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# Do Designated Market Makers Provide Liquidity During a Flash Crash?

SAFE Working Paper No. 270

# Do designated market makers provide liquidity during a flash crash?\*

Mario Bellia    Kim Christensen    Aleksey Kolokolov    Loriana Pelizzon  
Roberto Renò

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## Abstract

We show that (electronic) designated market makers are not necessarily beneficial to the stock market during flash crashes. They actually consume liquidity when it is most needed, even if they are rewarded by the exchange to provide immediacy. This behavior exacerbates the transient price impact, unrelated to fundamentals, typically observed during a flash crash. In their place, slow traders provide liquidity, taking advantage of the discounted price. We thus uncover a trade-off between the greater liquidity and efficiency provided by designated market makers in normal times, and the disruptive consequences of their quoting/trading activity during distressed times.

**JEL Classification:** G10, G14.

**Keywords:** flash crashes; designated market makers (DMMs); high-frequency traders (HFTs); market fragility.

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# 1 Introduction

Market making is a fundamental service that facilitates the allocation of wealth and transfer of risk in financial markets with search costs. Although any financial intermediary can in principle supply liquidity on a voluntarily basis, nowadays market making is overwhelmingly managed via electronic trading. Among electronic traders, some may adopt the role of “designated market maker” (DMM) by entering into a binding agreement with the exchange to supply liquidity (the exact role of DMMs in the market and the details of such agreements vary across exchanges).

This paper studies liquidity provision by electronic DMMs during flash crashes (events such as the Flash Crash of May 6, 2010) to examine whether they are in keeping with their agreement with the exchange during episodes of severe market distress. In contrast to [Anand and Venkataraman \(2016\)](#), [Clark-Joseph, Ye, and Zi \(2017\)](#) and [Bessembinder, Hao, and Zheng \(2020\)](#), who find that DMMs alleviate the effects of illiquidity shocks, we show that DMMs do not mitigate these effects during flash crashes. We actually document that DMMs reinforce the transient price change associated with these disruptive events. In particular, we find that, on average, DMMs do not provide enough liquidity to avoid flash crashes occurring in isolated stocks, and that they even consume liquidity when crashes affect several stocks at once. In their place, liquidity is endogenously provided by traditional “slow” traders, who take advantage of the discounted price.

Our findings can be reconciled by several mechanisms suggested by the existing literature on liquidity provision, mostly put forward to explain the behavior of High Frequency Traders (HFTs), who typically largely overlap with DMMs. For example, [van Kervel and Menkveld \(2019\)](#) document a “leaning-with-the-wind” behavior of HFTs during institutional orders. They motivate this by the strategic attempt of HFTs to profit on private information. An alternative explanation is offered by [Cespa and Vives \(2022\)](#), who show that liquidity providers may lean-with-the-wind if the market lacks transparency (modeled by a private endowment shock, which motivates the initial seller to change her optimal asset allocation). In these circumstances, the fear of trading against private information overshadows the foreseen revenue earned by providing liquidity, which increases market fragility.

Our analysis is performed on a unique data-set, obtained from the BEDOFIH database,<sup>1</sup> of tick-by-tick order-level data on 37 liquid French stocks belonging to the CAC40 index and traded on NYSE-Euronext Paris in 2013. The main feature of this dataset is its granularity that permits to uncover the role of different market participants, including DMMs and HFTs, during market distress. Indeed, order and trade data come with a flag indicating the trader class (slow or HFT) and the participation to the designated market making scheme (flagged MM), as determined by the French market authority (AMF, 2017), as well as the trader account provided by NYSE-Euronext. Another distinctive feature of our study is the definition of a “flash crash”, or “mini flash crashes” (Biais and Foucault, 2014), or more broadly of market distress. We rely on the econometric “drift burst” approach of Christensen, Oomen, and Renò (2022), which identifies periods where the price is trending sharply.

We investigate in detail the behavior of different group of traders during the events detected by this test. We show that flash crashes are mostly originated either by proprietary trading of investment banks, or by clients trading from investment banks via sponsored access,<sup>2</sup> and that this trading is, on average, informed. The crash is then magnified by the reaction of investment bank DMMs, especially when crashes are systematic, i.e. when they affect several stocks simultaneously. Pure HFT firms, both those having the role of DMMs in this market and those that voluntarily provide liquidity, contribute to the price decline with their quoting activity. One direct policy implication is thus that the compensation scheme offered by the exchange is not always a sufficient incentive for DMMs (neither of investment banks nor of pure HFT firms) to prevent, halt or even attenuate flash crashes.

