# High-Frequency Trading During Flash Crashes: Walk of Fame or Hall of Shame?*

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**Abstract**

We investigate the role of High Frequency Traders (HFTs) during flash crashes. By using a new methodology to identify flash crashes, defined as sudden and extreme price movements which occur in relatively short time and then reverts to the initial level, we identify 65 flash crashes episodes among 37 stocks that belong to the CAC40 traded in the NYSE-Euronext Paris market in 2013. We show that HFTs are responsible for initiating the crash in roughly 70% of the considered events, and that they strongly contribute to exacerbating the consequences of the crash, especially at his climax. In most of the cases, instead of providing liquidity, they start selling more as the crash develops. HFTs do not even contribute to recovery after the end of the crash, but they continue to initiate selling orders. This is worryingly true even for HFTs which agreed to provide liquidity under a market making agreement, especially if flash crashes occur simultaneously on several stocks. Among the HFTs, Investment Banks HFTs played the largest role and are those that are the most aggressive in selling during flash crashes.

**JEL Classification**: G10, G14.

**Keywords**: flash crashes; high-frequency traders (HFTs); liquidity provision; market making.

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# 1 Introduction

The existence of flash crashes casts doubts on the orderliness of the financial market architecture. The data, however, support the presence of a substantial number of such events. Therefore, in this paper, we study intraday market intermediation during the days including flash crash episodes, with the main emphasis on the role of High Frequency Traders (HFTs).

The importance of flash crashes in the financial literature exploded after the infamous event of May 6, 2010 (Easley, de Prado, and O'Hara, 2011; Madhavan, 2012; Andersen and Bondarenko, 2014; Andersen, Bondarenko, Kyle, and Obizhaeva, 2015; Menkveld and Yueshen, 2016). However, this was not an isolated event. Commenting on the recent Sterling flash crash of October 7, 2016, Bank for International Settlements (2017) write: "This event does not represent a new phenomenon but rather a new data point in what appears to be a series of flash events occurring in a broader range of fast, electronic markets than was previously the case in the post-crisis era, including those markets whose size and liquidity used to provide some protection against such events."

Our definition of a flash crash is: a sudden and extreme movement in price which occurs in relatively short time and then reverts to the initial level. Based on a formal implementation of this definition, Christensen, Oomen, and Renò (2017) provide evidence of frequent flash crashes in the futures markets on the stock index, gold, oil, EUR/USD, Treasury notes, and corn, a result also echoed in Golub, Keane, and Poon (2017) for the US equity market. Invariably, automated trading is indicated as a potential culprit for these events. However, the finance literature typically shows that automated trading is actually beneficial to market liquidity, see, e.g., Hendershott, Jones, and Menkveld (2011); Jones (2013), as well as to market efficiency, see, e.g., Chaboud, Chiquoine, Hjalmarsson, and Vega (2014). Do these conclusions still hold during flash crashes?

The objectives of the paper are twofold. First, to disentangle whether what it has been observed previously in the literature about the beneficial role of high-frequency traders for market liquidity and efficiency is confirmed for a large sample of flash crashes. Second, to uncover the role of categorized market participants during several flash crashes and the subsequent price recovery. In particular, we focus on the different kinds of HFTs populating the market, including designated market makers. We show that grouping HFTs in a single category would flatten the existing signal, which is instead revealed by subdividing HFTs into specific categories. To this purpose, we use a unique data set composed of tick-by-tick order-level data on 37 liquid French stocks traded on NYSE-Euronext Paris that belong to the CAC40 index. The data, obtained from the BEDOFIH database,[1] are recorded with microsecond time-stamps over the sample period of the year 2013. The peculiar feature of our data consists in the labeling of each order with a flag indicating the trader class

[1] www.eurofidai.org/en/high-frequency-data-bedofih

and the actual account used to submit a particular order. The French stock market regulator (AMF, 2017) determines, on the base of quoting and trading activity, if a trade is executed by an HFT or a Non-HFT. HFT traders are further divided into two groups: investment banks and large brokers, such as Goldman Sachs, labeled as IB-HFT, and the rest, mostly dedicated HFT firms with very low inventories at the end of the day, labeled as PURE-HFT. Inside these groups, we can distinguish among HFTs trading on the owner's account or the client account and HFTs trading as designated market makers (i.e., traders that signed a liquidity provision agreement with the exchange and have a reward by acting as market makers and respecting several rules). We focus our attention on this category because HFTs acting as designated liquidity providers are expected to prevent liquidity drying-out virtually eliminating the possibility of flash crashes. Using the granularity provided by the French market allows us conducting a detailed, in-depth analysis of different kinds of HFTs activity.

We address the following research questions: (i) to which extent HFTs and Non-HFTs originate a price drop, contribute to the crash development and recovery? (ii) How much liquidity is supplied by HFTs and Non-HFTs at different stages of flash crashes? (iii) Do the different types of designated market makers (pure and investment bank HFTs) provide liquidity during market crashes? Our conclusions are quite compelling in showing that HFTs are responsible for initiating the crash in roughly 70% of the considered events. Further, they strongly contribute to exacerbating the consequences of the crash, especially at his climax. Instead of providing liquidity, a role prevalently played by Non-HFTs during these events, they start selling more as the crash develops. HFTs do not even contribute to recovery after the end of the crash, but they continue to sell aggressively (that is, they initiate selling orders).

In particular, this is worryingly true even for HFTs which agreed to provide liquidity under a market making agreement, especially if flash crashes occur simultaneously on several stocks.

The behavior of HFTs during distressed events has been an intense subject of recent research. Our analysis has, with respect to the existing literature, two distinctive features. The first distinctive feature of our approach is using flash crashes as a measure of market distress. There are several advantages in doing so. First, flash crashes are a genuine measure of distress since they are, by construction, periods in which the price moves suddenly and largely, a phenomenon which cannot be ascribed to large volatility only, since the latter would imply a large movement, but not a *directional* movement. Second, flash crashes are not compatible with "normal" market behavior, and are typically attributed to market frictions, such as large trading imbalances with low market depth (Grossman and Miller, 1988), asymmetric information (Barlevy and Veronesi, 2003), costly market presence for market makers (Huang and Wang, 2009), predatory trading, (Brunnermeier and Pedersen, 2005), or just fat fingers. Third, they can be identified in a formally consistent way by using the novel econometric methodology recently introduced by Christensen, Oomen, and Renò (2017), which compares local drift to local volatility and identifies a flash crash when this ratio is large. Fourth, using flash crashes allows to identify

a large sample of distressed events in a relatively short time period that did not trigger any trading halt. In our sample, this amounts to 65 flash crashes. Visual inspection shows that the employed methodology filters out the actual directional price crash from the episodes of high volatility. Hence, from the statistical point of view, the precision of our results is substantially higher in comparison to alternative approaches. Fifth, our methodology allows identifying the exact time of a crash peak and disentangling different phases of a flash crash, e.g., the beginning of a price drop and the recovery.

In the existing literature, the definition of the distressed sample is typically different from what we propose. Most typically, this amounts to just the flash crash of May 6, 2010 (Kirilenko, Kyle, Samadi, and Tuzun, 2017), or a couple of events more (Megarbane, Saliba, Lehalle, and Rosenbaum, 2017; Hautsch, Noè, and Zhang, 2017). Another possibility is using scheduled news, such as macroeconomic announcements (Megarbane et al., 2017). Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov (2018) use their definition of extreme price movements, which is either "large volatility" or a jump test (Lee and Mykland, 2008). However, the methodology of extreme price movements detection "tends to oversample periods of high volatility'", as admitted by the authors. As a consequence, their sample might potentially be polluted by non-distressed events. Thus, the significance of their analysis could be jeopardized by the blending of HFTs activity during actual crashes and during non-distressed periods with just high volatility. On the contrary, all our flash crash episodes are authentic periods of distress followed by a price recovery. Thus, in our case, the danger of spurious contamination of the distressed sample is negligible.

The second distinctive feature of our analysis is the granularity of the traders' categorization. For this reason, our empirical analysis supports the previous findings only partially. Kirilenko et al. (2017) find that the trading pattern of HFTs did not change when prices of the E-mini S&P 500 stock index futures fell during the Flash Crash on May 6, 2010. Megarbane et al. (2017) find that HFTs provide liquidity to the markets, with the exception of the two extreme situations considered, when non-HFT provide liquidity in their place. Hautsch, Noè, and Zhang (2017) find that HFTs provide liquidity serving as market makers during general macroeconomic announcements, however, they change their activities to aggressive directional strategies during turbulent periods. Broogard et al. (2018) find that on average HFTs provide liquidity during extreme price movements, but they switch to demanding liquidity if several stocks experience a simultaneous crash. There is no evidence found of HFTs causing price crashes.

We show instead that these conclusions strongly depend on the kind of HFT considered, and that some groups of HFT traders play a major role in determining the occurrence of crashes. IB-HFT clients play a major role in generating and exacerbating the crash. Liquidity is provided, on average by Non-HFT traders, and in particular by Non-HFT Clients. Non-HFT traders are also those generating the subsequent recovery. Moreover, we show that designated market makers do not provide enough liquidity during the crash, on average. PURE-HFT market makers are not significantly active during flash crashes. IB-HFT market makers provide some liquidity in the early stage of a flash crash, and significantly so

if a flash crash is an isolated event, without spillovers to other stocks. However, on average, at the latest stage of a crash they start to "lean with the wind", a phenomenon similar to the behavior of HFTs around institutional orders at a much lower frequency (van Kervel and Menkveld, 2017). In particular, they sell aggressively during all stages of a crash, and during recovery, if the flash crash occurs in many stocks simultaneously.

The rest of the paper is organized as follows. Section 2 describes the data and presents the classification of market participants. Section 3 is dedicated to the methodology of flash crash detection and identification. The empirical results are presented in Section 4. Section 5 concludes.

# 2 Data description

## 2.1 Institutional structure

The Euronext stock market operates as an order-driven market with a limit order book. The actual trading infrastructure, the Universal Trading Platform (UTP) has been developed when Euronext was owned by the New York Stock Exchange (NYSE) during 2009. Until 2014, NYSE-Euronext was composed by the NYSE, plus the Amsterdam, Bruxelles, and Paris stock markets. The company has been acquired by Intercontinental Exchange (ICE), and the European part becomes public during 2014. Euronext Paris is the division of the exchange that includes all the French instruments, including equities and derivatives. The daily schedule for the most liquid stocks is divided into different segments. The trading session starts at 7:15 a.m with a pre-opening phase, followed by an auction at 9 a.m. The main trading phase, where most of the trading activity takes places, starts at 9:00 a.m. until 5:30 p.m. The daily schedule is then followed by a closing auction and a further trading period called "trading-at-last" phase, where additional trades could take place at the closing auction price. The focus of this study is on the main trading phase, thus opening and closing activity are excluded from the analysis.

According to the Rule 4403/2 of Rulebook I (Euronext, 2014), during the continuous trading Euronext have in place a set of trading safeguards that prevent price movements outside certain thresholds. Specifically, traded prices are constrained into a "collar", defined by a reference price plus/minus a percentage price change. The reference price is dynamic and is updated at every trade. Two types of collar are defined: the dynamic collar during the continuous phase, set to $\pm$ 3% of the reference price, and the static collar, set to $\pm$ 10% of the static reference price (usually the opening price). If the execution of an order causes the breach of the collar, two possible outcomes are possible: 1) the order is partially executed inside the collar, without halting the continuous trading; 2) the continuous trading is halted, and the market is put in "reservation mode". Continuous trading resume after an auction. None of the detected drift burst in our sample trigger any of these two events.

