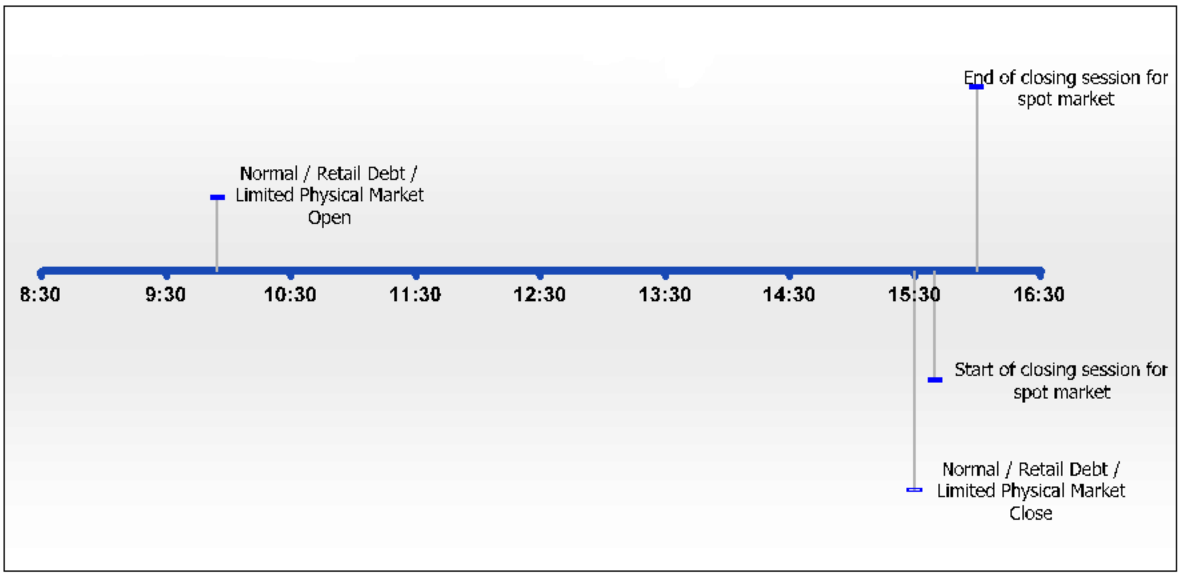
The NSE is a fully automated screen-based platform that works through an electronic limit order book in which orders are timestamped and numbered and then matched on price and time priority. The NSE requires all traders to submit their orders through certified brokers who are solely entitled to trade 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 NSE 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.

In 2006, trading sessions for both stock and futures markets were between 9:55 a.m. and 15:30 p.m., with a closing session of 20 minutes from 15:40 p.m. to 16:00 p.m., only for the spot market. Figure B1 show the trading day timeline in more detail.

Figure B1. Trading day timeline

This figure shows the trading day timeline of the 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

Internet Appendix for
"Recovery from Fast Crashes: Role of Mutual Funds"

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Darya Yuferova, *Norwegian School of Economics - NHH*

This Internet Appendix contains supplementary estimates, statistics, figures and tables that are described and mentioned in our paper but were not reported. The document is structured as follows. Section IA.1 provides summary statistics regarding trader and order types t for spot and single stock futures markets. Section IA.2 describes extended trader classification scheme. Section IA.3 describes the role of different trader types in providing liquidity using trading network centrality measure and market-making index for the whole sample period. Section IA.4 shows the results of the inventory sensitivity regression during crash periods in the spirit of Kirilenko, Kyle, Samadi, and Tuzun (2017). Section IA.5 describes the role of different trader types in providing liquidity using trading network centrality measure and market-making index during crash periods. Section IA.6 discusses the role of the short-term traders in causing crashes and recoveries.

IA.1. Traders and order types

In this section, we provide summary statistics regarding trader and order types that can be found in the data from National Stock Exchange of India (NSE) for spot and single stock futures markets.[1] Table IA.1 shows that there are 108,052 traders in the spot market, while in the futures market for this stock, there are only 35,951 traders during the sample period. In total, there were 137,830 traders that (i) traded in the spot market, (ii) traded in the futures market, (iii) traded in both spot and futures, or (iv) submitted the orders that were not executed during the period under consideration. The latter category includes 8.47% of traders (11,681 traders); therefore, the number of effective traders whose orders resulted in at least one trade during this time period is 126,149 (91.53%). The majority of the active traders on either the spot (70.65%) or futures (86.13%) markets execute their orders on both sides of the market (i.e., they both buy and sell). 67.47% of traders execute their orders in the spot market only, while 20.17% of traders execute their orders on the futures market only. Only 3.89% of traders are active in both markets; however, they are responsible for around 40% of trading activity in each of the markets.

INSERT TABLES IA.1 – IA.2 HERE

Table IA.2 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 the buy side and 15% for the sell side of the market) and modifications (around 13% for the buy side and 14% for the sell side of the market). Similar patterns also hold for the futures market.[2] We note that the numbers above are based on regular book orders only. Our data also include several stop-loss orders; however, none of them were executed during our sample period.

IA.2. Extended classification scheme

In this section, we extend the classification scheme used in the main text of the paper by zooming into the Other traders category. We note that traders that are classified as FIIs and MFs in the main text of the paper are the same as in this Internet Appendix. The NSE classifies all traders in terms of their legal affiliations. However, traders' legal classifications

[1] We note that this firm's stock is traded in both the spot and the single-stock futures markets, with the trading volume in the futures market being almost five times larger than the trading volume in the spot market.

[2] For example, momentum strategies employed by Numeric Investors (an investment-management company currently known as Man Numeric with assets under management around USD 30 billion in 2018) typically leave around 10% to 15% of orders unexecuted or cancelled (see Perold and Tierney (1997)).

might be not adequate to fully analyze traders' role in liquidity provision in different market conditions. Some traders could tolerate deviations from their desired inventory positions only for short periods of time, while other could tolerate persistent deviations from their target inventory positions. Therefore, we classify traders based on their trading behavior and their role in the market (see Figure IA.1). We focus our attention on those with a short inventory-holding horizon (STTs) and examine how their inventory positions affect market liquidity and how they manage their inventory risk. We do this based on the conjecture that STTs are continuously present in the market, whereas LTTs are present in the market only at periodic intervals and when trigger events happen.