These results provide new insights to the recent literature on electronic liquidity provision under distress market conditions, which is mainly focused on the behavior of algorithmic traders, and in particular HFTs. The literature has broadly suggested that the presence of electronic traders enhances both market efficiency (see, e.g., Chaboud, Chiquoine, Hjalmarsson, and Vega, 2014) and market liquidity (see, e.g. Hendershott, Jones, and Menkveld, 2011; Jones, 2013). However, the beneficial impact of algorithmic trading on market liquidity has recently

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<sup>1</sup>[www.eurofidai.org/en/high-frequency-data-bedofih](http://www.eurofidai.org/en/high-frequency-data-bedofih).

<sup>2</sup>We refer to “client” access when the Euronext member is granting access to the market via an Automated Routing System or a sponsored access. A detailed overview of the traders’ classes is presented in Section 2.

been challenged,<sup>3</sup> in particular in distressed market conditions. Kirilenko, Kyle, Samadi, and Tuzun (2017) could not find a change in the trading pattern of HFTs when prices of the E-mini S&P 500 stock index futures contract fell sharply during the Flash Crash on May 6, 2010. On our data, we show that this is not always true, since DMMs (including HFTs in the sense intended by Kirilenko et al., 2017) are found to exacerbate the price drop via their trading and quoting activity, especially for systematic crashes affecting several stocks. Regarding the specific role of DMMs, Anand and Venkataraman (2016) show, as we do, that market makers (mostly HFTs) scale back in unison when market conditions are unfavorable. However, they show that DMMs mitigate illiquidity when HFTs withdraw synchronously from the market. By contrast, our results show that DMMs are not always maintaining liquidity provision, and can actually reverse it, when illiquidity spreads across several stocks. A change in HFT behavior during distress is also documented by Hautsch, Noè, and Zhang (2017), who study high-impact news-driven events, and Megarbane, Saliba, Lehalle, and Rosenbaum (2018), who study releases of macroeconomic information also for stocks belonging to the CAC40 index. We differ from these contributions by the ability to describe the behavior of granular trader groups (in particular, DMMs) during market distress as defined by price records, instead of public announcements.

A related study is Brogaard, Carrion, Moyaert, Riordan, Shkillo, and Sokolov (2018), who use high-frequency price records to study HFTs during “extreme price movements” (EPMs). Our work is complementary to their analysis along different dimensions. First, the highly directional and sustained price trends experienced during flash crashes cannot be ascribed to EPMs, since the latter interpretation merely implies a wider price dispersion and materializes as large market volatility or jumps, but not as a *directional* move. Second, flash crashes can be associated with known market frictions, such as large trading imbalances with low market depth (Grossman and Miller, 1988), asymmetric information (Barlevy and Veronesi, 2003), costly market presence (Huang and Wang, 2009), or predatory trading (Brunnermeier and Pedersen, 2005). Third, flash crashes allow to identify a sample of distressed events covering a relatively short time span that

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<sup>3</sup>For example, Anand and Venkataraman (2016) show that liquidity provision is highly correlated among high-frequency traders (HFTs, see Section 2.2 for a definition of this category), which increases market fragility. Furthermore, van Kervel and Menkveld (2019) and Korajczyk and Murphy (2019) show that HFTs increase the cost of large institutional trades.

did not trigger a trading halt. This feature is shared with the EPMS of Brogaard et al. (2018). However, as we show in Section 3 and Appendix A, the volatility-based EPMS are a different sample compared to flash crashes, with limited overlap. Fourth, our procedure identifies the exact crash peak time and disentangles various phases of a flash crash, such as the beginning of the price drop and the subsequent recovery. Finally, Brogaard et al. (2018) conclude that HFTs do provide liquidity, on average, during EPMS, but they switch to the demand side if several stocks are affected. However, they do not disentangle endogenous from designated liquidity provision as we do.

In comparison to van Kervel and Menkveld (2019), this paper provides several additional contributions. First, we document that DMMs “lean-with-the-wind” also during flash crashes. Second, we show that this mostly happens during systematic flash crashes. Third, we disentangle the role of pure HFT DMMs from that of investment bank DMMs. Finally, while according to van Kervel and Menkveld (2019) leaning-with-the-wind during institutional orders makes the market more efficient in the short run, our results suggest that the behavior of DMMs during flash crashes makes the market less efficient in the short run.