The market model of Euronext Paris also relies on the provision of liquidity by electronic market makers. In 2011, NYSE Euronext introduced a specific program, called *Supplemental Liquidity Provision* (SLP) in response to the rise of the trading activity in alternative venues (Chi-X Europe, BATS Europe, and Equiduct). By signing an agreement with the exchange, an electronic trader agrees to post two-sides quotes for a certain amount of time during the day, to provide a minimum passive execution volume. Passive executions are rewarded with a rebate, and aggressive execution benefit of a reduction in the trading fee for SLP members[2]. The orders sent by SLP members have to be electronic, using only their own funds and excluding the customer orders.

## 2.2 Data

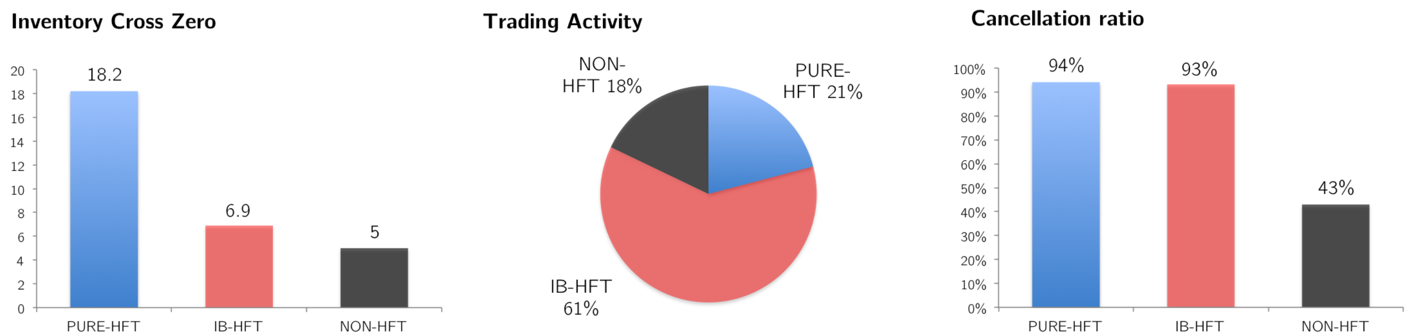
The database is provided by the Base Européenne de Données Financières à Haute Fréquence (BEDOFIH), and it is composed of tick-by-tick data for the most liquid stocks that are included in the CAC40 Index.[3] We can track the entire history of the orders, from the initial submission to the execution or the cancellation, with a timestamp at the microsecond level. One interesting feature of the database is that the data from the stock exchange are complemented by an identification flag, provided by the French stock market regulator (the Autorité des Marchés Financiers (AMF)), that categorize each trader into three groups: pure HFTs companies (PURE-HFT) such as Citadel or Virtu; Investment Banks with HFT activity (IB-HFT) such as Goldman Sachs, and all the remaining traders (Non-HFT). This classification is revised yearly, and the groups are mutually exclusive (see AMF (2017) for a description of the methodology applied to identify the traders). The identification algorithm is based on the median lifetime of an order (including both modifications and cancellations), plus a threshold based on the total number of cancellations. A further check is carried out taking into account the identity of the trader. In addition, each trader is required to flag every order, in compliance with the Rulebook, according to the following list of possible accounts (see NYSE-Euronext, 2012): own account or own account for client facilitation (OWN); own account of an affiliate, or when operating from a parent company of the stock (PARENT); account of a third party, or client account (CLIENT); orders submitted pursuant to a liquidity provision agreement (MM); orders submitted for retail liquidity provider (RLP) or retail matching facility (RMO). Finally, each trade carried out during the main trading phase has a flag that indicates the initiator of the trade, allowing to identify on the one hand which trader-account is trading aggressively and on the other hand which is providing liquidity.

Figure 1 shows three important features of the trading activity for aggregated trader categories. The left panel shows how many times the inventories of a particular trader type, on average for each stock-day, cross the value of zero. We

[2]The details of the scheme are available in NYSE-Euronext (2012). Bellia (2017) provides a detailed description of the SLP scheme and the role of electronic market makers in the NYSE Euronext

[3]Three stocks of the CAC40 are not included in our sample (Arcelor Mittal, Gemalto, and Solvay) since their main trading venues are not the Paris branch of Euronext

Figure 1: Trading activity by category.




*Note.* The Figure reports average number of times per stock day when inventory of a trader cross the zero value (left panel), trading activity (center panel) and the cancellation ratio (right panel).

expect this figure to be high for market makers, and small for traders taking positions in the market. The figure shows, indeed, that PURE-HFTs keep inventory more often close to the value of zero, as expected for typical market making activity. The center panel shows the percentage of trades done by a particular trader type. The absolute majority of trades (61% of all trades) are conducted by IB-HFTs, while 21% and 18% of trades are due to PURE-HFTs and NON-HFTs respectively. Hence, IB-HFTs are the most active category in this market. The right panel shows the cancellation ratio, that is the percentage of order which are submitted and canceled with respect to the total number of submitted orders. The average number of cancellations is high for both PURE-HFTs and IB-HFTs (94% and 93% respectively), and it is relatively low for NON-HFTs (43%).

Note that IB-HFTs may be classified as HFTs with regards to the number of messages or cancellations, but not regarding the inventory position, for instance. The common data-driven methodologies to identify HFT activity (see Hasbrouck and Saar, 2013) or the labeling provided by the exchange (among others, Broogard et al., 2018) usually identify only PURE-HFTs. This highlights a distinctive advantage of the database, which allows to track also the behavior of the investment banks with HFT activity and to differentiate them from the PURE-HFT group since their behavior is quite different in terms of strategies and capital constraints.

According to Megarbane et al. (2017), that have the regulatory database with traders' identities, all members of the SLP program are pure High Frequency Trading companies or Investment Banks with HFT activities. No market making activity is carried out by Non-High Frequency traders in our sample.

# 3 Identification of flash crashes

In this section, we describe how we go about to construct our database of flash crashes from the above sample of high-frequency data. We screen the data for flash crashes using a novel econometric approach and an effective algorithm, which supports the notion that a flash crash is (in relative terms) a large downtick in the price over a short time horizon, accompanied by subsequent price reversion. To explain the mechanics of the procedure, we need a minimal amount of notation. Let $(p_t)_{t \geq 0}$ be the log-price process of an asset, which is defined on a filtered probability space $(\Omega, \mathcal{F}, (\mathcal{F}_t)_{t \geq 0}, \mathbb{P})$. We assume $p_t$ evolves according to the model:

$$dp_t = \mu_t \mathrm{d}t + \sigma_t \mathrm{d}W_t, \tag{1}$$

where $\mu_t$ is the instantaneous drift, $\sigma_t$ is the associated spot volatility, and $W_t$ is a standard Brownian motion.

We suppose $p_t$ is observed on $[0, T]$ at irregular time points $0 = t_0 < t_1 < \ldots < t_n = T$, such that $\max_i (t_i - t_{i-1}) \to 0$ as $n \to \infty$. The discretely sampled log-return is defined as:

$$r_{t_i} = p_{t_i} - p_{t_{i-1}}, \quad i = 1, \ldots, n. \tag{2}$$

We build on a recent paper by Christensen, Oomen, and Renò (2017), who propose a statistical test for "drift burst" detection. At time $t$, the computation of the test statistic is as follows:

$$T_t^n = \sqrt{\frac{h_n}{K_2}} \frac{\hat{\mu}_t^n}{\hat{\sigma}_t^n}, \tag{3}$$

where

$$\hat{\mu}_t^n = \frac{1}{h_n} \sum_{i=1}^{n} K\left(\frac{t_{i-1} - t}{h_n}\right) r_{t_i}, \quad \text{and} \quad \hat{\sigma}_t^n = \sqrt{\frac{1}{h_n} \sum_{i=1}^{n} K\left(\frac{t_{i-1} - t}{h_n}\right) r_{t_i}^2}. \tag{4}$$

Here, $K$ is a kernel, $h_n$ is a bandwidth, and $K_2 = \int_{\mathbb{R}} K(x)^2 \mathrm{d}x$.

The measure $\hat{\mu}_t^n / \hat{\sigma}_t^n$ can be interpreted as the current velocity of the market. If the price is moving fast relative to the volatility (i.e., price changes are directional), the ratio is large. A drift burst can then be thought of as a time point $\tau_{\text{db}}$, where $\mu_t / \sigma_t \to \pm\infty$ as $t \to \tau_{\text{db}}$. A large and growing value of the test statistic thus indicates the market is under increasing (upward or downward) pressure and is starting to give in.

Christensen, Oomen, and Renò (2017) show that without a drift burst, for every $t \in (0, T]$, as $n \to \infty$, $h_n \to 0$ such that $nh_n \to \infty$:

$$T_t^n \xrightarrow{d} N(0, 1). \tag{5}$$

In contrast, in presence of a drift burst:

$$|T_t^n| \to \infty. \tag{6}$$

as $t \to \tau_{\text{db}}$.

To implement the test, we compute an estimator of the drift and volatility based on a kernel-weighted average of observations in the vicinity of $t$, as defined in Eq. (4). The bandwidth determines how fast we downweight observations farther away from $t$. We employ a 5-minute bandwidth for the mean and a 25-minute bandwidth for the volatility. This means that, by construction, we are interested in flash crashes which develop on a time span of roughly 5 minutes. We also set $K(x) = \exp(-|x|)\mathbb{1}(x \leq 0)$, such that $\hat{\mu}_t^n$ and $\hat{\sigma}_t^n$ are computed with a left-sided exponential moving average (based on backward-looking data) to avoid look ahead bias. This setup is consistent with Christensen, Oomen, and Renò (2017).

We compute the above test statistic every second during the course of a trading session.[4] A significant negative value of $T_t^n$ reveals large and fast downward movement in the price, which is our crash criterion. On the other hand, the test is not informative about the subsequent price behavior. To filter out a reversal—a defining characteristic of a flash crash—from a continuation, we adopt the following rule. We compute the log-return from the onset of a crash to its peak, where the peak corresponds to the time $T_t^n$ achieves its most negative value, say $t_1$. The beginning of the crash is assumed to be the closest point in time *prior* to $t_1$, such that $T_t^n$ does not exceed the value $1$ in absolute value. The latter is labelled $t_0$ and the duration of the crash is then $\tau = t_1 - t_0$. If a crash is to be categorized as a reversal, we require that the log-price should retrace at least one-third of its initial decline in the subsequent "post-drift burst" recovery window by time $t_2 = t_1 + \tau$ the latest.

Table 1 reports a summary of flash crashes identified with this procedure. Average duration of a flash crash is $12.25$ minutes with standard deviation of $12.65$ minutes. An average price drop during a flash crash is $-1.58\%$ with standard deviation of $0.94$ %. During the largest crash, which occurred in Schneider on September 3, 2013, the price fall by $-4.69\%$, while during the smallest one, which occurred in BNP on April 5,2013, the price declined by $-0.45$ %. Note that flash crashes may occur in different stocks simultaneously. As shown by Table 8 in the Appendix, there are four simultaneous events in our sample. The first one occurred simultaneously in 12 stocks at around 9:51 a.m., April 17, 2013. The second one occurred simultaneously in $6$ stocks at around 10:54 a.m. September 3, 2013. The last two simultaneous events occurred in $2$ stocks. The middle and lower panels of Table 1 report the summary statistics of simultaneous and idiosyncratic flash crashes respectively. Typically, the duration of both simultaneous and non-simultaneous flash crashes are similar. For example, the median durations of simultaneous and idiosyncratic events are $8.72$ and $8.42$ minutes

[4]To account for the multiple testing, we exploit the simulation-based algorithm from Christensen, Oomen, and Renò (2017) to set an appropriate critical value.