INSERT FIGURE IA.1 HERE

As Figure IA.1 shows, on a given day, we classify traders into Small and Other. Small traders are traders whose trading volume is less than or equal to 750 shares (equivalent of one futures contract) on a given day.[3] Other traders' trading volume exceeds 750 shares on a given day. We further classify other traders by their end-of-day inventory. STTs are traders whose end-of-day inventory is less than 10% of traded volume. LTTs are traders whose end-of-day inventory is more than 10% of traded volume. We further split LTTs into MFs, FIIs, and other long-term traders (OLTTs). MFs and FIIs are legal entities according to the NSE. To determine a trader's final category, we look at its modal classification 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, we assign it as a trader category if and only if it is classified as a Small trader on more than two-thirds of days; otherwise, we use the next most frequent classification as the trader's category.[4]

INSERT TABLE IA.3 HERE

Table IA.3 shows buy and sell trading volume for each of the three trader categories. In particular, we find that STTs are responsible for 61.1% (67.6%) of the total (buy and sell) trading volume for the spot (futures) market. LTTs are responsible for 22.4% (31.1%) of the total trading volume for the spot (futures) market. Small traders are responsible for 16.5% (1.3%) of the total trading volume for the spot (futures) market. Besides that, a considerable portion of trading activity stems from STTs who are active in spot and futures markets alike: 35.6% and 28.6% for spot and futures markets, respectively, while all other trader categories

[3]The size of a futures contract is 750 shares in our sample. Therefore, traders that trade less than 750 shares per day do not have an opportunity to use the futures market for hedging purposes.

[4]For some of the forthcoming analysis, we also split traders into those active in the spot market only, those active in the futures market only, and those active in both markets.

are active mainly in either the spot market or the futures market. We also note that the futures market is five times larger than the spot market, but the spot market is more diverse in terms of market participants.

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

For the remainder of the Internet Appendix we use extended classification scheme.

IA.3. Liquidity provision: Alternative measures

In this section, we expand liquidity provision definition by considering degree centrality measure of different traders in both the spot and futures markets and market-making index (i.e., balance in terms of their passive buys and passive sells) for the whole sample period.

IA.3.1. Trading network

Table IA.4 shows the average degree centrality (i.e., the number of counterparties each individual trader has) across traders per each trader category during the whole trading day, during the first and last 30 minutes and the rest of the trading day. We note that there are more traders active during the rest of the day (4 hours and 30 minutes) than during the first and last 30 minutes of the trading day, as expected from the different duration of the periods under consideration.

INSERT TABLE IA.4 HERE

We document that top STTs (the largest STTs, who are jointly responsible for 50% of STTs' trading volume and are present on almost every day in our sample period) exhibit the highest degree centrality of more than 33,000 (5,000) counterparties on the spot (futures) market during the whole trading day, which is 46 (17) times larger than the amount of counterparties the next-most-connected trader category (FIIs) has. Intraday patterns on spot and futures markets also show that STTs' relative importance in the trading network is lower at the beginning and end of the trading day, with the most profound intraday patterns observed in the spot market. In particular, on the spot market, top STTs have 35 (20) times more connections than FIIs in the first (last) 30 minutes of the trading day, as compared to 42 times during the rest of the trading day. This intraday pattern is in line with the fact that STTs prefer to end their day with flat inventory positions, and thus are less likely to act as intermediaries for other market participants in the first and last 30 minutes of the trading day.

We also note that although MFs have only 155 (67) counterparties during the whole trading day on the spot (futures) market, and thus are not central to the trading network during normal times, we show that their role is crucial during turbulent periods in Section IA.5.

INSERT FIGURE IA.2 HERE

Figure IA.2 plots the trading network for the spot and futures markets, with vertex's size representing the total trading volume by each trader category and the width of the edges representing the trading activity among the trader categories for the whole trading day. Figure IA.2 shows that the majority of the trading volume occurs between STTs themselves in both the spot and futures markets. We also show that STTs act as main counterparties for other trader categories in spot and futures markets alike, as depicted by the width of the edges connecting STTs and other trader categories. Overall, we document that STTs are in the center of the trading network for both spot and futures markets alike during normal times.

IA.3.2. Market-making index

We estimate a market-making index (absolute difference between passive buying and passive selling volume relative to passive trading volume) following Comerton-Forde, Malinova, and Park (2018) and Korajczyk and Murphy (2019). A trader engaging in market-making activity should be balanced in terms of its passive execution on both sides of the market. A fully balanced trader's market-making index should be close to zero.

INSERT TABLE IA.5 HERE

Table IA.5 shows the average market-making index for the trader category as a whole, as well as for individual traders within each trader category, for the whole trading day as well as during the first and last 30 minutes and the rest of the trading day separately for spot and futures markets. We show that as a whole, STTs have the smallest market-making index among all categories for both the spot (5.9%) and futures (8.3%) markets for the whole trading day. The respective number for LTTs is 15.9% (9.0%), and for their subsets (namely, FIIs and MFs), the respective number does not fall below 58.0% (81.5%) on the spot (futures) market.

At the individual trader level for STTs, the market-making index is larger than the one for STTs as a whole. We document that top STTs (who are the largest STTs, jointly responsible for 50% of STTs trading volume and are present on almost every day in our sample period) are the ones who exhibit the most pronounced market-maker characteristics with a market-making index of 26.6% (26.8%) for the whole trading day on the spot (futures) market. For comparison, Korajczyk and Murphy (2019) classifies traders as market-makers if their median market-making index is below 20%.

We note that intraday patterns are especially profound for STTs' liquidity provision. Namely, top STTs have a market-making index of 44.5% (46.5%) and 50.7% (50.5%) during the beginning and end of the trading day and 29.0% (29.2%) during the rest of the trading day for the spot (futures) market. Intraday patterns are in line with the fact that STTs tend to start and end their day flat in term of inventory, and therefore are less balanced in terms of trading volume direction in the beginning and end of the trading day. To sum up, our results suggest that STTs (especially top STTs) exhibit market-maker characteristics more than any other trader category.

IA.4. Inventory sensitivity regression during crashes as in Kirilenko, Kyle, Samadi, and Tuzun (2017)

IN this section, we investigate whether MFs, FIIs, and STTs change their behavior during crashes. We follow Kirilenko, Kyle, Samadi, and Tuzun (2017) and estimate the following equation that measures the sensitivity of the inventory changes, $\triangle Inv_{ikt}$, of trader category i (STT, FII, and MF) 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 ($\triangle Inv_{ik,t-1}$), day fixed effects (FE_k), and time fixed effects (TD_b):

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

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

INSERT TABLE IA.8 HERE

In Table IA.8, we document the estimation results of equation (IA.1). The first column reports the sensitivity of STTs' as a whole (STT-All) inventories to the spot and futures returns (Panel A and Panel B, respectively). We show that for STT-All, the coefficient in front of the spot return is positive and significant, indicating that as a whole, STT-All move with the spot market (Panel A), and the coefficient in front of the futures return is negative and significant, indicating that STT-All are contrarian (Panel B). The result for the spot market is in line with Kirilenko, Kyle, Samadi, and Tuzun (2017), who document that HFTs are moving with the market during normal times (based on the coefficient in front of contemporaneous returns). However, this comparison is misleading, as some STTs trade in either the spot or futures market only, while other STTs trade across both markets. Hence, we split STT-All into three categories: STT-Spot, STT-Futures, and STT-Both.