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. An Appendix contains additional results and statistical analysis.

## 2 Data description

### 2.1 Institutional structure and data

The Euronext stock market operates as an order-driven market with a limit order book. 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 9:00 a.m. The main trading phase starts at 9:00 a.m. and ends at 5:30 p.m. The daily schedule is followed by a closing auction and a further trading session called “trading-at-

last,” where additional trades can be executed at the closing price. In this study, we only look at the main trading phase, where the vast majority of trading activity is concentrated, thus opening and closing activity are excluded from our analysis.

According to the Rule 4403/2 of Rulebook I (Euronext, 2014), during the continuous trading, Euronext has in place a set of trading safeguards that prevents price movements outside certain thresholds. Specifically, traded prices are constrained into a “collar,” defined by a reference price plus/minus a percentage price change. If the execution of an order causes the breach of the collar, two outcomes are possible: 1) the order is partially executed inside the collar, without halting the continuous trading; 2) the trading process is halted, and the market is put in “reservation mode.” Continuous trading resumes after an auction. None of the flash crashes considered in our analysis triggers any of these measures. Thus, the collars are ineffective against preventing the occurrence of our detected flash crashes.

The market model of Euronext Paris relies on the provision of liquidity by electronic market makers. Since 2011, NYSE Euronext have in place a program, called *Supplemental Liquidity Provision*, where electronic traders agree to post two-sided quotes during the day and to provide a minimum passive execution volume. This program identifies our DMMs. Liquidity provision is rewarded with a rebate, whereas aggressive executions by DMMs are available at reduced trading fees.<sup>4</sup> The orders sent by DMMs must be electronic, using only their own funds, and excluding customer orders.<sup>5</sup> We should point out that this agreement does not contain any special incentive for DMMs to provide liquidity during stressed market conditions. However, a recent review report by the European Securities and Markets Authority (ESMA) is now looking into this design (ESMA, 2021).

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 37 liquid stocks that are included in the CAC40 Index in 2013.<sup>6</sup> We can track the entire history of the orders, from the initial submission

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<sup>4</sup>The details are available in NYSE-Euronext (2012). Bellia (2017) provides a detailed description of the Supplemental Liquidity Provision scheme and the role of electronic market makers in the NYSE Euronext.

<sup>5</sup>Differently from the NYSE (US) market, Euronext Paris does not have a single Designated Market Maker (DMM) for each stock, but relies on the DMMs that act as non-voluntarily liquidity providers under a market making agreement with the exchange.

<sup>6</sup>The three stocks of the CAC40 that are excluded from our analysis are Arcelor Mittal, Gemalto, and Solvay, since their main trading venue is not the Paris branch of Euronext.



to the execution or the cancellation, with a timestamp at the microsecond level. Each trade struck during the main trading phase has a flag that indicates the trade initiator, allowing to unambiguously identify on the one hand which trader-account is trading aggressively (demanding liquidity) and on the other hand which trader-account is trading passively (supplying liquidity).

## 2.2 Trader classification

Euronext requires each trader to flag every order in compliance with the [Euronext \(2014\)](#) “Rulebook,” according to the following list of possible accounts (see [NYSE-Euronext, 2012](#)): orders submitted pursuant to the Supplemental Liquidity Provision agreement (MM); own account (OWN) for proprietary trading; account of an affiliate, or when operating from a parent company of the Euronext main member (PARENT);<sup>7</sup> account of a third party (CLIENT), when the Euronext member grants access to his client via an Automated Routing System or through sponsored access;<sup>8</sup> orders submitted for retail investors only.<sup>9</sup>

An interesting feature of this specific database is that the data from the stock exchange are complemented with an high-frequency trading (HFT) identification flag, provided by the French stock market regulator (the *Autorité des Marchés Financiers*, AMF). The classification is based on the lifetime of cancelled orders and a trader is classified as HFT if one of the two criteria below is met:

1. “the average lifetime of its cancelled orders is less than the average lifetime of all orders in

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<sup>7</sup>According to rule 3.4 of the Rulebook, the “Relevant Euronext Market Undertaking may consider an application from a Member who wishes to obtain direct access to an Euronext Market for its Affiliate(s). The Affiliates are a person who (i) owns 95 per cent or more of the Member; or (ii) is owned 95 per cent or more by the Member; or (iii) is owned 95 per cent or more by a third party who also owns 95 per cent or more of the Member.”