Table 1: Summary statistics of Flash Crash events

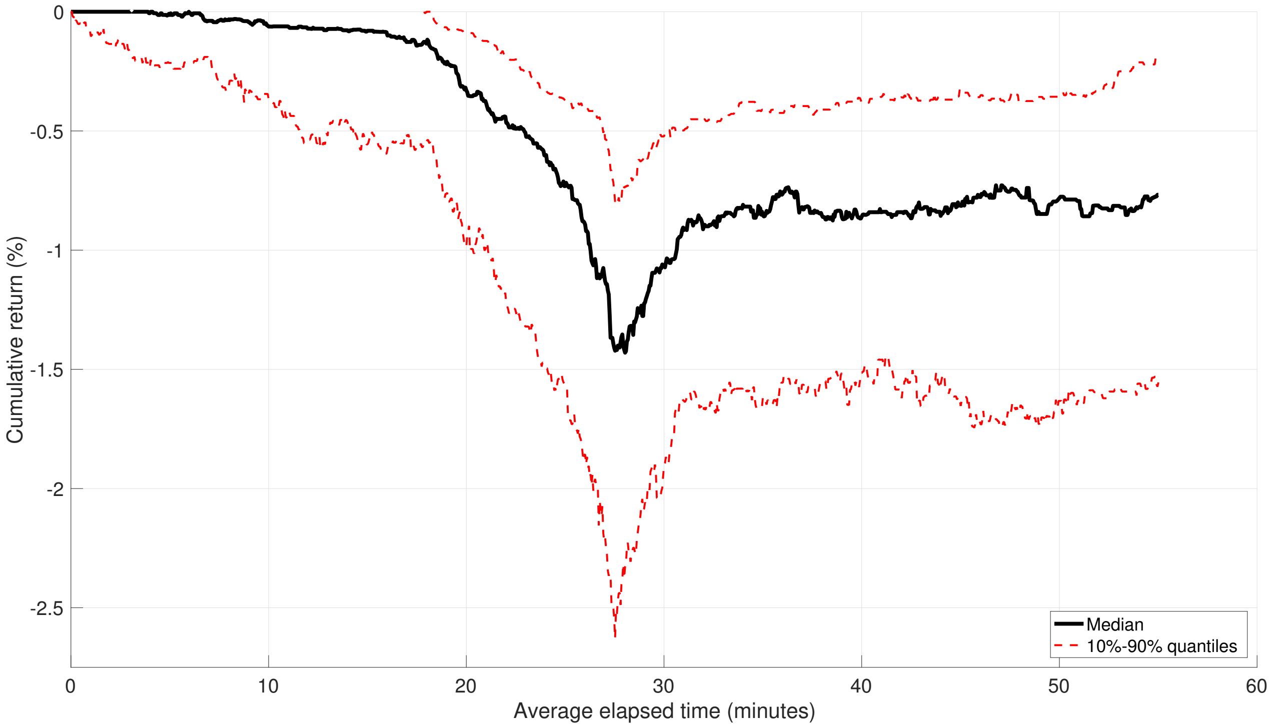
| | mean | std | min | max | quantile(0.1) | quantile(0.5) | quantile(0.9) |
|---|---|---|---|---|---|---|---|
| | | | | **All Flash Crashes (65 events)** | | | |
| **return** | -1.58 | 0.94 | -4.69 | -0.45 | -2.87 | -1.34 | -0.74 |
| **duration** | 12.25 | 12.65 | 1.78 | 51.50 | 2.42 | 8.63 | 32.28 |
| **Market Cap** | 31021.11 | 28399.60 | 5035.00 | 145995.00 | 7876.00 | 23630.00 | 48784.00 |
| **N. trades** | 15824.85 | 6936.49 | 7872.00 | 33015.00 | 9677.00 | 13152.00 | 27238.00 |
| **Volume** | 151.28 | 94.45 | 44.00 | 400.00 | 61.00 | 124.00 | 317.00 |
| | | | | **Simultaneous Flash Crashes (22 events)** | | | |
| **return** | -1.93 | 1.06 | -4.69 | -0.74 | -3.87 | -1.63 | -0.93 |
| **duration** | 13.93 | 16.18 | 1.78 | 51.50 | 1.97 | 8.72 | 51.44 |
| **Market Cap** | 39969.61 | 35751.52 | 5035.00 | 145995.00 | 9993.20 | 32047.00 | 92401.90 |
| **N. trades** | 17089.14 | 7286.89 | 7872.00 | 33015.00 | 10554.50 | 13735.00 | 30714.20 |
| **Volume** | 173.32 | 102.07 | 49.00 | 400.00 | 82.50 | 128.00 | 348.00 |
| | | | | **Flash Crashes in only one stock (43 events)** | | | |
| **return** | -1.40 | 0.84 | -4.27 | -0.45 | -2.82 | -1.22 | -0.69 |
| **duration** | 11.38 | 10.52 | 1.88 | 51.47 | 2.69 | 8.42 | 20.71 |
| **Market Cap** | 24249.27 | 19125.98 | 5035.00 | 101851.00 | 7832.80 | 20858.00 | 42909.80 |
| **N. trades** | 14868.08 | 6597.68 | 7872.00 | 32204.00 | 9677.00 | 12774.00 | 26013.20 |
| **Volume** | 134.59 | 85.91 | 44.00 | 400.00 | 60.20 | 99.00 | 296.00 |

*Note.* This table reports summary statistics of the price drop during Flash Crashes, flash crash duration and the characteristics of the stocks in which flash crashes occur: yearly market capitalization, daily number of trades and trading volume. The upper panel shows means, median, standard deviation, minimum, maximum and 10 and 90% quantiles computed across all detected events. The middle and lower panes reports the same statistics computed across simultaneous and non-simultaneous flash crashes respectively.

respectively. The price crashes, which occur at the same in many stocks, are, on average, slightly deeper in comparison to flash crashes in single stocks. For example, 10% and 90% quantiles of the price drop are respectively $-3.87\%$ and $-0.93\%$ for simultaneous events and $-2.82\%$ and $-0.69\%$ for non-simultaneous ones.

A detailed summary of all 65 identified flash crashes is provided in Table 8 in the Appendix. Table 9 in the Appendix reports a summary of the detected flash crashes groped according to each stock. It shows that in our sample flash crashes occur in 30 different stocks. The number of flash crashes per year ranges from 1 to 5 with an average rate of 2.2 events per year. For 9 stocks flash crashes occur only once. The largest number of crashes per year correspond to Société Générale.

Figure 2: Average cumulative return dynamics during a Flash Crash.




*Note.* This figure report the median, 10% and 90% quantile of the price evolution over the average time span across the 65 flash crash events considered in this study.

# 4 Empirical results

We identify 65 flash crash events in our data, listed in Table 8. For each event, we denote by $t_0$ and $t_1$ the beginning and the end of the crash, respectively, whose precise identification has been described in Section 3. We denote by $t_2 = t_1 + \tau$ the end time of the recovery, by $t_{-1} = t_0 - \tau$ the beginning of the pre-crash period, and by $t_3 = t_1 + 3\tau$ the end time of the post-recovery period. The analysis in this section is based on prices and book information, for each crash, from time $t_{-1}$ to time $t_3$. In order to harmonize information coming from crashes with different duration, we use the crash duration $\tau$ as the same time unit for every crash. In these units, each crash is observed from time $-1$ to time 3, divided in the pre-crash period (from $-1$ to 0), the crash period (from 0 to time 1), and the full recovery period (from 1 to 3). We further subdivide the crash period in three stages: early, intermediate and late crash. Figure 2 shows the median cumulative return, across the 65 crashes, as a function of time expressed in the harmonized time units, together with 10% and 90% quantiles. The figure illustrates the output of our identification strategy. Our selected 65 events display a pronounced drop, followed by a partial recovery. This patterns is similar across the 65 events. The median cumulative return in Figure 2 is superimposed in all the next figures to be used as a visual landmark of the average crash development.

Figure 3 shows what happens to typical measures of illiquidity during a flash crash: trading intensity (i.e., volume traded per unit minute), signed volume, market depth and bid-ask spread. The figures are averaged across the $65$ events. Panel A clearly shows that trading activity sharply increases in the early-crash with an exponential increase than during the late crash, and rapidly declining afterward to the original level upon completion of the recovery. Panel B shows that flash crashes are accompanied by massive selling, and that recovery starts after selling stops. This is consistent with standard economic theory, as in Grossman and Miller (1988), who predict a V-shape behavior for the trading process when market makers accommodate the need for immediacy of a large seller. Panel C shows that the ability of the market to absorb orders literally pulverizes during a crash, recovering slower than the price itself, in line with the finding in Kirilenko et al. (2017) during the Flash Crash of May 6, 2010. This is again consistent with Grossman and Miller (1988), since the price change in their model is predicted to be deeper in illiquid market conditions. Finally, Panel D shows that the bid-ask spread increases during a flash crash, indicating increasing cost of transacting during these events, as well as the increased uncertainty on market fundamentals which is indeed typically accompanied by a widening of the bid-ask spread. Overall, Figure 3 suggests that a flash crash occurs when a selling pressure increases and not enough liquidity is provided to the sellers.