The second column of Panel A of Table IA.8 reports the sensitivity of STT-Spot inventories with respect to the spot return. We show that this coefficient is negative and significant, indicating that STT-Spot are contrarian (i.e., in general, they provide liquidity). During market drawdown, STT-Spot inventory sensitivity to the spot return does not change, since the coefficient is not significant. However, during market recovery, STT-Spot inventory sensitivity to the spot return becomes zero (the interaction coefficient between dummy for the recovery and the spot return is positive and significant, and is of the same magnitude as the coefficient of the spot return itself). That is, STT-Spot withdraw from the market, perhaps due to exhausting their inventory capacity. In Section IA.6.2, we investigate this issue in depth.

The second column of Panel B in Table IA.8 performs the same analysis for STT-Futures. In this case, the coefficients are not statistically significant, indicating that, as a whole, STT-Futures do not exhibit any particular pattern of inventory sensitivity to the futures return.

The third column of Table IA.8 reports the sensitivity of STT-Both inventory with respect to spot return (Panel A) and futures return (Panel B). We show that, in general, STT-Both have a positive and significant coefficient in the spot market and a negative and significant coefficient in the futures market – that is, STT-Both are taking opposite positions in the spot and futures markets consistent with cross-market arbitrage activity. During market drawdown and recovery, STT-Both become contrarian in the spot market and less contrarian in the futures market.[5] This is consistent with them taking the same positions across both

[5] The result for the spot market is consistent with the contemporaneous results of Kirilenko, Kyle, Samadi, and Tuzun (2017) for HFTs. Therefore, based on the contemporaneous inventory sensitivity to spot/futures returns, we do observe a change in STTs' behavior during market drawdown and recovery periods. Unfortu-

markets (i.e., STT-Both did not seem to engage in cross-market arbitrage activities during the crashes), and thus cross-market arbitrage broke down during the crashes.

The analysis performed following Kirilenko, Kyle, Samadi, and Tuzun (2017) considers STTs as a whole and does not distinguish between different traders within the STT category. We open up the STT category and investigate the behavior of each individual trader (i.e., whether a trader withdraws from the market during the market drawdown period, and whether a trader hits her inventory constraints during crash days) in Section IA.6.

Table IA.8 also reports FIIs' and MFs' inventory sensitivity. It is important to emphasize that FIIs and MFs who trade in the spot and futures markets are different traders (i.e., they do not trade in both markets). Hence, both FIIs and MFs are not engaging in cross-market arbitrage. We document that FIIs move with the market during normal times and intensify such behavior during market drawdown in the spot market, while in the futures market, FIIs move with the price during normal times and become contrarian during drawdowns and recoveries.

We document that MFs' inventories seem to be insensitive to the price movement neither during normal nor during turbulent periods for the spot and futures markets alike. Due to the nature of MFs' slow-moving capital, MFs do not change their inventories as frequently as one-minute changes in returns.

IA.5. Liquidity provision during crashes: Alternative measures

In this section, we expand liquidity provision definition by considering degree centrality measure of different traders in both the spot and futures markets and market-making index (i.e., balance in terms of their passive buys and passive sells) during fast crash periods only.

IA.5.0.1. Trading network

Table IA.6 shows the average degree centrality (i.e., number of counterparties each individual trader has) across traders per each trader category during crashes and recovery defined as +/- 30 minutes from the crash's trough for the bidirectional network as well as a split between buy and sell networks.

INSERT TABLE IA.6 HERE

nately, trading activity in our data is not frequent enough to sample at as high frequency, as in Kirilenko, Kyle, Samadi, and Tuzun (2017), and thus we are not able to perform a joint test on the changes of inventory sensitivity to contemporaneous and lagged returns during market drawdown and recovery periods, which is the main test performed by Kirilenko, Kyle, Samadi, and Tuzun (2017).

We document that contrary to normal times (see Table IA.4), top STTs (the largest STTs, jointly responsible for 50% of STTs' trading volume and present on almost every day in our sample period) do not stand out in terms of the number of counterparties during crashes and recoveries. In particular, during crashes, the number of counterparties top STTs have is equal to the number of counterpaties FIIs have on the spot market and is only two times larger on the futures markets, as opposed to 46 (spot market) and 17 (futures market) times during normal periods. During recoveries, tops STTs are at par with FIIs in terms of number of counterparties on the spot market, and they lose their leading position to FIIs on the futures market.

Splitting up the bidirectional network into buy and sell networks yields interesting results. Namely, we show that while STTs remain relatively balanced during both crashes and recoveries on the spot and futures markets alike, FIIs and MFs tend to be present only on one side of the network. In particular, on the spot market, FIIs (MFs) are present only on the sell (buy) network, consistent with FIIs generating large selling pressure, leading to a crash. On the futures market, both FIIs and MFs tend to be present on the buy network only.

IA.5.0.2. Market-making index

We estimate a market-making index (absolute difference between passive buying and passive selling volume relative to passive trading volume) for crashes and recoveries defined as -/+ 30 minutes from the crash's trough.

INSERT TABLE IA.7 HERE

Table IA.7 shows the average market-making index for the trader category as a whole, as well as for individual traders within each trader category, for crashes and recoveries for both the spot and futures markets.

During crashes, STTs as a category have a market-making index of 17.5% (19.3%), as opposed to 5.9% (8.3%) during normal times for the spot (futures) market (see Table IA.5). At the individual trader level, top STTs have a market-making index of 40.7% (46.4%), as opposed to 26.6% (26.8%) during normal times for the spot (futures) market (see Table IA.5). Recoveries exhibit similar patterns.

This results suggest that STTs become less balanced in terms of their passive buys and sells during turbulent times. The market-making index for other trader categories remained largely unchanged.

IA.6. The role of STTs during crashes

In this section, we argue that STTs could not prevent crashes from happening as well as could not reduce recovery process due to limited inventory capacity and thus, there is a need for standby well-capitalized liquidity providers such as MFs. First, we show that STTs tried to "lean against the wind" by documenting their cash flows during the crash days, but could not do so (see Section IA.6.1). Second, we show that STTs indeed were inventory constrained during the crash days (see Section IA.6.2).

IA.6.1. STTs' cash flows

In this section, we provide evidence of whether STTs "lean against the wind." Given that STTs tend to end each day with flat positions, we make a simplifying assumption that at the end of the day, they do not have any positions to liquidate, and hence, each day, they start with a zero-inventory position. We note that we compute aggregate cash flows for the 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 STTs, $Cash\ Flow_{STTkt}$, which increases with sell transactions and decreases with buy transactions, and regress it on dummy variables for market drawdown ($Down_{kt}$) and recovery (Up_{kt}) periods, day fixed effects (FE_k), and half-hour time dummies (TD_b):

$$Cash\ Flow_{STTkt} = \gamma Down_{kt} + \delta Up_{kt} + \sum_k \alpha_k FE_k + \sum_b d_b TD_b + \epsilon_{kt} \tag{IA.2}$$

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

INSERT TABLE IA.9 HERE

Table IA.9 shows the results of the cash flow regression estimation around the two crashes in our sample (on May 19, 2006, and May 22, 2006) for the spot and futures markets. Panels A and B of Table IA.9 report the results of the cash flow analysis (in millions of rupees) for the spot and futures markets, respectively. We observe that cash flows decrease during the market drawdown period and increase during the market recovery period for both markets alike. Although we lack statistical power for this test, to further support our hypothesis, we depict STTs' cumulative cash flows during the two crash days (Figure IA.3). We find that STTs' cumulative cash flows decrease during market drawdowns and increase during recovery periods.