<sup>8</sup>Euronext members can grant access to the market and the facilities like co-location, via a sponsored access, according to Rule 3.2 and 3.3 of the Rulebook. However, “All business undertaken by a Client via an Automated Order Routing System or via Sponsored Access on an Euronext Market will be done in the name of the Member and the Member retains full responsibility for the conduct of all such business” (Rule 3201/2).

<sup>9</sup>Orders for retail investors are flagged as RLP (Retail Liquidity Provider) or RMO (Retail Member Organisation) and belong to a specific program designated for them on Euronext. Euronext member banks and brokers can execute their retail orders flow via the Retail Matching Facility (RMF) against new price-improving liquidity provided by RLPs. Details about the program are available at <https://www.euronext.com/en/media/4053/download>. However, the amount of liquidity provided via this channel is not visible in the central limit order book and is only accessible to retail clients under the RMO. The amount of trades and orders categorized with this flag is negligible compared to the overall market activity carried out by the remaining trading accounts.

the book and if it has cancelled at least 100,000 orders during the year.”

2. “the participant must have cancelled at least 500,000 orders with a lifetime of less than 0.1 second (i.e. the participant quickly updates the orders in the limit order book) and the top percentile of the lifetime of its cancelled orders must be less than 500 microseconds (i.e. the participant regularly uses fast access to the market).”

HFTs are further divided by AMF into two sub-categories: pure HFTs companies, such as Citadel or Virtu, and investment banks with HFT activity such as Goldman Sachs (labelled “mixed” by AMF). This classification is revised yearly, and the groups are mutually exclusive.

[Figure 1 about here.]

We merge the AMF definition of high-frequency trading with the memorandum of the SEC (SEC, 2014), which adds proprietary trading as typical feature of HFTs and we group traders in the following categories (displayed in Figure 1):

- pure HFTs companies according to AMF are labelled, according to their trading accounts, as PURE-HFT MM, PURE CLIENT and PURE-HFT OWN. We remove the flag “HFT” from clients given that the AMF classification does not guarantee that these trades are proprietary. PURE-HFT MM are DMMs.
- mixed HFTs companies according to AMF are labelled IB-HFT MM, IB CLIENT, IB-HFT OWN and IB-HFT PARENT. Again, we remove the flag “HFT” from clients. We prefer the label “IB” to the label “MIXED” because we think this is clearer in defining the trading groups. IB-HFT MM are DMMs.
- non-HFTs according to AMF are labelled NON-HFT CLIENT and NON-HFT OWN.

In the above definitions, we leave out groups with negligible trading activity (such as RMO), accounting for only 0.56% of total volume. Figure 1 shows that most of the trading activity in our sample is due to PURE-HFT MM, IB-HFT MM, IB-CLIENT, and IB-HFT OWN. Together, they account for roughly 76% of the total double-counted volume (buy and sell). NON-HFTs account for 18%.

### 3 Identification of flash crashes

Flash crashes got the attention of financial economists after the infamous S&P 500 flash crash 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, 2019). The existence of flash crashes casts doubts on the orderliness of the financial market architecture. However, the S&P 500 flash crash was not an isolated event. Indeed, the data supports the presence of a substantial number of flash crashes. Commenting on the Sterling flash crash of October 7, 2016, Bank for International Settlements (2017) writes: *“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.”*

How do we define a flash crash? According to Bank of England (2019), *“Flash episodes are large and rapid changes in the price of an asset that do not coincide with – or in some cases substantially overshoot – changes in economic fundamentals, before typically retracing those moves shortly afterwards”*. These events are sometimes called “mini flash crashes” (Biais and Foucault, 2014). Based on a formal implementation of these ideas, Christensen, Oomen, and Renò (2022) provide evidence of frequent flash crashes in the futures markets on the S&P 500, gold, oil, EUR/USD, Treasury notes, and corn; a result echoed in Golub, Keane, and Poon (2017) for the US equity market. Thus, even supposedly liquid markets are subject to flash crashes. Invariably, suspicion is directed towards automated trading as a potential culprit for these events, although the evidence is mostly anecdotal.

In this section, we describe how we build our flash crashes database. We detect flash crashes using a novel econometric approach, proposed by Christensen, Oomen, and Renò (2022), which supports the notion that a flash crash is (in relative terms) a large downtick in the price over a short time horizon. As we will show, this is typically accompanied by a reversion in the price.