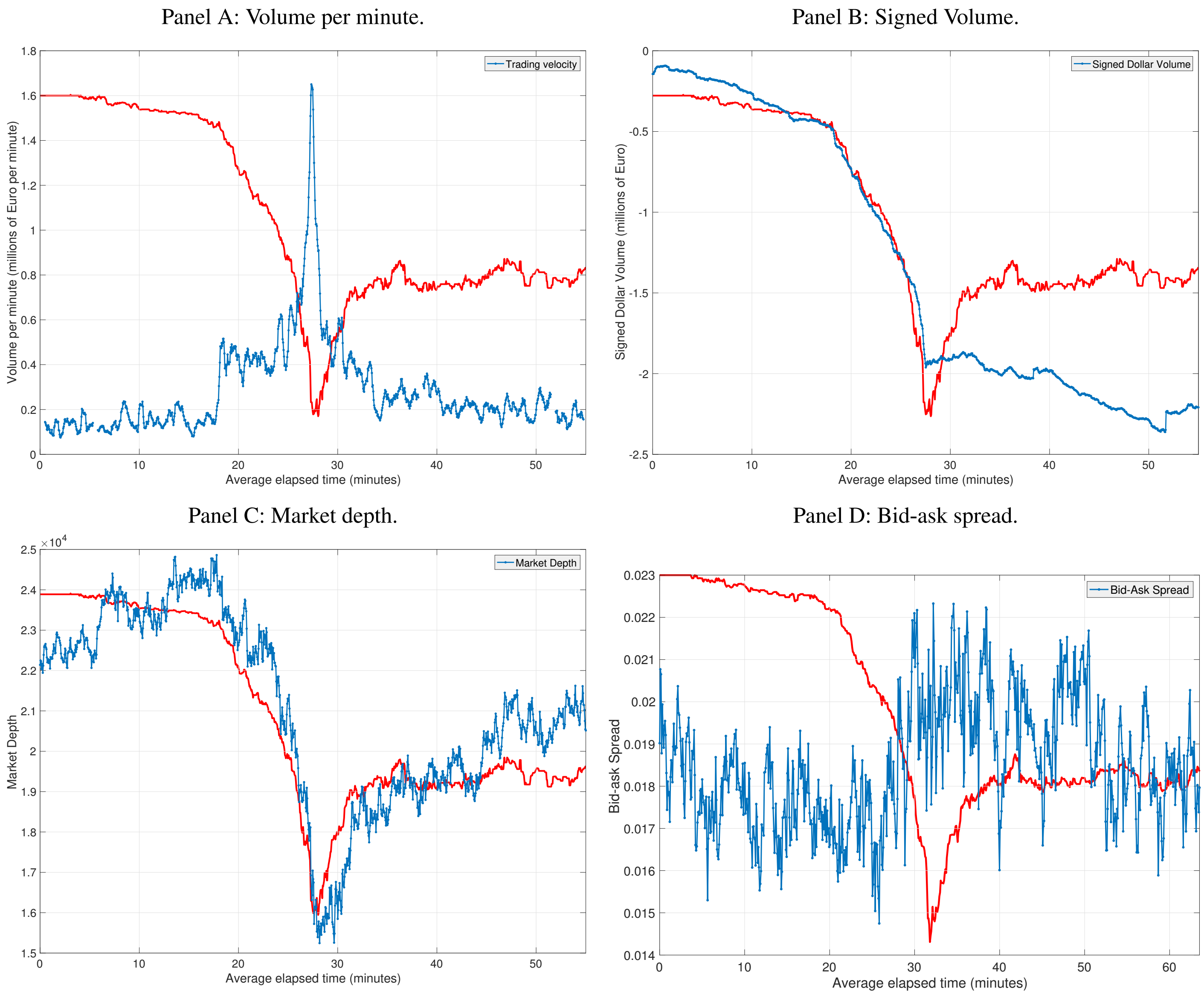
In order to measure the activity of different trader groups during flash crashes we use monetary net trade imbalances, computed as the total money invested to buy the stock (with a positive sign) and the total money gained during the crash by selling the stock (with a negative sign), for each considered period and for each trading category. We also split imbalances in initiating and liquidity supplying trades as follows. For each trade, denote by $i$ the category which is initiating the trade with his demand for buy or sell, and by $j$ the category who is accepting the buy/sell offer ($i$ and $j$ may coincide). We assume that a buy order contributes positively to the imbalance and a sell order negatively. The quantity of money exchanged in the trade $t$ is $Q_t \cdot P_t$, where $Q_t$ is the number of stocks exchanged and $P_t$ is the stock price. Thus, for the category $i$, the imbalance on initiating trades on a given period will be will

$$\mathcal{I}_{\text{period}}^{(i),\text{init}} = \sum_{t\in\text{period}} s_t \cdot Q_t \cdot P_t \cdot I_{\{\text{t initiated by } (i)\}}$$

where $s_t = +1$ for buy orders, and $s_t = -1$ for sell orders, while $I_{\{\cdot\}}$ is the indicator function. The imbalance on liquidity providing trades for the category $j$ in a given period is similarly:

$$\mathcal{I}_{\text{period}}^{(j),\text{liq}} = \sum_{t\in\text{period}} s_t \cdot Q_t \cdot P_t \cdot I_{\{\text{t accepted by } (j)\}}$$

Figure 3: Volume per minute, signed volume market depth and bid-ask spread during a Flash Crash.




*Note.* The Figure reports four measure of liquidity averaged across the 65 flash crash events considered in this study. Panel A: average monetary volume traded per minute. Panel B: cumulative signed volume (negative volume = sell). Panel C: market depth. Panel D: bid-ask spread. On each panel, we superimpose the median price evolution for visual comparison.

The monetary net imbalance for the category $(i)$ in a given period is given by:

$$\mathcal{I}^{(j)}_{\text{period}} = \mathcal{I}^{(i),\text{init}}_{\text{period}} + \mathcal{I}^{(j),\text{liq}}_{\text{period}}.$$

This measure is similar to that used by Brogaard et al. (2018), except for the fact that, in their paper, they use number

of traded shares instead of monetary volume. The interpretation of monetary net imbalances is straightforward. For example, a negative net imbalance of a trader during a crash indicates that the trader contributes to a price drop; a positive net imbalance of a trader after a peak of a crash indicates that the trader contributes to price recovery.

Table 2 reports the cross-sectional average and standard deviation of net trade imbalances $\mathcal{I}^{(j)}_{\text{period}}$ in the five different periods of a flash crash, for the trading categories for which this number is non-negligible. The numbers are expressed in thousands of euro, and reported with their standard deviation below.

For the three first phases of a flash crash net imbalances of HFTs and NON-HFTs (by construction, they have opposite sign) do not show a systematic pattern, since the average imbalances are not significantly different from zero given the large standard deviation of the imbalances among the 65 flash crashes for these two categories. This indicates that there is a lot of heterogeneity in the behavior of HFTs and Non-HFTs in the 65 flash crashes and it is difficult to identify a unique pattern. This result highlights how crucial it is to look to several flash crashes, since looking only at few of them might lead to distorted conclusions. During the late crash, the net trade imbalance of HFTs is significantly negative, which clearly indicates that HFTs significantly contribute to the exacerbation of the flash crash in its most dramatic phase. After the crash peak, HFTs increase their negative net imbalance, which becomes three times larger. This means that they increase their selling on average, hence they do not contribute to price recovery. In contrast, the net trading imbalance of Non-HFTs is significantly positive during the late phase of a crash, meaning they are providing liquidity, on average, to HFTs, and they increase their buying in the post-crash period. Hence, Non-HFTs play the role of major liquidity providers during flash crashes and are the main driver of the subsequent price recovery.

The bottom panel of Table 2 reports the net trade imbalances for each trader category. Substantial heterogeneity also emerges in the behavior of trader groups. Indeed, they behave differently during early phases of different flash crashes, as discussed below. PURE-HFTs do not significantly contribute to the crash, and the recovery, their imbalance for all the categories is not statistically different from zero, and the standard deviation of their net trade imbalance is very low. This means that in almost all the cases considered, they largely stop to participate to the market during flash crashes, and this is in line with what found in the recent literature (see, e.g., Kirilenko et al., 2017). Thanks to the granularity of our database we could also investigate whether PURE-HFT market makers contribute to reduce the crash and help the recovery. Unfortunately, it does not seem that PURE-HFT market makers provide any significant contribution during the crash (i.e., buy when the price drop). This contrasts the findings in Bellia (2017), who instead shows that in "normal" market periods, PURE-HFT market makers activity improves market liquidity significantly. This conclusion does not hold any more in distressed times. Regarding the other HFT category, IB-HFTs, we observe more heterogeneity. The imbalance of IB-HFT owners is not significantly different from zero during the whole length of a flash crash. Regarding IB-HFT market makers, the table shows that they do not provide enough liquidity during price drop. During the recovery

they significantly sell, but we need to investigate whether they sell in order to provide liquidity or by actively selling (i.e., initiating a selling trade).

The main takeaway of Table 2 is probably that IB-HFT clients contribute significantly to the explosion of the crash. Analyzing the flash crash of May 6, 2010, Menkveld and Yueshen (2016) argue that is has been caused by large investors. However, they do not provide information on whether large investors used HFTs or Non-HFTs for placing their orders. Our results indicate that HFTs of investment banks are the most likely culprit.

Importantly, Table 2 also shows that Non-HFTs plays an important role in reducing the negative effects of the crash and helping the price recovery after a crash occurs. The net trade imbalance of Non-HFT clients is positive and highly significant during both price drop and recovery. Non-HFTs owners contribute to originating a crash: their trading imbalance is negative at the first stages of a crash, in particular, it is mildly significant during the early crash. However, their trading imbalance becomes positive at the late crash and very high and significant during the recovery period. Our results thus shed light on the findings of Menkveld and Yueshen (2016), who underlined that large investors do also have the capacity to use high frequency trading. Therefore they do not have the need to post large orders, but could split them in small orders and still cause the crashes.

Now, in order to separate liquidity provision from aggressive trading, we analyze the monetary imbalances, invested by a trader who is initiating a trade separately from the money invested when providing liquidity ($\mathcal{I}^{(i),\text{init}}_{\text{period}}$ and $\mathcal{I}^{(j),\text{liq}}_{\text{period}}$, respectively). The aim of this analysis is to investigate whether the net imbalance is due to a low activity (i.e. low initiated trading and low liquidity provision) or to a significant large activity (i.e. high initiated trading and high liquidity provision).

Table 3 reports average amounts of money invested in initiating trades ($\mathcal{I}^{(i),\text{init}}_{\text{period}}$) by different trader categories at different stages of a flash crash. It shows that during a crash aggressive trades of both HFTs and Non-HFTs contribute to the price decline, but the volume of aggressive trades of HFTs is much larger. After the peak of a crash HFTs continue selling aggressively, while Non-HFTs start buying pushing the price up. When looking at trader groups, we see that not only IB-HFT clients are selling aggressively, but also IB-HFT owners. Even market makers sell aggressively, both of PURE-HFT type and IB-HFT type, even if with less intensity than clients and owners. After the end of the crash, all the HFTs (with the exception of PURE clients), continue to sell, while Non-HFTs start to buy. In particular, IB-HFT market makers are aggressively selling during the post-crash period. On average they invest 120 k€ in aggressive trades during this period, which constitutes approximately two-thirds of their net trading balance, which is equal to a total selling of roughly 180 k€ during the same period (see Table 2). Hence, only a third of the activity of IB-HFT market makers consists of the actual market making (by supplying the liquidity during the recovery), while the most of their activity can be interpreted as opportunistic trading.

Table 2: Average net trade imbalances (k€).

| | pre-crash | early crash | intermediate crash | late crash | recovery |
|---|---|---|---|---|---|
| HFT | $-112.52$ | $39.30$ | $-70.68$ | $-237.85^{***}$ | $-543.92^{***}$ |
| | (86.15) | (70.26) | (63.19) | (84.45) | (165.00) |
| Non-HFT | $112.52$ | $-39.30$ | $70.68$ | $237.85^{***}$ | $543.92^{***}$ |
| | (86.15) | (70.26) | (63.19) | (84.45) | (165.00) |
| PURE-HFT CLIENT | $2.48$ | $2.18$ | $11.97$ | $19.53$ | $1.98$ |
| | (3.22) | (5.83) | (8.74) | (18.04) | (8.60) |
| PURE-HFT MM | $-36.71$ | $-8.92$ | $-29.59$ | $-9.67$ | $-56.69$ |
| | (34.24) | (16.74) | (20.77) | (26.61) | (45.47) |
| PURE-HFT OWN | $-5.18$ | $2.23$ | $6.74$ | $6.08$ | $-0.03$ |
| | (11.34) | (8.76) | (5.94) | (6.81) | (14.46) |
| IB-HFT CLIENT | $-82.92^{*}$ | $-61.30^{*}$ | $-107.45^{***}$ | $-142.73^{**}$ | $-27.44$ |
| | (43.45) | (33.33) | (33.15) | (60.14) | (155.15) |
| IB-HFT MM | $13.25$ | $62.19^{*}$ | $49.36^{*}$ | $-20.28$ | $-188.55^{***}$ |
| | (28.45) | (33.87) | (27.60) | (35.39) | (70.75) |
| IB-HFT OWN | $25.77$ | $25.34$ | $-7.07$ | $-44.85$ | $-185.67$ |
| | (66.12) | (54.71) | (51.36) | (74.72) | (146.49) |
| IB-HFT PARENT | $-28.98^{**}$ | $17.58$ | $5.35$ | $-46.69$ | $-87.31^{**}$ |
| | (14.23) | (11.76) | (13.77) | (31.70) | (43.24) |
| Non-HFT CLIENT | $159.56^{*}$ | $80.36^{**}$ | $109.63^{***}$ | $215.06^{***}$ | $293.20^{***}$ |
| | (87.80) | (38.65) | (32.07) | (61.67) | (101.22) |
| Non-HFT OWN | $-47.35$ | $-107.74^{**}$ | $-38.96$ | $23.29$ | $249.55^{***}$ |
| | (34.91) | (52.17) | (55.89) | (49.63) | (95.61) |

*Note.* This table reports the cross-sectional average, and standard errors in brackets, computed on the 65 flash crashes considered in this study, of the trade imbalances measured in k€, in the five different periods of the crash described in Figure 2. Panel A: reports averages for HFT vs non-HFT. Panel B: reports averages for seven trading categories, as described in the main text. The significance of the mean is evaluated with a standard $t$-test. One star denotes 90% significance, two stars 95% significance and three stars 99% significance.