INSERT FIGURE IA.3 HERE

IA.6.2. STTs' inventory capacity

In this section, we provide evidence that STTs hit their inventory limits during the crash days. First, we show summary statistics of STTs' participation during the crash days. Second, we present the dynamics of STTs' inventory capacity at daily and intraday levels (the latter for the two crash days only).

INSERT FIGURE IA.4

Figure IA.4 shows the number of STTs that were active either on May 19, May 22, or both for the spot and futures markets (the latter one is reported in parentheses). We divide STTs into categories based on whether they belong to the top category of STTs or not, whether they are active during the market drawdown period or not, and whether they were inventory constrained or not.

We define top STTs as those with large trading volume who jointly generate 50% of STT trading volume. There are only 27 (64) top STTs out of 6,547 (20,524) STTs in the spot (futures) market. Naturally, having one of the top STTs hitting its inventory limits is more problematic for the market than one of the smaller STTs hitting its inventory limits.

We define STTs as inventory-constrained STTs if the trader's maximum of absolute value of one-minute median inventory, either on May 19 or on May 22 (or both), is above this trader's 95th percentile of the maximum of the absolute value of one-minute median inventory over the sample period, excluding May 19 and May 22.

We show that on the two crash days, there were 1,099 STTs on the spot market. Out of them, 26 traders were from the top category, with 19 of the top traders actively engaging in cross-market trading. Out of 19 top traders active on both markets, 17 participated during the crash, with 27% of them hitting their inventory constraints. Overall, 22 (17 + 5) traders from the top category of STTs participated during the market drawdown, with 27% of them hitting their inventory constraints. Out of the smaller STT category, 20% were active on both markets, but less than half of the smaller cross-market traders were active during the crash (86 traders). Moreover, 51 of these 86 traders were constrained during the crash days. Overall, out of the smaller STT category, only 441 (86 + 355) traders participated during the market drawdown (41%), with 275 (51 + 224) of them hitting their inventory constraints, and 632 (125 + 507) traders preferring to stay away from the market during the crash. Overall, more than 50% of STTs disappeared from the market during the turbulent periods, and 60% of those STTs who continued to participate in the market during the turbulent periods hit their inventory constraints. STTs in the futures market exhibited similar participation patterns. This detailed analysis shows, therefore, that not all STTs behave in the same way during crashes as they do during normal times. In particular, many STTs hit their inventory constraints and withdraw from the market.

Figure IA.5 plots a time series of the STTs' inventory capacity for the daily frequency over the whole sample period (Panels A and B) and intraday inventory capacity on May 19 and May 22 (Panels C and F). At the daily frequency, inventory capacity is defined as follows. First, for each day, we compute the maximum absolute one-minute median inventory for each trader. Second, we normalize this number by the maximum for the whole sample period, excluding May 19 and May 22. Finally, we take the average across all traders. Hence, the larger the measure, the more constrained STTs are. Panels A and B of Figure IA.5 show the time series of daily inventory capacity measures for the spot and futures markets, respectively. For the spot market, the inventory capacity measure reached 80% (100%) on May 19 (May 22), while for other days in the sample period, it never exceeded 20%. For the futures market, the picture was similar, although less extreme.

Most traders have exhausted their inventory capacity during the crash days. We now zoom in and show the dynamics of STTs' inventory capacity at the intraday level. Panels C and F plot STTs' intraday capacity measure, which is an average ratio of the absolute value of one-minute median inventory to the whole-sample maximum of the absolute value of one-minute median inventory, excluding May 19 and May 22, for the spot and futures markets. We observe that capacity measure increased with the evolution of the crash and stabilized during the recovery period. On May 19, due to the second event, the capacity measure continued to increase after recovery had taken place. On May 22, the capacity measure decreased slowly after the recovery for the spot market and remained constant for the futures market.

INSERT FIGURE IA.5 HERE

Overall, this confirms that STTs tried to "lean against the wind" during the two crashes in our sample. However, their limited inventory capacity did not allow them to stop the crash.

Internet Appendix References

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Table IA.1: Number of traders

This table shows the number and proportion of traders who are active in the 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 the spot and futures markets. We also divide traders into those who execute trades in both the spot and futures markets, only in the spot market, only in the futures market, or do not execute trades at all. For the futures market, we include only those traders who submit orders and/or execute trades for contracts with maturity dates within the same month as the transaction occurs.

	Panel A: Spot Market		**Panel B: Futures Market**		**Panel C: Spot and Futures Market**		
Buy & Sell	76,343	70.65%	30,966	86.13%	Spot & Futures	5,362	3.89%
Only Buy	15,317	14.18%	941	2.62%	Only Spot	92,989	67.47%
Only Sell	6,691	6.19%	1,253	3.49%	Only Futures	27,798	20.17%
No Execution	9,701	8.98%	2,791	7.76%	No Execution	11,681	8.47%
Total	108,052	100.00%	35,951	100.00%	Total	137,830	100.00%

Table IA.2: Order types

This table shows the number and proportion of new orders, cancellations, and modifications for the 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 the futures market, we include only those orders for contracts with maturity dates within the same month as the order was submitted, modified, or cancelled.

	Panel A: Spot Market				**Panel B: Futures Market**			
	Buy		Sell		Buy		Sell	
New	1,163,764	70.93%	1,173,244	70.59%	649,907	62.46%	642,629	63.13%
Cancel	271,342	16.54%	254,006	15.28%	244,271	23.48%	207,005	20.33%
Modify	205,615	12.53%	234,905	14.13%	146,309	14.06%	168,388	16.54%

Table IA.3: Trading volume per trader category

This table shows the number of traders in each trader category, the number of shares bought and sold by each trader category, as well as the total trading volume and proportion of trading volume attributable to each trader category (for traders active on one market only and on both markets). For the futures market, we include only transactions for the contracts with expiry dates within the same month as the transaction occurs. We classify traders into three categories: long-term traders (LTTs), short-term traders (STTs), and small traders (Small). We further split the LTT category into: foreign institutions (FIIs), domestic mutual funds (MFs), and other long-term traders (OLTTs).