[Figure 2 about here.]

Before explaining the mechanics of the procedure in detail, we look at an example of a

distressed event, reported in Figure 2. The top panel of the figure shows the evolution of the price of Technip on June 25, 2013. Around 11:50am the price starts to decline rapidly until it reaches a minimum a few seconds after 12:05. The return over the 15-minutes is  $-2.35\%$ . After the crash, the price partially recovers. This is an example of what we consider a “flash crash”: a large price drop in a short time followed by a partial recovery. The intermediate panel shows the test statistics of [Christensen, Oomen, and Renò \(2022\)](#). As it can be seen, the peak of the test statistics coincides with the peak of the crash.

Figure 2 highlights an important difference between our flash crash detection technique and those based on volatility (or jumps), such as Extreme Price Movements (EPMs) by Brogaard et al. (2018). The basic EPMs detection consists of extracting—often disconnected—10-second absolute midquote returns exceeding the 99.9th percentile of the distribution of such returns for a stock. However, despite of the cumulated price drop being large during a flash crash, the individual high-frequency (10-second) returns, displayed in the bottom panel of Figure 2, are typically small and compatible with the overall volatility of that day. The largest negative 10-second return ( $-0.25\%$ ) occurred inside the volatility cluster before 11:00am. In fact, the price level did not change significantly in the surrounding 30-minute window, as highlighted by the pink shaded area. Hence, in this instance EPMs would identify intervals of high volatility (or jumps) before identifying the flash crash.

To lay down our flash crash identification 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:

$$dp_t = \mu_t dt + \sigma_t dW_t + dJ_t, \quad (1)$$

where  $\mu_t$  is the instantaneous drift,  $\sigma_t$  is the associated spot volatility,  $W_t$  is a standard Brownian motion, and  $J_t$  is a jump process. The log-price  $p_t$  is observed on  $[0, T]$  at irregular time points  $0 = t_0 < t_1 < \dots < t_n = T$ , such that  $\max_i(t_i - t_{i-1}) \rightarrow 0$  as  $n \rightarrow \infty$ . The discretely sampled log-return is defined as:

$$r_{t_i} = p_{t_i} - p_{t_{i-1}}, \quad i = 1, \dots, n. \quad (2)$$

In model (1), the price changes,  $dp_t$ , include three components:  $\sigma_t dW_t$  and  $dJ_t$  are responsible for volatility clusters and jumps, while the drift term  $\mu_t dt$  represents the local trend. As discussed, our methodology relies on the drift term. A natural estimator of  $\mu_t$  is the kernel estimator:

$$\hat{\mu}_t^n = \frac{1}{h_n} \sum_{i=1}^n K\left(\frac{t_{i-1} - t}{h_n}\right) r_{t_i}, \quad (3)$$

where  $K$  is a kernel (a localizing function) and  $h_n$  is a bandwidth (approximately, the localization window). The estimator (3) is asymptotically unbiased, however, its variance does not decrease as  $h_n \rightarrow 0$ , hence the estimator is inconsistent (Bandi, 2002; Kristensen, 2010).

To circumvent this issue, it is sufficient to rescale the drift estimator properly, as shown by Christensen, Oomen, and Renò (2022) who propose the following test statistics:

$$T_t^n = \sqrt{\frac{h_n}{K_2}} \frac{\hat{\mu}_t^n}{\hat{\sigma}_t^n}, \quad (4)$$

where

$$\hat{\sigma}_t^n = \sqrt{\frac{1}{h_n} \sum_{i=1}^n K\left(\frac{t_{i-1} - t}{h_n}\right) r_{t_i}^2} \quad (5)$$

is a consistent estimator the spot volatility and  $K_2 = \int_{\mathbb{R}} K^2(x) dx$ .

The ratio  $\hat{\mu}_t^n / \hat{\sigma}_t^n$  can be interpreted as a measure of the current price velocity. In “normal” markets (if the instantaneous drift is locally bounded) the ratio is small, as evident from Figure 2 in the morning and afternoon. If the price is moving too fast relative to the volatility (i.e., price changes are directional) the ratio is large, as evident from Figure 2 during the flash crash at noon. Christensen, Oomen, and Renò (2022) formalize the latter condition by assuming that there exists a “drift burst” time point  $\tau_{db}$ , where  $\mu_t \rightarrow \pm\infty$  as  $t \rightarrow \tau_{db}$ . They prove that, in such points,  $|T_t^n| \rightarrow \infty$  as  $t \rightarrow \tau_{db}$ . In points in which the drift  $\mu_t$  is bounded, the test statistic is instead standard normal. Therefore,  $T_t^n$  can be used for identifying a flash crash around time  $t$  by rejecting the “normal” market conditions in favour of the presence of a drift burst, when  $|T_t^n|$  is larger than a quantile of the standard normal distribution.