PURE-HFT market makers on average invest 30 k€in aggressive trades during the price recovery period, which is, however, not significantly different from zero. Their net trading imbalance for this period is negative and significant only at 10% confidence level and it is equal to a total selling of roughly 80 k€. This suggests that PURE-HFT market makers tend to provide a relatively small amount of liquidity for the recovery period.

Table 4 reports average amounts of money invested in liquidity supply trades, and complements Table 3. It shows that HFTs significantly provide liquidity during the price drop. However, the amount of liquidity provided is much smaller in comparison to the amount of money invested by HFTs in initiated trades (see Table 3). For example, at the late stage of the price crash, HFTs invest only 349.50 k€ in liquidity supply trades, while they invest $-587.35$ k€ in initiated trades.

In contrast, Non-HFTs provide more liquidity than they consume. For example, they invest $413.08$ k€ in liquidity supply trades and $-175.23$ k€in initiated trades, during the late crash. During the recovery, Non-HFTs continue to provide a significant amount of liquidity, while HFTs do not invest significantly in liquidity supply trades. The larges liquidity providers among HFTs are IB-HFTs owners and IB-HFTs market makers. However, at the same time, IB-HFTs owners are the largest liquidity consumers among HFTs, that balances the liquidity provision to a total net imbalance which is not significantly different from zero (see Table 2). Thus, their activity does not contribute either to slow down the price crash nor to contribute to price recovery. As discussed above, PURE-HFTs market makers provide barely significant amounts of liquidity during the early and late phase of the crash. During this periods, similarly to IB-HFTs, their activity in liquidity provision is compensated by their investing in initiating trades. During the other periods of flash crash, PURE-HFTs market makers do not significantly provide liquidity and are not particularly active in general. Finally, during the price reversal phase, none of HFTs significantly invest in liquidity supply trades. Non-HFTs are the only significant liquidity suppliers during this period, in particular, the largest amount of liquidity is supplied by Non-HFT clients and owners.

Overall, Table 4 confirms and complements the previous finding on categorized traders activity during flash crashes. Altogether the evidence provided in this section shows that both HFTs and Non-HFTs play an ambivalent role during flash crashes by consuming and providing liquidity simultaneously. However, on average HFTs tend to contribute more to the price drop and do not help to restore the price level after the crash. Price recovery is achieved mainly due to the activity of Non-HFTs. Designated market makers do not provide enough liquidity during the crash, in particular, PURE-HFTs market makers are not particularly active during flash crashes.

## 4.1 Simultaneous flash crashes

The advantage of looking at a large sample of flash crashes allow us to investigate the inherent heterogeneity of the different crashes and the different behavior of the traders. In this section, we classify flash crashes in simultaneous and non-simultaneous ones, and repeat earlier analyses for different event types separately. We define simultaneous flash crashes as those that occur in two or more stocks at the same time. Accordingly, non-simultaneous flash crashes occur in a single stock only. As shown in Table 8 in our sample we detect two large simultaneous flash crashes. The first one occurred simultaneously in 12 stocks at around 9:51 a.m. April 17, 2013. The second large flash crash involves 6 stocks and occurred at around 10:54 a.m. September 3, 2013. In addition, we have two small simultaneous events, for each of which flash crashes occur simultaneously in only a pair of stocks. In total, we consider a subsample of 22 simultaneous flash crashes.

Tables 5 and 6 report average mmonetnetaryy net trade imbalances of categorized market participants across simultaneous and non-simultaneous flash crashes respectively. In both cases, during the price recovery period, net trading

Table 3: Average money invested in initiated trades (k€).

| | pre-crash | early crash | intermediate crash | late crash | recovery |
|---|---|---|---|---|---|
| HFT | $-308.49^{***}$ | $-220.80^{***}$ | $-256.11^{***}$ | $-587.35^{***}$ | $-584.16^{***}$ |
| | (108.38) | (71.76) | (59.35) | (92.58) | (209.83) |
| Non-HFT | $-54.49^{**}$ | $-116.18^{***}$ | $-117.85^{***}$ | $-175.23^{***}$ | $185.85^{**}$ |
| | (24.23) | (34.92) | (37.61) | (44.35) | (94.66) |
| PURE-HFT CLIENT | 2.40 | 1.37 | 0.26 | $-1.39$ | $8.83^{*}$ |
| | (1.73) | (5.61) | (0.40) | (6.05) | (4.94) |
| PURE-HFT MM | $-34.06^{*}$ | $-41.03^{***}$ | $-28.48$ | $-40.13^{*}$ | $-30.44$ |
| | (19.50) | (15.55) | (18.80) | (23.52) | (46.24) |
| PURE-HFT OWN | $-5.32$ | 1.58 | 0.94 | 2.74 | $-18.80$ |
| | (8.47) | (4.74) | (3.28) | (5.01) | (16.56) |
| IB-HFT CLIENT | $-83.33^{***}$ | $-82.31^{***}$ | $-93.47^{***}$ | $-180.84^{***}$ | $-69.47$ |
| | (31.91) | (24.46) | (21.86) | (38.03) | (74.95) |
| IB-HFT MM | $-21.36$ | $-33.25^{***}$ | $-18.64^{*}$ | $-90.20^{***}$ | $-120.63^{***}$ |
| | (13.55) | (9.10) | (11.02) | (20.05) | (44.56) |
| IB-HFT OWN | $-142.51^{**}$ | $-73.82$ | $-104.75^{***}$ | $-223.89^{***}$ | $-258.88^{*}$ |
| | (63.50) | (50.61) | (40.50) | (72.17) | (151.03) |
| IB-HFT PARENT | $-24.38^{**}$ | 6.66 | $-11.97$ | $-54.41^{**}$ | $-94.76^{***}$ |
| | (11.70) | (9.63) | (11.46) | (22.92) | (26.51) |
| Non-HFT CLIENT | $-37.17^{*}$ | $-34.61^{**}$ | $-42.10^{***}$ | $-115.68^{***}$ | $101.81^{*}$ |
| | (20.03) | (17.30) | (14.77) | (31.09) | (54.72) |
| Non-HFT OWN | $-17.61$ | $-81.14^{***}$ | $-75.74^{**}$ | $-59.55^{*}$ | $101.10^{*}$ |
| | (16.39) | (28.98) | (32.42) | (32.35) | (53.62) |

*Note.* This table reports the cross-sectional average, and standard errors in brackets, computed on the 65 flash crashes considered in this study, of the money invested in initiating trades measured in k€, in the five different periods of the crash described in Figure 2. Panel A: reports averages for HFT vs non-HFT. Panel B: reports averages for seven trading categories, as described in the main text.

imbalances of HFTs and Non-HFTs are significant and respectively negative and positive. Hence, in case of both simultaneous and non-simultaneous flash crashes, the price recovers after a crash mainly due to the activity of Non-HFTs. However, during the crash itself, net trading imbalances of HFTs and Non-HFTs are remarkably different.

If a crash is simultaneous, the net trading imbalance of HFTs is largely negative and highly significant for all phases of a crash. Net trading imbalance of Non-HFTs is also highly significant but positive. Hence, HFTs significantly contribute to a crash occurrence, development and the boom, while Non-HFTs provide liquidity to them. If a crash is non-simultaneous, net trading imbalances of HFTs and Non-HFTs take different signs at different phases of a crash, and they are not significantly different from zero. Such a difference is mainly a by-product of the heterogeneous activity of investment banks during simultaneous/non-simultaneous events. In particular, net trading imbalance of IB-HFT market

Table 4: Average money invested in liquidity supply trades (k€).

| | pre-crash | early crash | intermediate crash | late crash | recovery |
|---|---|---|---|---|---|
| HFT | 195.96** | 260.10*** | 185.42*** | 349.50*** | 40.24 |
| | (95.50) | (71.43) | (59.07) | (82.67) | (235.40) |
| Non-HFT | 167.01** | 76.87 | 188.53*** | 413.08*** | 358.07*** |
| | (75.39) | (55.03) | (49.74) | (71.72) | (98.64) |
| PURE-HFT CLIENT | 0.08 | 0.81* | 11.71 | 20.92 | −6.85 |
| | (2.45) | (0.46) | (8.67) | (14.96) | (8.77) |
| PURE-HFT MM | −2.64 | 32.11** | −1.12 | 30.46* | −26.25 |
| | (23.67) | (13.36) | (11.53) | (15.54) | (28.41) |
| PURE-HFT OWN | 0.14 | 0.65 | 5.80 | 3.34 | 18.77 |
| | (6.25) | (5.15) | (4.37) | (4.49) | (12.19) |
| IB-HFT CLIENT | 0.41 | 21.01 | −13.97 | 38.10 | 42.03 |
| | (25.57) | (23.72) | (18.65) | (37.83) | (101.91) |
| IB-HFT MM | 34.61 | 95.44*** | 68.00*** | 69.92*** | −67.91 |
| | (22.75) | (30.96) | (22.26) | (24.07) | (44.65) |
| IB-HFT OWN | 168.28** | 99.16** | 97.68** | 179.04*** | 73.21 |
| | (75.33) | (39.34) | (42.55) | (55.95) | (179.68) |
| IB-HFT PARENT | −4.60 | 10.92*** | 17.32*** | 7.72 | 7.45 |
| | (7.55) | (4.11) | (5.43) | (12.71) | (34.55) |
| Non-HFT CLIENT | 196.73** | 114.96*** | 151.73*** | 330.74*** | 191.39*** |
| | (79.57) | (36.83) | (31.25) | (57.92) | (61.31) |
| Non-HFT OWN | −29.74 | −26.61 | 36.79 | 82.84*** | 148.45** |
| | (26.33) | (32.26) | (35.05) | (32.14) | (60.83) |

*Note.* This table reports the cross-sectional average, and standard errors in brackets, computed on the 65 flash crashes considered in this study, of the money invested in liquidity providing trades measured in k€, in the five different periods of the crash described in Figure 2. Panel A: reports averages for HFT vs non-HFT. Panel B: reports averages for seven trading categories, as described in the main text.