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	17,357,955	17,336,561	34,694,516	15.7%	219	7,622,099	7,260,429	14,882,528	6.7%	49,577,044	22.4%
FII	107	5,273,086	6,891,532	12,164,618	5.5%	20	1,746,656	1,934,157	3,680,813	1.7%	15,845,431	7.2%
MF	262	2,823,229	5,024,574	7,847,803	3.6%	6	124,500	158,950	283,450	0.1%	8,131,253	3.7%
OLTT	1,102	9,261,640	5,420,455	14,682,095	6.6%	193	5,750,943	5,167,322	10,918,265	4.9%	25,600,360	11.6%
STT	5,597	27,945,058	28,262,521	56,207,579	25.4%	950	39,287,510	39,373,997	78,661,507	35.6%	134,869,086	61.1%
Small	90,646	18,018,051	17,995,050	36,013,101	16.3%	513	213,797	215,912	429,709	0.2%	36,442,810	16.5%
											220,888,940	100.0%

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	127,703,250	131,735,250	259,438,500	27.2%	219	21,497,250	15,598,500	37,095,750	3.9%	296,534,250	31.1%
FII	40	5,710,500	3,239,250	8,949,750	0.9%	20	7,121,250	2,894,250	10,015,500	1.0%	18,965,250	2.0%
MF	9	664,500	114,000	778,500	0.1%	6	150,750	214,500	365,250	0.0%	1,143,750	0.1%
OLTT	6,564	121,328,250	128,382,000	249,710,250	26.2%	193	14,225,250	12,489,750	26,715,000	2.8%	276,425,250	29.0%
STT	19,574	185,267,250	186,960,000	372,227,250	39.0%	950	136,363,500	136,211,250	272,574,750	28.6%	644,802,000	67.6%
Small	5,628	5,644,500	5,949,000	11,593,500	1.2%	513	614,250	636,000	1,250,250	0.1%	12,843,750	1.3%
											954,180,000	100.0%

Table IA.4: Trading network

This table shows the average degree centrality measure (number of counterparties) of bidirectional trading network (both buys and sells) for each trading category for spot (Panel A) and futures (Panel B) markets, respectively. We compute the degree centrality measure for the whole trading day, for the first and last 30 minutes of the trading day, and the rest of the trading day. For the futures market, we include only transactions for the contracts with an expiry date within the same month as the transaction occurs. We classify traders into three categories: long-term traders (LTTs), short-term traders (STTs), and small traders (Small). We further split the LTT category into foreign institutions (FIIs), domestic mutual funds (MFs), and other long-term traders (OLTTs). We further split the STT category into the largest STTs (STT Top), who jointly generate 50% of STT trading volume, and small STTs (STT Not Top).

	Panel A: Spot market				**Panel B: Futures market**			
	Total	First 30 minutes	The rest of the trading day	Last 30 minutes	Total	First 30 minutes	The rest of the trading day	Last 30 minutes
LTT	210	57	175	75	44	9	33	10
FII	713	111	602	164	291	52	244	42
MF	155	61	134	92	67	19	59	25
OLTT	171	50	138	62	42	9	31	10
STT	292	60	233	52	37	10	29	10
STT Not Top	156	30	124	31	20	5	16	6
STT Top	33,051	3,952	25,806	3,292	5,104	678	3,796	631
Small	14	4	11	4	3	1	2	1

Table IA.5: Market-making index

This table shows liquidity provision by trader categories as measured by market-making index ($\frac{|Passive\ buy\ volume - Passive\ sell\ volume|}{Passive\ buy\ volume + Passive\ sell\ volume}$). We report the market-making index for a trader category as a whole as well as on average for traders within each trader category for the spot (Panel A) and futures (Panel B) markets, respectively. We compute the market-making index for the whole trading day, for the first and last 30 minutes of the trading day, and the rest of the trading day. For the futures market, we include only transactions for the contracts with expiry date within the same month as the transaction occurs. We classify traders into three categories: long-term traders (LTTs), short-term traders (STTs), and small traders (Small). We further split the LTT category into foreign institutions (FIIs), domestic mutual funds (MFs), and other long-term traders (OLTTs). We further split the STT category into the largest STTs (STT Top), who jointly generate 50% of STT trading volume, and small STTs (STT Not Top).

	Total		First 30 minutes		The rest of the trading day		Last 30 minutes	
	By trader	By category	By trader	By category	By trader	By category	By trader	By category
Panel A: Spot market								
LTT	76.6%	15.9%	88.0%	43.9%	79.0%	20.1%	87.9%	36.5%
FII	100.0%	67.2%	99.5%	88.1%	100.0%	70.5%	100.0%	80.2%
MF	96.7%	58.0%	100.0%	89.6%	98.2%	65.1%	98.8%	84.5%
OLTT	72.9%	27.6%	86.3%	48.3%	75.4%	30.3%	86.0%	50.3%
STT	50.7%	5.9%	74.6%	10.2%	56.3%	6.6%	79.5%	15.0%
STT Not Top	51.8%	6.7%	78.2%	13.4%	57.7%	7.4%	82.1%	15.7%
STT Top	26.6%	6.2%	44.5%	12.6%	29.0%	7.4%	50.7%	18.5%
Small	68.9%	11.0%	88.8%	19.9%	72.3%	12.4%	90.6%	20.4%
Panel B: Futures market								
LTT	72.6%	9.9%	89.4%	16.5%	74.5%	11.5%	89.8%	17.8%
FII	96.5%	81.5%	100.0%	90.6%	97.0%	82.4%	98.6%	85.3%
MF	90.3%	83.2%	100.0%	100.0%	98.2%	92.4%	100.0%	100.0%
OLTT	72.3%	12.8%	89.2%	19.5%	74.1%	14.1%	89.6%	17.8%
STT	58.6%	8.3%	74.0%	10.5%	61.7%	8.2%	78.2%	15.0%
STT Not Top	60.3%	8.7%	78.4%	11.1%	63.8%	8.6%	82.5%	17.8%
STT Top	26.8%	8.1%	46.5%	11.6%	29.2%	8.3%	50.5%	13.6%
Small	94.8%	31.5%	98.7%	47.6%	94.9%	36.5%	97.9%	44.5%

Table IA.6: Trading network during crashes

This table shows the average degree centrality measure (number of counterparties) of the bidirectional trading network (both buys and sells) as well as buy and sell networks for each trading category for spot (Panel A) and futures (Panel B) markets, respectively. We compute the degree centrality measure for the crash and recovery periods as defined -/+ 30 minutes from the crash's trough. For the futures market, we include only transactions for the contracts with expiry date within the same month as the transaction occurs. We classify traders into three categories: long-term traders (LTT), short-term traders (STT), and small traders (Small). We further split the LTT category into foreign institutions (FIIs), domestic mutual funds (MFs), and other long-term traders (OLTTs). We further split the STT category into the largest STTs (STT Top), who jointly generate 50% of STT trading volume, and small STTs (STT Not Top).