The drift burst test statistic is robust to compound Poisson jumps, infinite activity small

jumps, autocorrelated market microstructure noise and pre-announced jumps which occur at a pre-determined time, e.g. as a consequence of dividends or macro announcements. Further, the test is robust to volatility spikes. Thus, our distress measure is not picking up neither jumps nor large volatility episodes, but genuine directional trends.

How good is this test in identifying the typical V-shape behavior of a flash crash? [Christensen, Oomen, and Renò \(2022\)](#) show that the test is effective along several dimensions. First, the test statistics is able to detect all the major flash crashes popularized in the press (such as S&P 500 flash crash of May 6, 2010, the Treasury market flash crash of October 15, 2014, or the Twitter flash crash of April 23, 2013, and many more). Second, extensive Monte Carlo simulations show that the test is correctly sized, and that for events with a sufficiently large test statistic, the probability of contamination by false positives is essentially zero. We refer the reader to [Christensen, Oomen, and Renò \(2022\)](#) for details.

To implement the test, we compute the estimator of the drift and volatility based on a kernel-weighted average of observations in the vicinity of  $t$ , as defined in Eq. (5). The bandwidth  $h_n$  determines how fast we down-weight observations further away from  $t$ , with weights decided by the kernel function. We 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. 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 10 minutes. Transaction prices are pre-averaged following [Jacod, Li, Mykland, Podolskij, and Vetter \(2009\)](#) to soften the impact of market microstructure noise, and the volatility estimator in (5) is robustified with a HAC correction. This setup is consistent with [Christensen, Oomen, and Renò \(2022\)](#).

We compute the test statistic every second during the course of a trading session. To account for multiple testing, we exploit the simulation-based algorithm from [Christensen, Oomen, and Renò \(2022\)](#) to set an appropriate critical value. We use a 99.9% confidence interval. The average threshold value is  $-4.9$ : drift burst test statistics below this threshold are labelled as flash crashes. We search for crashes after 9:30am. Appendix A is devoted to the comparison of the events detected by the drift burst test statistics with those detected with the EPM

methodology of Brogaard et al. (2018), showing that the flash crashes we detect and EPMs are largely disjoint samples with limited overlap.

## 4 Empirical results

### 4.1 Anatomy of flash crashes

Table 1 reports summary statistics of events identified by the procedure explained in Section 3. The average crash duration is 9.5 minutes. The average price drop during a flash crash is  $-1.35\%$ . During the largest crash, which occurred in ST Microelectronics on March 12, 2013, the price fell by  $-5.18\%$ , while during the smallest one, which occurred in Pernod Ricard on October 2, 2013, the price declined by  $-0.37\%$ . Table 1 also shows that while the crash duration represents only 1.87% of the duration of the trading day, on average, the crash accounts for 5.43% of daily trading volume (in days with a flash crash), nearly 6% of the number of trades, and roughly 21% of total selling volume in that day.

[Table 1 about here.]

A detailed summary of all 148 identified flash crashes is provided in Table E.1 and E.2 in Appendix E. Additionally, Table E.3 in Appendix E reports a summary of the detected flash crashes grouped according to each stock. It shows that in our sample flash crashes occur in 34 different stocks. For one stock, flash crashes occur only once. The largest number of crashes in a single stock is ten for Alstom (ISIN FR0010220475). There is no apparent relationship among the number of flash crash occurrences and the stocks' market capitalization, volatility and average return.

A pictorial representation of the temporal distribution of the 148 crashes over the year and the trading hour during the day is provided in Figure 3. The figure shows that crash events are scattered across the year and the time of the day uniformly, without a clear pattern emerging, for example around a specific time of the day. In two prominent cases, clearly visible in the figure, we have crashes affecting multiple stocks simultaneously: on April 17, 2013 (with 14

stocks involved) and on September 3, 2013 (with 13 stocks involved).<sup>10</sup> From now on, we label these 27 events as “systematic”. The remaining 121 events will be labelled as “non-systematic”.