makers is negative during simultaneous crashes, while it is positive during non-simultaneous events (the magnitude of the imbalance are mostly statistically significant, especially during the late phase of the crashes). IB-HFTs parents behave similarly to IB-HFT market makers: their imbalance is negative during simultaneous crashes, but positive during non-simultaneous ones. IB-HFTs clients, in contrast, demand a significant amount of liquidity during non-simultaneous flash crashes, and their imbalances are not significantly different from zero during simultaneous events. The activity of Non-HFTs also differs across the flash crash classes. Non-HFTs clients provide liquidity during both classes of crashes, however, the amount of liquidity provided statistically significant only during simultaneous crashes. Non-HFTs owners mainly sell during idiosyncratic crashes but provide liquidity during simultaneous ones. The activity of PURE-HFTs is not significant during both simultaneous and non-simultaneous events. In particular, net trading imbalances of PURE-HFTs

Table 5: Average monetary net trade imbalances (thousands of euros) during **simultaneous flash crashes**.

| | pre-crash | early crash | intermediate crash | late crash | recovery |
|---|---|---|---|---|---|
| HFT | $-307.04^{*}$ | $-221.96^{**}$ | $-337.17^{**}$ | $-690.01^{***}$ | $-423.24^{*}$ |
| | (180.57) | (104.78) | (133.90) | (143.85) | (217.02) |
| Non-HFT | $307.04^{*}$ | $221.96^{**}$ | $337.17^{**}$ | $690.01^{***}$ | $423.24^{*}$ |
| | (180.57) | (104.78) | (133.90) | (143.85) | (217.02) |
| PURE-HFT CLIENT | 0.00 | 0.00 | $-0.81$ | 0.00 | $4.59^{**}$ |
| | (0.00) | (0.00) | (0.81) | (0.00) | (2.12) |
| PURE-HFT MM | $-93.91$ | $-30.19$ | $-56.66$ | $-9.51$ | $-20.21$ |
| | (84.93) | (27.22) | (35.42) | (40.74) | (91.77) |
| PURE-HFT OWN | $-10.61$ | $-13.97$ | 23.56 | 5.09 | $-4.80$ |
| | (18.07) | (15.21) | (15.16) | (11.26) | (9.08) |
| IB-HFT CLIENT | 46.67 | $-63.82$ | $-24.92$ | $-131.34$ | 50.06 |
| | (46.67) | (58.68) | (29.78) | (117.05) | (75.37) |
| IB-HFT MM | $-109.00^{***}$ | $-64.50^{**}$ | $-42.05$ | $-277.40^{***}$ | $-444.55^{***}$ |
| | (36.24) | (31.64) | (43.72) | (58.84) | (117.88) |
| IB-HFT OWN | $-83.41$ | $-75.90$ | $-176.71^{**}$ | $-33.30$ | 233.37 |
| | (84.83) | (105.39) | (86.80) | (142.70) | (281.64) |
| IB-HFT PARENT | $-56.85^{*}$ | 26.42 | $-59.58^{*}$ | $-243.57^{***}$ | $-242.01^{***}$ |
| | (30.39) | (28.83) | (30.80) | (72.66) | (69.57) |
| Non-HFT CLIENT | $295.13^{*}$ | $204.32^{***}$ | $237.26^{***}$ | $486.28^{***}$ | 116.58 |
| | (161.10) | (78.30) | (69.43) | (104.10) | (126.02) |
| Non-HFT OWN | 11.92 | $53.39^{**}$ | 99.91 | $201.58^{**}$ | $253.78^{**}$ |
| | (61.55) | (22.11) | (114.06) | (89.87) | (113.46) |

*Note.* This table reports the cross-sectional average, and standard errors in brackets, computed on the 22 flash crashes (out of 65) that happen simultaneously, of the trade imbalance measured in k€, in the five different periods of the crash described in Figure 2. Panel A: reports averages for HFT vs non-HFT. Panel B: reports averages for seven trading categories, as described in the main text.

market makers are mostly negative, though insignificant, at all stages of the crashes.

Overall, Tables 5 and 6 suggest that IB-HFTs market makers provide liquidity during idiosyncratic crashes by absorbing imbalances created IB-HFTs clients and Non-HFTs owners. But when several stocks experience simultaneous flash crash, liquidity demand IB-HFTs market makers strongly dominates their liquidity supply. Other HFT trading firms are not particularly active during both simultaneous and non-simultaneous events. In particular, designated market makers do not provide liquidity during price downfall.

Table 6: Average trade imbalances (thousands of euros) during **non-simultaneous flash crashes**.

| | pre-crash | early crash | intermediate crash | late crash | recovery |
|---|---|---|---|---|---|
| HFT | $-13.00$ | $172.97^{**}$ | $65.66$ | $-6.51$ | $-605.67^{***}$ |
| | (89.77) | (85.46) | (57.46) | (85.84) | (224.48) |
| Non-HFT | $13.00$ | $-172.97^{**}$ | $-65.66$ | $6.51$ | $605.67^{***}$ |
| | (89.77) | (85.46) | (57.46) | (85.84) | (224.48) |
| PURE-HFT CLIENT | $3.76$ | $3.30$ | $18.51$ | $29.52$ | $0.64$ |
| | (4.88) | (8.84) | (13.14) | (27.26) | (13.00) |
| PURE-HFT MM | $-7.44$ | $1.97$ | $-15.75$ | $-9.75$ | $-75.35$ |
| | (28.18) | (21.15) | (25.68) | (34.73) | (50.83) |
| PURE-HFT OWN | $-2.40$ | $10.52$ | $-1.86$ | $6.58$ | $2.41$ |
| | (14.57) | (10.62) | (4.14) | (8.63) | (21.44) |
| IB-HFT CLIENT | $-149.22^{**}$ | $-60.01$ | $-149.67^{***}$ | $-148.56^{**}$ | $-67.09$ |
| | (59.01) | (40.96) | (46.68) | (69.46) | (232.13) |
| IB-HFT MM | $75.79^{**}$ | $127.01^{***}$ | $96.13^{***}$ | $111.27^{***}$ | $-57.57$ |
| | (35.39) | (45.73) | (33.35) | (27.96) | (82.27) |
| IB-HFT OWN | $81.63$ | $77.13$ | $79.72$ | $-50.76$ | $-400.06^{**}$ |
| | (89.51) | (62.17) | (60.16) | (87.45) | (160.95) |
| IB-HFT PARENT | $-14.72$ | $13.05$ | $38.57^{***}$ | $54.04^{***}$ | $-8.16$ |
| | (14.70) | (10.21) | (10.78) | (15.82) | (51.27) |
| Non-HFT CLIENT | $90.20$ | $16.93$ | $44.33$ | $76.29$ | $383.56^{***}$ |
| | (103.81) | (39.86) | (28.91) | (68.07) | (137.71) |
| Non-HFT OWN | $-77.67^{*}$ | $-190.18^{**}$ | $-110.00^{*}$ | $-67.93$ | $247.38^{*}$ |
| | (42.12) | (75.27) | (59.27) | (54.98) | (133.28) |

*Note.* This table reports the cross-sectional average, and standard errors in brackets, computed on the 43 flash crashes (out of 65) that do not happen simultaneously, of the trade imbalance measured in k€, in the five different periods of the crash described in Figure 2. Panel A: reports averages for HFT vs non-HFT. Panel B: reports averages for seven trading categories, as described in the main text.

## 4.2 Directional liquidity provision during flash crashes

In order to understand who is supplying and who is demanding liquidity during flash crashes, for each flash crash phase, and for each trader category, we compute the average volume invested in trades initiated by the other market participants relative to the total trading volume. Herein we distinguish between trades initiated by buyers and sellers. Hence, traders supplying liquidity for trades initiated by sellers during price drops are the ones who are trying to prevent the crash. In order to compare the amounts of liquidity provided, we represent the relative volumes in the form of directional network graphs. The vertices represent different categorized market participants. The direction of arrows shows the direction of liquidity provision (for example, an arrow from a node labeled as IB-HFT market makers to a node labeled as IB-HFT

own illustrates the amount of liquidity provided by IB-HFT market makers to IB-HFT own), while the width of the arrow indicates the relative amount of liquidity provided.

Figure 4 illustrates liquidity provision at different phases of different types of flash crashes. The rows correspond to 5 stages of flash crashes, from the pre-crash to the recovery. The columns correspond to different types of flash crashes. Column A shows the result based on a control sample, which is constituted by days preceding the considered flash crashes. For each of these days, the sample period for computing the liquidity provision coincide with the time of recovery phase of a next day flash crash. Columns B, C and D illustrate liquidity provision during an average flash crash, an average simultaneous flash crash and an average non-simultaneous flash crash respectively.

Column B of Figure 4 illustrates liquidity provision (liquidity provided to a seller) at different stages of an average flash crash. It shows that before a crash occurs PURE-HFT market makers are the largest liquidity providers as they are meant to be. They provide liquidity mainly to IB-HFT owners, who, in their turn, provide liquidity mainly to PURE-HFT market makers and Non-HFT clients. During an early crash, the role of PURE-HFT market makers changes. Non-HFT owners start demanding a lot of liquidity, which is supplied by IB-HFT owners. Instead, liquidity provided by PURE-HFT market makers reduces in relative terms, but their liquidity demand rises. This situation is aggravating as a crash develops. IB-HFT clients start to demand a large portion of liquidity. PURE-HFT market makers provide liquidity mainly to themselves and consume liquidity provided by IB-HFT owners. Finally, at the late phase of a crash, IB-HFT owners stay the major liquidity providers, supplying liquidity to PURE-HFT market makers and IB-HFT clients. Overall, Column B of Figure 4 clearly shows that designated market makers do not cope with their duties during flash crashes.

Column C and D of Figure 4 illustrate liquidity provision during different flash crash stages of simultaneous and non-simultaneous events respectively. In line from what discussed above, simultaneous flash crashes are remarkably different from non-simultaneous ones, especially with respect to the activity of market makers. If a crash occurs in many stocks simultaneously, PURE-HFT and IB-HFT market makers consume a significant fraction of liquidity provided by IB-HFT owners, Non-HFTs and PURE HFT market makers themselves. During the early crash, IB-HFT owners provide a significant amount of liquidity to Non-HFT parents and IB-HFT clients, who contribute to the emergence of a crash. However, at the later stages of a crash, PURE HFT and IB-HFT market makers become the largest liquidity consumers. This confirms the findings of the previous section, which suggests that during simultaneous crashes HFT market makers behave opportunistically instead of providing liquidity. The largest liquidity consumers during idiosyncratic flash crashes are Non-HFT owners, Non-HFT clients, PURE-HFT market makers and IB-HFT clients, while the largest liquidity providers are IB-HFT owners. Both IB-HFT and PURE-HFT market makers tend to provide relatively much less amount of liquidity. The difference in their behavior consists of the level of liquidity demand, which is low for IB-HFT market makers and high for PURE-HFT market makers.

Table 7: Who initiates the crash?

| | rate of crash initiation (%) | rate of liquidity provision (%) | overlap (%) |
|---|---|---|---|
| HFT | 73.85 | 60.00 | 7.69 |
| Non-HFT | 26.15 | 40.00 | 1.54 |
| PURE-HFT MM | 12.31 | 6.15 | 0.00 |
| IB-HFT CLIENT | 15.38 | 3.08 | 1.54 |
| IB-HFT MM | 6.15 | 15.38 | 0.00 |
| IB-HFT OWN | 36.92 | 35.38 | 6.15 |
| IB-HFT PARENT | 3.08 | 0.00 | 0.00 |
| Non-HFT CLIENT | 12.31 | 35.38 | 1.54 |
| Non-HFT OWN | 13.85 | 4.62 | 0.00 |

*Note.* The column "rate of crash initiation" reports the fraction of events for which the category is the largest seller on initiating trades in the pre-crash period. The column "rate of liquidity provision" reports the fraction of the events for which the category is the largest buyer on liquidity providing trades. The column "overlap" reports the fraction of the events for which the category is simultaneously the largest buyer on liquidity providing trades and the largest seller on initiating trades.