	Panel A: Spot market						**Panel B: Futures market**					
	Crash			Recovery			Crash			Recovery		
	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell	Total	Buy	Sell
LTT	40	9	30	36	19	16	3	2	2	4	3	2
FII	262	0	262	157	0	157	13	12	1	62	54	8
MF	56	53	3	83	73	9	-	-	-	11	11	-
OLTT	20	7	13	25	14	11	3	1	2	4	2	2
STT	25	12	13	23	10	12	5	3	2	6	3	3
STT Not Top	13	6	7	13	6	7	3	2	1	3	1	2
STT Top	262	116	146	198	97	101	25	14	12	28	13	15
Small	2	2	1	2	1	1	1	0	1	1	0	1

Table IA.7: Market-making index during crashes

This table shows liquidity provision by trader categories as measured by market-making index ($\frac{|Passive\ buy\ volume - Passive\ sell\ volume|}{Passive\ buy\ volume + Passive\ sell\ volume}$). We report the market-making index for a trader category as a whole as well as on average for traders within each trader category for the spot (Panel A) and futures (Panel B) markets, respectively. We compute the market-making index for the crash and recovery periods as defined -/+ 30 minutes from the crash's trough. For the futures market, we include only transactions for the contracts with expiry date within the same month as the transaction occurs. We classify traders into three categories: long-term traders (LTTs), short-term traders (STTs), and small traders (Small). We further split the LTT category into foreign institutions (FIIs), domestic mutual funds (MFs), and other long-term traders (OLTTs). We further split the STT category into the largest STTs (STT Top), who jointly generate 50% of STT trading volume, and small STTs (STT Not Top).

	Panel A: Spot market				**Panel B: Futures market**			
	Crash		Recovery		Crash		Recovery	
	By trader	By category	By trader	By category	By trader	By category	By trader	By category
LTT	91.8%	16.0%	93.4%	43.9%	90.6%	10.2%	86.3%	17.5%
FII	100.0%	100.0%	100.0%	100.0%	100.0%	97.5%	100.0%	64.1%
MF	100.0%	97.0%	100.0%	85.3%	-	-	100.0%	100.0%
OLTT	89.9%	36.6%	91.5%	50.9%	90.3%	4.8%	85.9%	11.9%
STT	72.6%	17.5%	71.3%	6.1%	70.0%	19.3%	74.3%	19.0%
STT Not Top	76.0%	25.3%	75.0%	5.9%	75.6%	17.8%	80.6%	17.5%
STT Top	40.7%	10.2%	34.4%	10.9%	46.4%	21.4%	49.8%	21.1%
Small	89.2%	41.2%	85.1%	16.2%	96.7%	49.4%	97.5%	27.0%

Table IA.8: Inventory sensitivity to price movements during crashes

This table shows the results of the inventory-sensitivity regression estimation based on one-minute intervals from 16-May-2006 through 25-May-2006 for the spot (Panel A) and futures (Panel B) markets (see equation (IA.1)). We regress changes in inventory in the spot market for STTs, FIIs, and MFs 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 crash's trough. For the futures inventory computation, we use only transactions for the contracts with expiry dates within the same month as the transaction occurs. We use day fixed effects. We use robust standard errors. ***, **, and * denote significance level at 1%, 5%, and 10%, respectively. We classify traders into three categories: long-term traders (LTTs), short-term traders (STTs), and small traders (Small).

Panel A: Spot market

	STT			FII	MF
	STT-All	STT-Spot	STT-Both		
Spot Return	69.02**	-80.72***	138.08***	93.78***	24.36
	(2.07)	(-3.00)	(3.99)	(3.27)	(1.00)
Down*Spot Return	-274.02**	69.91	-346.47***	294.02*	31.52
	(-2.53)	(1.32)	(-3.33)	(1.81)	(0.55)
Up*Spot Return	-111.07**	87.46**	-174.03***	-55.02	-28.11
	(-2.50)	(2.25)	(-2.86)	(-1.18)	(-0.52)
Down	3.26**	1.16	1.58**	-0.36	3.08*
	(2.44)	(0.88)	(2.35)	(-0.53)	(1.93)
Up	-0.35	-0.36	0.09	-8.44***	3.61
	(-0.33)	(-0.36)	(0.13)	(-2.82)	(1.13)
Constant	-0.57	0.24	-0.50*	0.06	-0.09
	(-1.63)	(1.05)	(-1.92)	(0.37)	(-0.62)
Observations	1,909	1,909	1,909	1,909	1,909
Adjusted R^2	0.162	0.089	0.108	0.319	0.186

Panel B: Futures market

	STT			FII	MF
	STT-All	STT-Futures	STT-Both		
Futures Return	-235.59**	42.38	-316.23***	134.98***	-19.58
	(-2.44)	(0.61)	(-5.71)	(3.12)	(-0.55)
Down*Futures Return	161.79	-109.11	278.69**	-228.72***	23.59
	(0.63)	(-0.48)	(2.06)	(-3.13)	(0.64)
Up*Futures Return	3.38	-96.71	206.40**	-233.58*	39.53
	(0.02)	(-1.00)	(2.54)	(-1.83)	(0.99)
Down	5.95**	2.76**	3.32**	-0.25	-0.20
	(1.99)	(2.57)	(2.25)	(-0.57)	(-1.46)
Up	-3.76**	0.76	-2.38*	2.37	0.49
	(-2.19)	(0.71)	(-1.71)	(1.52)	(1.37)
Constant	-0.98	-1.28**	0.15	1.29***	-0.06
	(-1.22)	(-2.23)	(0.31)	(3.04)	(-0.56)
Observations	1,909	1,909	1,909	1,909	1,909
Adjusted R^2	0.099	0.068	0.111	0.280	0.292
Day FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes

Table IA.9: Cash flow regression for STTs during crashes

This table shows the results of the cash flow regression estimation based on one-minute intervals from 16-May-2006 through 25-May-2006 for the spot (Panel A) and futures (Panel B) markets. We regress cumulative one-minute cash flows for STTs on crash and recovery dummy variables defined as -/+ 30 minutes from the crash's trough (see equation (IA.2)). We use day and time fixed effects. We cluster standard errors by day. ***, **, and * denote significance level at 1%, 5%, and 10%, respectively. *t*-stats are reported in parentheses. For the futures market, we use only transactions for the contracts with maturity dates within the same month as the transaction occurs. We classify traders into three categories: long-term traders (LTTs), short-term traders (STTs), and small traders (Small).

	Panel A: Spot market			**Panel B: Futures market**		
	STT-All	STT-Both	STT-Spot	STT-All	STT-Both	STT-Futures
Down	-0.241	-0.192	0.013	-2.289	-0.631	-1.690*
	(-0.71)	(-0.63)	(0.23)	(-1.77)	(-1.28)	(-2.26)
Up	0.300	-0.002	-0.024	2.446	1.472	0.886
	(1.35)	(-0.01)	(-0.31)	(1.03)	(1.19)	(1.14)
Constant	-0.093	-0.052	0.053	0.545	-0.106	0.546*
	(-0.59)	(-0.32)	(0.89)	(1.07)	(-0.56)	(2.02)
Day FE		Yes			Yes	
Time FE		Yes			Yes	
Cluster SE		By Day			By Day	
Observations	1,871	1,709	1,839	1,871	1,709	1,839
Adjusted R^2	0.002	-0.003	0.003	0.012	0.007	0.006

Figure IA.1: Trader Classification

This figure shows the trader classification scheme used in this paper.