[Figure 3 about here.]

For each event, we denote by  $t_{\text{crash}}$  the point in time associated with the lowest value of the t-statistics after crossing the significance threshold. The beginning of the crash, labelled  $t_{\text{start}}$  is identified by the first crossing time of the t-statistics with  $-1$  before  $t_{\text{crash}}$ . The difference  $\tau = t_{\text{crash}} - t_{\text{start}}$  is the crash duration. The end of the recovery period is identified by the time  $t_{\text{end}} = t_{\text{crash}} + 3\tau$ . We also consider a pre-crash period, starting at the time  $t_{\text{pre}} = t_{\text{start}} - 2\tau$ . The analysis in this paper is based on price and order information, for each crash, from time  $t_{\text{pre}}$  to time  $t_{\text{end}}$ .<sup>11</sup>

[Figure 4 about here.]

Figure 4 shows the average cumulative return for systematic and non-systematic crashes, together with 10% and 90% quantiles for all events. This figure clearly illustrates the output of our identification strategy, described in Section 3, and also allows for a qualitative description of the average price process. The overall pattern of the detected events is the typical “skewed V” displayed by a flash crash. While on average the market price moves towards a new price level, it substantially overshoots and declines to a price which is lower than the new fundamental level. This picture is consistent with informed trading conveying new information into a permanent price impact (from the beginning to the end of the recovery period). The V-shape is deeper and more pronounced for systematic events, indicating more overshooting than for non-systematic events, on average.

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<sup>10</sup>The collective flash crashes of April 17, 2013 are likely due to the announcement, that morning, of new austerity budget measures due to the pessimistic revision of growth figures by the French government, see e.g. <https://lexpansion.lexpress.fr/actualite-economique/ce-qu-il-faut-retenir-du-nouveau-plan-budgetaire-de-la-france.1404490.html>; the event of September 3 cannot instead be associated to any news, to the best of our knowledge. However, flash crashes in several stocks with no news can be explained by the phenomenon of liquidity spillovers, see e.g. Cespa and Foucault (2014). The behavior of the 37 stocks around the two crashes is shown in Figure F.1 in the Appendix F.

<sup>11</sup>In the figures, we harmonize time units to the average crash duration, which is 10.59 minutes. That is, in Figure 4 and subsequent ones, each trade time (after subtracting  $t_{\text{start}}$ ) is multiplied by 10.59 minutes and divided by the actual duration of the flash crash event. When this is done, the resulting time units, still in minutes, are indicated with “average elapsed time”.



For each event, we define the permanent price impact (PPI) as:

$$\text{PPI} = \log p_{t_{\text{end}}} - \log p_{t_{\text{pre-crash}}}, \quad (6)$$

that is the logarithmic return from beginning to recovery<sup>12</sup>, while the crash price impact (CPI) is defined as:

$$\text{CPI} = \log p_{t_{\text{crash}}} - \log p_{t_{\text{pre-crash}}}, \quad (7)$$

and the transient price impact (TPI) is defined as:

$$\text{TPI} = \text{CPI} - \text{PPI} = \log p_{t_{\text{crash}}} - \log p_{t_{\text{end}}}. \quad (8)$$

To better understand who is contributing to the transient and permanent components of the crash return, we further subdivide the crash period (from  $t_{\text{start}}$  to  $t_{\text{end}}$ ) in three stages with equal duration: early, intermediate and late crash, as shown in Figure 4.

Figure 5 shows the relation between PPI and TPI, as well as the relation between CPI and crash duration. From Panel A, we can see that both the average PPI and the average TPI are highly significant in our detected sample, and this is true for both systematic and non-systematic events. The fact that PPI is mostly negative (with few exceptions) is an indication of informed trading. The fact the TPI is always negative (with one exception) is an indication of overshooting. In particular, the transient component of systematic events is  $-0.78\%$  on average, half of the average permanent component, and it is still  $-0.33\%$  (and significantly negative) for non-systematic events, roughly one third of the permanent component. Panel B shows that the typical duration of the crash event ranges from a few minutes to 45 minutes, with an average duration of 9.5 minutes. The longer the crash, the more negative the CPI.

[Figure 5 about here.]