The bottom panel of Figure 4 illustrates liquidity provision during the price recovery phase of different flash crashes. In contrast to the other panels, the graphs at the bottom panel show liquidity supplied for trades initiated by sellers, who procure price recovery. Altogether the bottom panels of Figure 4 suggest that the structure of liquidity provision during recovery in relative terms is similar to the liquidity provision during calm periods.

### 4.3 Who is the largest seller?

Which category of traders is more likely to originate the crash? In order to answer this question, and also to identify which category is providing liquidity to large sellers, we compare, for each of the 65 events, the signed volume of aggressive and passive trades during the pre-crash and early crash periods, across different categories of market participants. More precisely, we proceed as follows. For each crash, we compute the signed money invested (negative = sell) on initiated trades and liquidity providing trades, for each trading category from the beginning of the pre-crash period to the end of the early crash period. For each flash crash, we identify the trading category with the largest negative value on initiating trades, and we consider this category responsible for the crash (the largest seller before crash starts), and the largest positive value on liquidity providing trades, and we consider this category as the one absorbing the sell order (the largest buyer before crash starts).

Table 7 shows the percentage of flash crashes in which a particular trader category constitutes the largest sellers and the largest liquidity providers. It shows that HFTs are responsible (in the sense that they sell the largest amount of the

asset) for the absolute majority of the flash crashes (73.85%). In particular, most often the larger sellers are HFTs who are investment banks (IB-HFT) trading from their own account. They are responsible for 36.92% of flash crashes. The second largest sellers are Non-HFT (considered as a single category), who are responsible for (26.15%) of flash crashes. Designated HFTs (PURE-HFT) market makers and investment bank HFTs (IB-HFT) market makers play the role of the larges sellers in respectively 12.31% and 6.15% of the cases. In the majority of cases, the largest liquidity providers are IB-HFT owner and Non-HFT clients – 35.38% for both. Therefore, the category of market participants who are selling more during the beginning of a crash (IB-HFT owners) corresponds to the category of traders which is, at the same time, more frequently responsible for a crash occurrence. IB-HFT and PURE-HFT market makers appear to be the largest liquidity providers only in 15.38% and 6.15% of the cases. Thus, Table 7 shows that HFTs do provide some liquidity, but they also initiate large selling, and more often that the frequency of events in which they act as the main liquidity providers.

# 5 Conclusions

In this paper, we investigate the role of high frequency trading during flash crashes. Using a methodology proposed by Christensen, Oomen, and Renò (2017) we detect 65 flash crashes in one year of liquid French stocks. The granularity of our database allow us to distinguish between PURE-HFT i.e. traders that use high frequency trading but with almost zero inventories at the end of the day (that is with limited inventory capacity), and IB-HFT, that also use high frequency trading but do not have the constraint to have zero inventory at the end of the day. Importantly, PURE-HFT have been largely investigated in the literature, while IB-HFT to a much lesser extent. Our analysis shows that HFT, and in particular IB-HFT, do play a significant role in causing flash crashes. Moreover, they do not even help with the recovery. Regarding designated market makers, both PURE-HFT and IB-HFT market makers do not play any systematic role in providing liquidity during these events, differently on what they are usually doing in "tranquil" phases. The only category that mostly tries to prevent the crash and support the recovery is the Non-HFT.

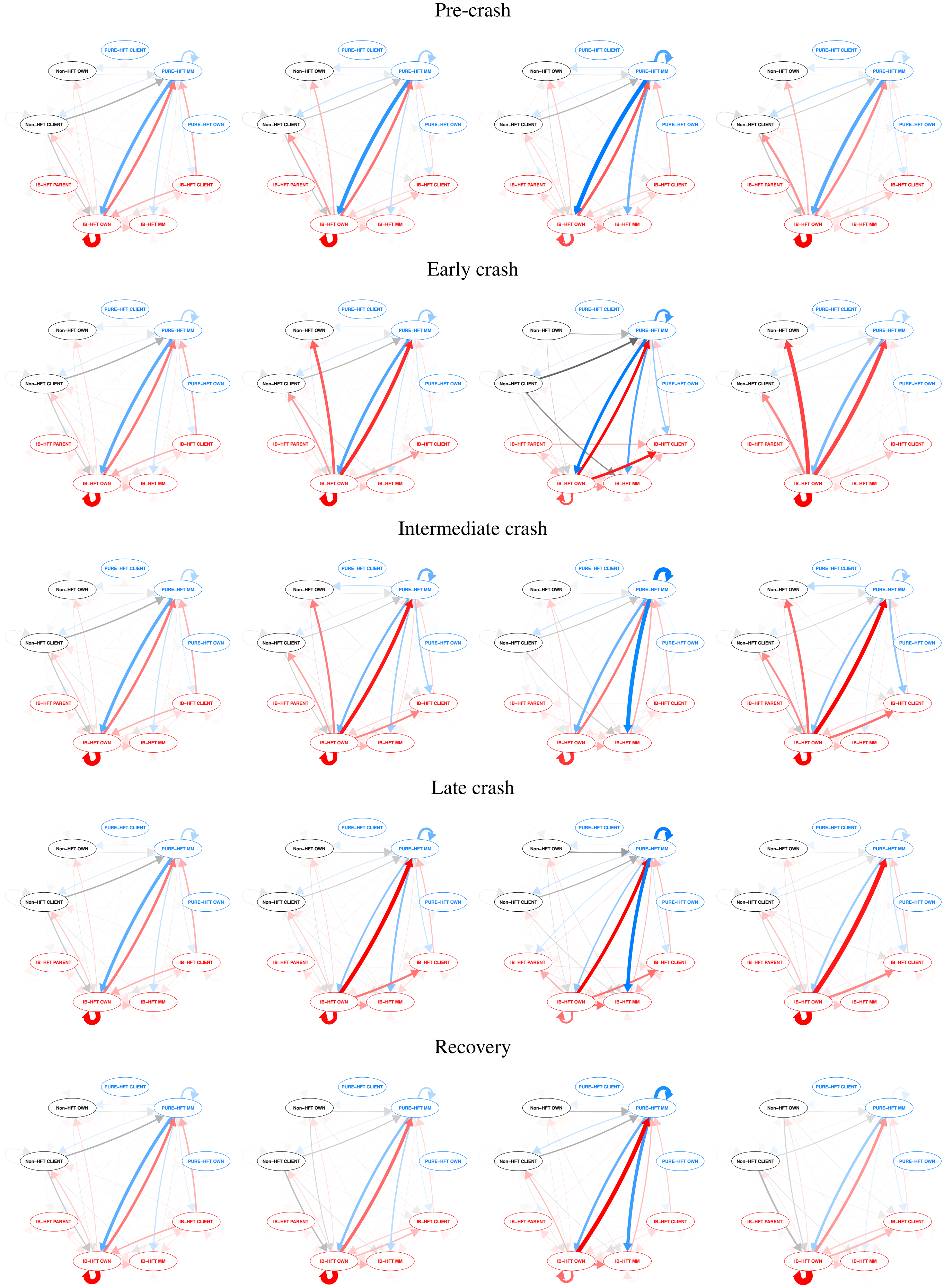
Moreover, our analysis also shows that one story does not fit all the cases. There is a large heterogeneity across the different crashes in terms of the behavior of the different traders. However, given the clearly cut contribution to the flash crashes of IB-HFT documented in this paper, we conclude that this category could be potentially included in the hall of shame. Instead, Non-HFT seems to feet well with the walk of fame.

Our study delivers important insights for market participants and policy makers. For market participants, we show that there is not a single category that trades opportunistically to either avoid to trade during crashes, or to push the price down. We do not find a regular pattern for any of the different categories, but there are some of them that do directly cause

or collaborate to generate crashes more often than others. This is, again, particularly true for IB-HFTs. For policy makers, our study recommends a deeper evaluation of the the recent MiFID II. In fact, MiFiD II recognized algorithmic liquidity provision as pivotal to the sound functioning of financial markets. The new regulation specifically endorses the automatic liquidity provision by electronic market makers, imposing specific binding agreements between the exchange and the trading firms. What our analysis shows is that this rule, already in place at the NYSE Euronext Paris stock exchange, is not sufficient to prevent flash crashes.

Figure 4: Liquidity provided for trades initiated by a **seller** during different flash crashes.

| Column A | Column B | Column C | Columnd D |
|---|---|---|---|
| Control sample. | Average flash crash. | Simultaneous flash crashes. | Non-simultaneous flash crash. |




*Note.* This figure shows the directional network graph representing the relative amount of liquidity provided for trades initiated by a buyer during the price recovery phase of different flash crashes.

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# A Appendix: Additional tables

Tables 8 provides the detailed list of the 65 flash crash events in our sample. For each event it shows the date and time (of the crash beginning and the peak) of a flash crash occurrence, the duration of a flash crash and the name and isin code of a corresponding stock.

Table 9 reports a summary of the detected flash crashes groped according to each stock. It shows that in our sample flash crashes occur in 30 different stocks. The number of flash crashes per year ranges from 1 to 5 with an average rate of 2.2 events per year. For 9 stocks flash crashes occur only once. The largest number of crashes per year (five events) correspond to Société Générale.