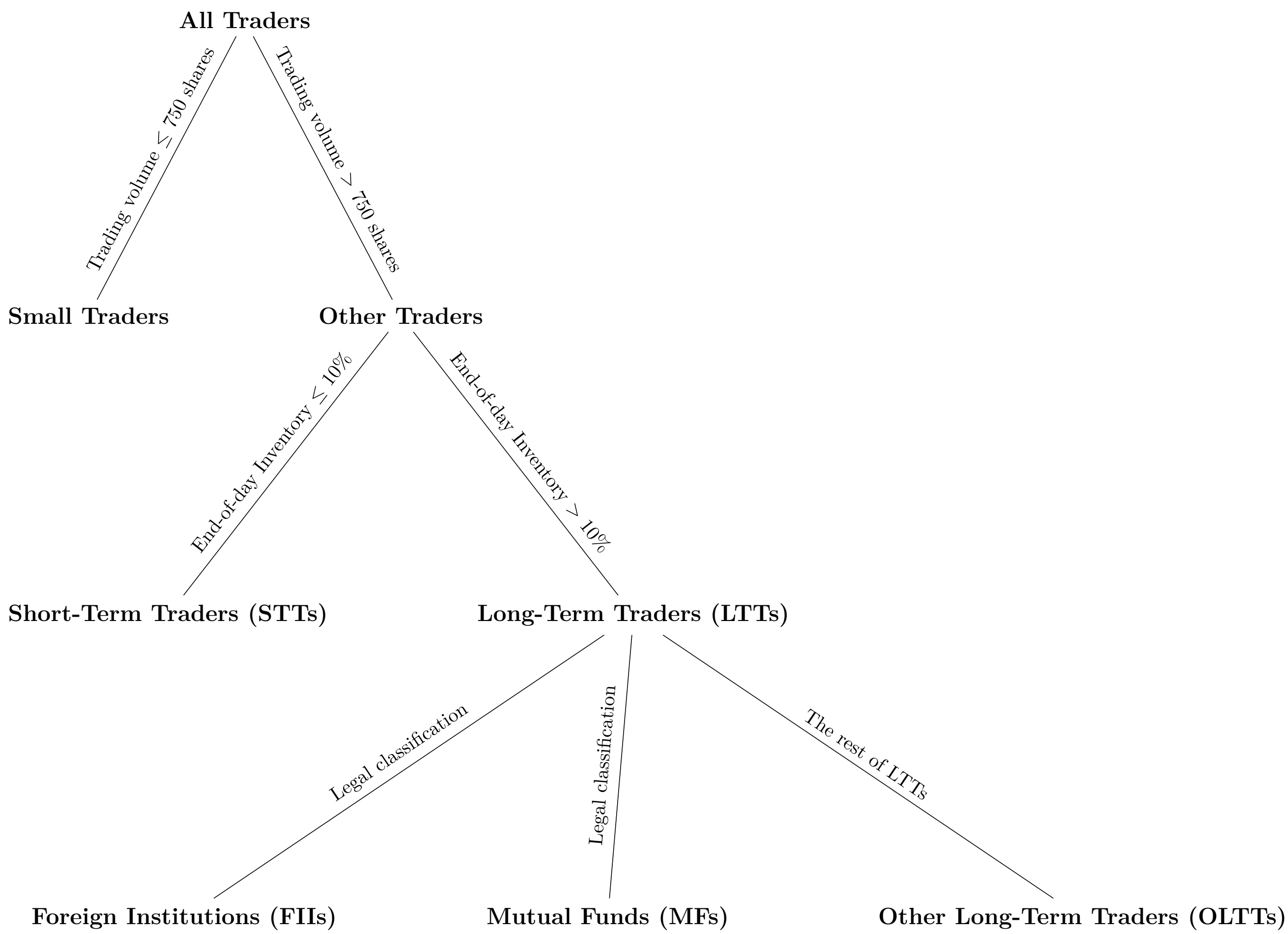
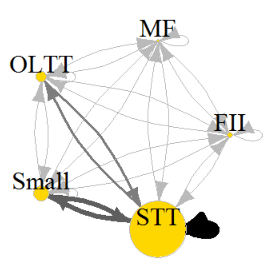


Figure IA.2: Trading network

This figure shows the trading network for the spot and futures markets for April-June, 2006, where each vertex corresponds to the trader type; the size of the vertex represents the proportion of total trading volume; and the width of the edges represents the proportion of total trading volume between two categories.

Panel A: Spot market



Panel B: Futures market

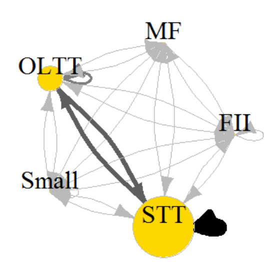
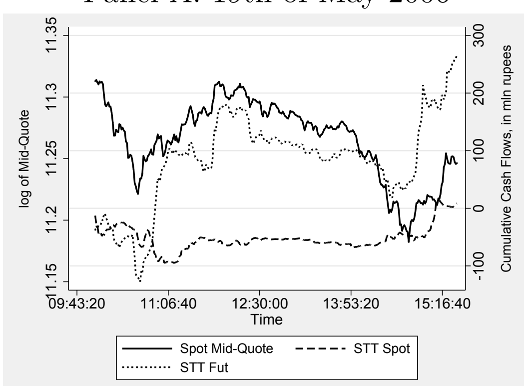


Figure IA.3: STTs' cumulative cash flows during the crashes

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

Panel A: 19th of May 2006



Panel B: 22nd of May 2006

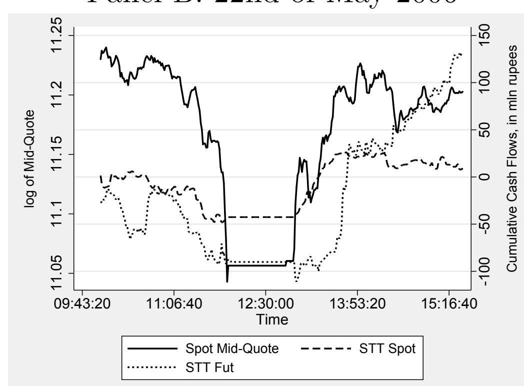


Figure IA.4: STTs' activity during the two crash days

This figure shows shows STTs' activity during the two crash days in our sample. We document the number of active traders for the crash, recovery, and normal periods during either May 19, 2006, or May 22, 2006, for the spot (futures) markets. Crash/recovery periods are measured as -/+30 minutes from the crash's trough. We split all active STTs on the crash days based on their activity during the crash periods, whether they belong to the most active STTs (STTs that generate 50% of total volume), and whether they were constrained during the crash days (their maximum one-minute inventory was above 95% of the maximum inventories on non-crash days).

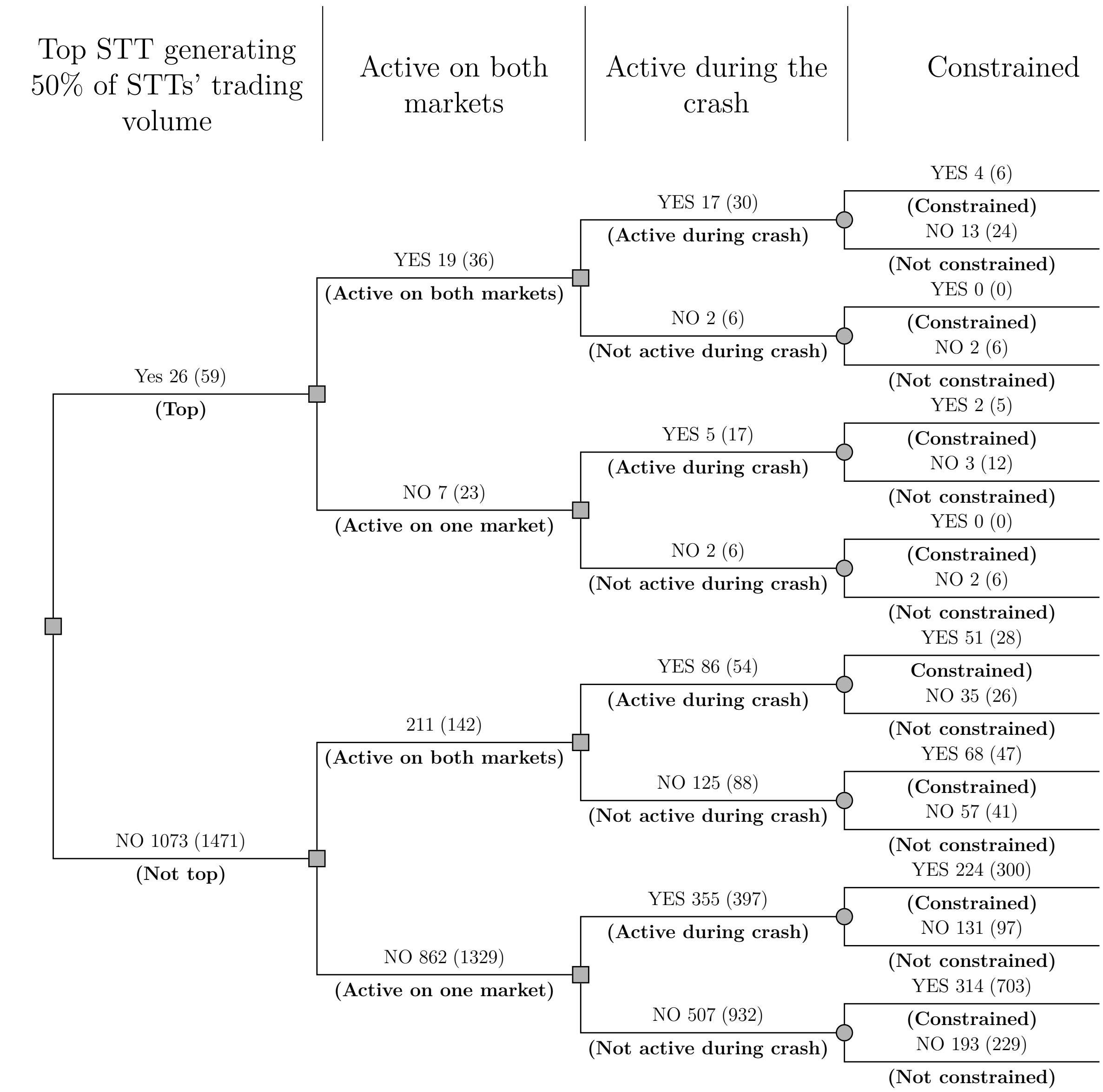
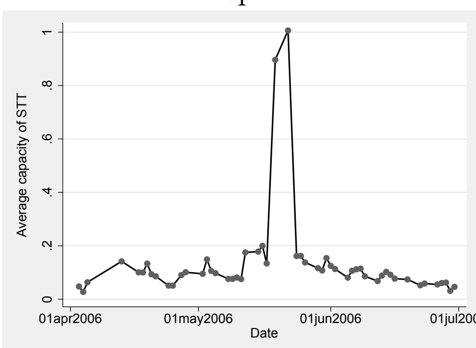


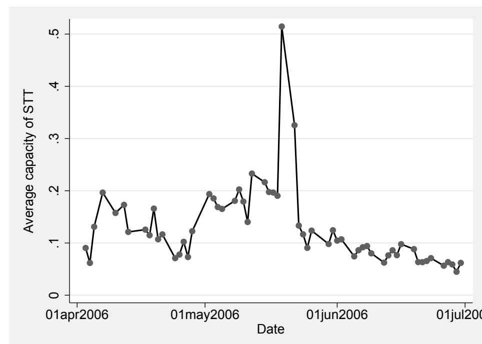
Figure IA.5: STTs' inventory capacity

This figure shows STTs' average capacity. Panels A and B show the maximum absolute value of one-minute median inventory positions during the day relative to the maximum absolute inventory position in our sample period, excluding the two crash days (May 19 and May 22, 2006) for the spot and futures markets, respectively. Panels C and D (Panels E and F) show the absolute value of one-minute median inventory positions relative to the maximum absolute inventory position in our sample period, excluding the two crash days (May 19 and May 22, 2006) for the spot and futures markets, respectively, for May 19 (22), 2006.

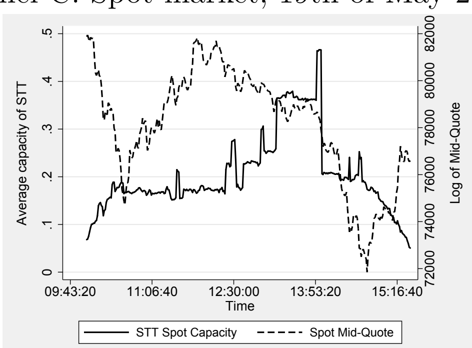
Panel A: Spot market



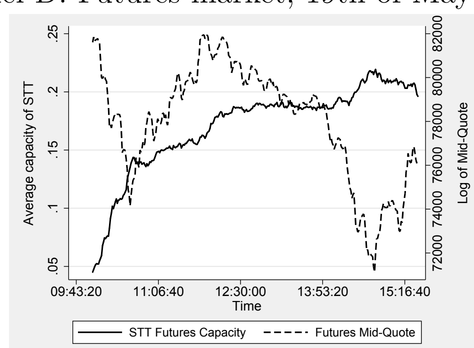
Panel B: Futures market



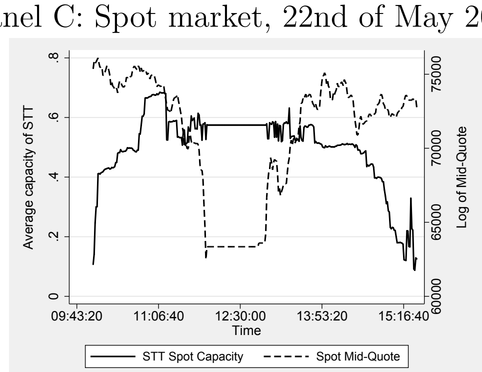
Panel C: Spot market, 19th of May 2006



Panel D: Futures market, 19th of May 2006



Panel C: Spot market, 22nd of May 2006



Panel D: Futures market, 22nd of May 2006