Table 8: Flash Crash Events constituting the distressed sample

| Date | Isin | Company | Time Begin | Time Peak | Duration (min:sec) |
|---|---|---|---|---|---|
| 8-Jan | FR0010220475 | Alstom | 14:47:54 | 15:03:40 | 15:46 |
| 9-Jan | FR0000120172 | Carrefour | 10:07:42 | 10:25:18 | 17:36 |
| 14-Jan | FR0000125338 | Cap Gémini | 16:45:52 | 16:52:20 | 06:28 |
| 22-Jan | FR0000121261 | Michelin B | 09:54:07 | 10:06:05 | 11:58 |
| 29-Jan | FR0000045072 | Credit Agricole | 10:02:42 | 10:15:25 | 12:43 |
| 31-Jan | FR0000120644 | Danone | 11:54:52 | 12:12:21 | 17:29 |
| 11-Feb | FR0000120578 | Sanofi Synthélabo | 15:31:45 | 15:36:10 | 04:25 |
| 20-Feb | FR0000133308 | Orange | 09:32:28 | 09:49:00 | 16:32 |
| 26-Feb | NL0000235190 | EADS | 16:29:03 | 16:38:35 | 09:32 |
| 6-Mar | FR0000133308 | Orange | 15:22:29 | 15:24:25 | 01:56 |
| 7-Mar | FR0000130809 | Société Générale | 10:42:26 | 10:49:45 | 07:19 |
| 8-Mar | FR0000125338 | Cap Gémini | 13:59:34 | 14:10:35 | 11:01 |
| 12-Mar | FR0000121261 | Michelin B | 16:22:32 | 16:28:04 | 05:32 |
| 21-Mar | FR0000125338 | Cap Gémini | 15:15:37 | 15:33:26 | 17:49 |
| 26-Mar | FR0000073272 | Safran | 12:50:52 | 13:06:22 | 15:30 |
| 5-Apr | FR0000120073 | Air Liquide | 11:47:43 | 11:53:20 | 05:37 |
| 5-Apr | FR0000131104 | BNP | 11:49:35 | 11:53:15 | 03:40 |
| 16-Apr | FR0010208488 | ENGIE | 12:36:04 | 12:47:55 | 11:51 |
| 17-Apr | FR0000121972 | Schneider | 09:30:00 | 09:51:29 | 21:29 |
| 17-Apr | FR0010220475 | Alstom | 09:30:01 | 09:51:26 | 21:25 |
| 17-Apr | FR0000120354 | Vallourec | 09:30:02 | 09:51:25 | 21:23 |
| 17-Apr | FR0000120271 | Total | 09:30:09 | 09:51:34 | 21:25 |
| 17-Apr | FR0000125486 | Vinci | 09:30:09 | 09:51:45 | 21:36 |
| 17-Apr | FR0000120073 | Air Liquide | 09:41:34 | 09:51:30 | 09:56 |
| 17-Apr | FR0000120172 | Carrefour | 09:42:34 | 09:51:29 | 08:55 |
| 17-Apr | FR0000121261 | Michelin B | 09:42:50 | 09:51:40 | 08:50 |
| 17-Apr | FR0000120628 | Axa | 09:42:50 | 09:51:45 | 08:55 |
| 17-Apr | FR0000127771 | Vivendi Universal | 09:42:54 | 09:51:24 | 08:30 |
| 17-Apr | FR0000120578 | Sanofi Synthélabo | 09:42:55 | 09:51:30 | 08:35 |
| 17-Apr | FR0010208488 | ENGIE | 09:44:54 | 09:51:34 | 06:40 |
| 26-Apr | FR0000120693 | Pernod Ricard | 10:18:56 | 10:27:19 | 08:23 |
| 29-Apr | FR0000127771 | Vivendi Universal | 13:55:11 | 14:02:29 | 07:18 |
| 30-Apr | FR0000127771 | Vivendi Universal | 15:48:25 | 15:57:40 | 09:15 |
| 7-May | FR0000121972 | Schneider | 12:17:56 | 12:27:00 | 09:04 |
| 5-Jun | FR0000120172 | Carrefour | 11:23:47 | 11:26:35 | 02:48 |
| 24-Jun | FR0000125007 | Saint-Gobain | 10:15:02 | 10:33:25 | 18:23 |
| 24-Jun | FR0000130809 | Société Générale | 10:15:26 | 10:33:25 | 17:59 |
| 23-Jul | FR0010220475 | Alstom | 11:18:39 | 11:22:57 | 04:18 |
| 20-Aug | FR0000120537 | Lafarge | 09:54:11 | 10:07:20 | 13:09 |
| 27-Aug | FR0000120537 | Lafarge | 09:44:47 | 09:51:56 | 07:09 |
| 29-Aug | FR0000120693 | Pernod Ricard | 12:25:04 | 12:59:15 | 34:11 |
| 29-Aug | FR0000121667 | Essilor International | 15:01:36 | 15:04:20 | 02:44 |
| 3-Sep | FR0000125007 | Saint-Gobain | 10:51:03 | 10:55:04 | 04:01 |
| 3-Sep | FR0000120073 | Air Liquide | 10:51:15 | 10:54:55 | 03:40 |
| 3-Sep | FR0000121972 | Schneider | 10:52:38 | 10:55:07 | 02:29 |
| 3-Sep | NL0000235190 | EADS | 10:52:56 | 10:54:55 | 01:59 |
| 3-Sep | FR0000120271 | Total | 10:53:00 | 10:54:55 | 01:55 |
| 3-Sep | FR0000130809 | Société Générale | 10:53:18 | 10:55:10 | 01:52 |
| 6-Sep | FR0000121014 | LVMH Moet Henessy | 15:39:26 | 15:47:35 | 08:09 |
| 17-Sep | FR0000120354 | Vallourec | 16:37:51 | 16:40:15 | 02:24 |
| 20-Sep | FR0010208488 | ENGIE | 10:37:10 | 10:40:05 | 02:55 |
| 24-Sep | FR0000121261 | Michelin B | 15:25:05 | 15:30:00 | 04:55 |
| 2-Oct | FR0000121667 | Essilor International | 15:21:32 | 15:28:50 | 07:18 |
| 25-Oct | FR0000120628 | Axa | 15:31:14 | 15:47:16 | 16:02 |
| 28-Oct | FR0000120628 | Axa | 13:00:01 | 13:11:11 | 11:10 |
| 28-Oct | FR0000125486 | Vinci | 17:25:06 | 17:29:35 | 04:29 |
| 29-Oct | FR0000124141 | Veolia Environnement | 09:29:59 | 09:40:05 | 10:06 |
| 5-Nov | FR0000130809 | Société Générale | 14:46:45 | 14:50:15 | 03:30 |
| 7-Nov | FR0000130809 | Société Générale | 16:32:20 | 16:36:35 | 04:15 |
| 20-Nov | FR0000131708 | Technip | 15:37:23 | 16:09:40 | 32:17 |
| 21-Nov | NL0000226223 | STMicroelectronics | 13:56:25 | 13:58:30 | 02:05 |
| 26-Nov | FR0000120404 | Accor | 11:49:31 | 11:59:05 | 09:34 |
| 26-Nov | FR0000121667 | Essilor International | 16:37:43 | 16:41:02 | 03:19 |
| 3-Dec | FR0000131906 | Renault | 10:09:54 | 10:13:25 | 03:31 |
| 17-Dec | FR0000120404 | Accor | 11:05:41 | 11:16:16 | 10:35 |

*Note.* The table reports the detailed list of the 65 flash crash events in our sample. For each event it shows the date and time (of the crash beginning and the peak) of a flash crash occurrence, the duration of a flash crash and the name and isin code of a corresponding stock.

Table 9: Summary of Flash Crashes grouped by stocks

| Isin | Name | Market Cap (M Euro) | Average daily trading (N. trades) | Average daily volume (M Euro) | No. DBs | Mean return | Median return | Std return | Mean Duration | Median Duration | Std Duration |
|---|---|---|---|---|---|---|---|---|---|---|---|
| FR0000045072 | Credit Agricole | 23'221 | 12'774 | 88 | 1 | -1.62 | -1.62 | 0.00 | 12.70 | 12.70 | 0.00 |
| FR0000073272 | Safran | 21'064 | 8'569 | 60 | 1 | -0.96 | -0.96 | 0.00 | 15.53 | 15.53 | 0.00 |
| FR0000120073 | Air Liquide | 32'047 | 12'821 | 128 | 3 | -0.99 | -0.95 | 0.27 | 6.37 | 5.50 | 3.24 |
| FR0000120172 | Carrefour | 20'858 | 13'152 | 116 | 3 | -2.04 | -1.99 | 0.58 | 9.72 | 8.97 | 7.54 |
| FR0000120271 | Total | 145'995 | 26'025 | 348 | 2 | -1.19 | -1.19 | 0.38 | 5.49 | 5.49 | 5.01 |
| FR0000120354 | Vallourec | 5'035 | 9'902 | 51 | 2 | -2.22 | -2.22 | 2.08 | 26.89 | 26.89 | 34.71 |
| FR0000120404 | Accor | 7'822 | 7'872 | 49 | 2 | -0.72 | -0.72 | 0.02 | 9.10 | 9.10 | 2.07 |
| FR0000120537 | Lafarge | 15'652 | 11'512 | 76 | 2 | -1.63 | -1.63 | 0.01 | 10.22 | 10.22 | 4.31 |
| FR0000120578 | Sanofi Synthélabo | 101'851 | 27'238 | 400 | 2 | -1.25 | -1.25 | 0.96 | 6.30 | 6.30 | 3.18 |
| FR0000120628 | Axa | 48'784 | 19'042 | 200 | 3 | -1.45 | -1.02 | 0.84 | 11.95 | 11.03 | 3.69 |
| FR0000120644 | Danone | 30'688 | 14'526 | 176 | 1 | -1.44 | -1.44 | 0.00 | 17.42 | 17.42 | 0.00 |
| FR0000120693 | Pernod Ricard | 21'799 | 10'385 | 96 | 2 | -1.37 | -1.37 | 0.80 | 21.31 | 21.31 | 18.23 |
| FR0000121014 | LVMH Moet Henessy | 66'353 | 13'133 | 200 | 1 | -1.52 | -1.52 | 0.00 | 8.15 | 8.15 | 0.00 |
| FR0000121261 | Michelin B | 14'350 | 12'618 | 99 | 4 | -1.27 | -1.31 | 0.63 | 7.80 | 7.20 | 3.28 |
| FR0000121667 | Essilor International | 16'592 | 10'950 | 86 | 3 | -0.95 | -0.88 | 0.17 | 4.29 | 2.88 | 2.58 |
| FR0000121972 | Schneider | 35'628 | 16'767 | 164 | 3 | -2.31 | -1.34 | 2.07 | 21.01 | 9.10 | 26.62 |
| FR0000124141 | Veolia Environnement | 6'338 | 10'989 | 68 | 1 | -3.58 | -3.58 | 0.00 | 40.15 | 40.15 | 0.00 |
| FR0000125007 | Saint-Gobain | 22'193 | 13'639 | 116 | 2 | -1.71 | -1.71 | 0.17 | 11.14 | 11.14 | 10.15 |
| FR0000125338 | Cap Gémini | 7'876 | 9'677 | 61 | 3 | -1.03 | -0.93 | 0.21 | 11.76 | 11.03 | 5.73 |
| FR0000125486 | Vinci | 28'713 | 14'361 | 124 | 2 | -1.28 | -1.28 | 1.13 | 13.08 | 13.08 | 12.08 |
| FR0000127771 | Vivendi Universal | 25'660 | 13'320 | 143 | 3 | -1.40 | -1.34 | 0.15 | 8.40 | 8.63 | 1.00 |
| FR0000130809 | Société Générale | 33'722 | 32'204 | 317 | 5 | -1.81 | -1.67 | 0.97 | 6.88 | 4.07 | 6.49 |
| FR0000131104 | BNP | 70'354 | 33'015 | 364 | 1 | -0.94 | -0.94 | 0.00 | 3.62 | 3.62 | 0.00 |
| FR0000131708 | Technip | 7'942 | 10'665 | 75 | 1 | -1.15 | -1.15 | 0.00 | 32.28 | 32.28 | 0.00 |
| FR0000131906 | Renault | 17'064 | 14'722 | 118 | 1 | -1.34 | -1.34 | 0.00 | 3.57 | 3.57 | 0.00 |
| FR0000133308 | Orange | 23'630 | 21'114 | 167 | 2 | -1.85 | -1.85 | 1.44 | 9.16 | 9.16 | 10.29 |
| FR0010208488 | ENGIE | 40'349 | 13'831 | 148 | 3 | -1.98 | -1.60 | 0.81 | 6.52 | 6.67 | 3.56 |
| FR0010220475 | Alstom | 8'126 | 11'838 | 81 | 3 | -3.25 | -4.27 | 1.76 | 39.39 | 51.47 | 20.92 |
| NL0000226223 | STMicroelectronics | 7'098 | 8'668 | 44 | 1 | -1.25 | -1.25 | 0.00 | 2.05 | 2.05 | 0.00 |
| NL0000235190 | EADS | 43'550 | 20'886 | 212 | 2 | -0.98 | -0.98 | 0.16 | 5.72 | 5.72 | 5.28 |

*Note.* This table reports summary of Flash Crashes, which occurred in 30 different stocks during the year 2013. For each stock, which experienced a flash crash, the table reports average yearly market capitalization, average daily number of trades and trading volume, the number of detected events, mean, median and standard deviation of flash crash durations and of the price drop during the crash.