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<sup>12</sup>Our choice of using the price after, on average 27 minutes, is in line with the typical approach of the market microstructure literature when estimating effective spreads, see e.g. [Glosten \(1987\)](#). Alternatively, we could employ the price observed at the end of the day, or in the next day, as in [van Kervel and Menkveld \(2019\)](#). No differences would emerge in the subsequent analysis.

## 4.2 Liquidity during a flash crash

In Figure 6, we report average volume, market depth, bid-ask spread and executed order age for the 121 non-systematic flash crashes (the corresponding and qualitatively identical figures for systematic events are reported in Figure F.2 in Appendix F). Market depth is the total number of shares offered across the first ten price levels on the bid and the ask side. The bid-ask spread is calculated as the logarithmic difference between the one minute average of the best bid and the best ask price. The executed order age is the time between trade and the time stamp at which the order was posted (or last modified). The mean cumulative return shown in Figure 4 is superimposed in all the figures as a visual landmark of the average crash development. Statistical significance of these quantities across crash phases is presented in Table 2.

[Figure 6 about here.]

[Table 2 about here.]

Panel A of Figure 6 shows that the crash is associated with a large selling pressure, as expected, and that recovery starts after selling stops. The fact that selling produces a permanent price change is consistent with informed trading. Panel B shows that the bid-ask spread steadily 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. Panel C shows that market depth, that is the ability of the market to absorb orders, is strongly reduced during a crash, recovering slower than the price itself, in line with the finding in Kirilenko, Kyle, Samadi, and Tuzun (2017) during the Flash Crash of May 6, 2010. This is consistent with Grossman and Miller (1988), since the price change in their model is predicted to be deeper in illiquid market conditions. Panel D shows that the age of the average executed order increases during the sell-off. This is in line with “quote sniping”, i.e. stale limit orders that were posted before the start of the crash are executed on the way down (e.g., Kirilenko, Kyle, Samadi, and Tuzun, 2017). Table 2 indicates that the effects are statistically significant, and largely so for the executed order age and market depth change. Overall, Figure 6 suggests that a flash crash occurs when selling pressure increases and there is insufficient liquidity in the market to accommodate the demand.

Figure 7 shows the average Euro volume traded per minute, divided in buyer-initiated (Panel A) and seller-initiated (Panel B) trades for the non-systematic events (the corresponding and qualitatively identical figure for systematic events is reported in Figure F.3 in Appendix F). The two patterns are similar even if the trading intensity of selling is much higher. We observe a sudden peak in average trading activity associated with the beginning of the crash. This behavior in correspondence of the initial price drop is compatible with a large selling order which is executed in a series of child trades. Then trading slows down, only to strongly accelerate again before the end of the crash. During recovery, the intensity of trading reverts back to normal activity. Figures 4 and 7 suggest that there are two distinct phases of the crash: an initial phase, triggered by sudden selling pressure, and a final phase, which occurs in a more illiquid market and precipitates the price much more.

[Figure 7 about here.]

### 4.3 Trade analysis

We now turn to the analysis of the trading behavior of different trader groups during a flash crash, answering the following questions: Who is responsible for the permanent price impact? Who is responsible for the transient price impact? And what motivates the trading behavior of different traders?

We analyze net trade imbalances (or net inventories) of each trader group. We split imbalances in initiating and liquidity supplying trades as follows. For each trade, denote by  $i$  the category which is initiating the trade with its demand, and by  $j$  the category who is accepting the offer ( $i$  and  $j$  may coincide). 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 category  $i$ , the imbalance on initiating trades on a given period is computed as:

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

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 supplying trades for category  $j$  in a given period is:

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

The monetary net imbalance for category  $i$  (or  $j$ ) in a given period is then computed as:

$$\mathcal{I}_{\text{period}}^{(i)} = \mathcal{I}_{\text{period}}^{(i),\text{init}} + \mathcal{I}_{\text{period}}^{(i),\text{liq}}. \quad (9)$$

This measure is equivalent to that used by Brogaard et al. (2018), except they use number of traded shares instead of Euro volume.

Figure 8 reports average net imbalance, computed as in Eq. (9), and prices for systematic flash crashes (in Panel A) and non-systematic flash crashes (in Panel B). In both cases the figure shows that the selling activity of IB-HFT OWN (followed by IB CLIENT for non-systematic events) can be associated with the beginning of the crashes. This appears to be informed selling since it moves the price toward a new fundamental level. By market design, the order imbalance generated by sellers should be absorbed by DMMs, either PURE-HFT MM or IB-HFT MM, without generating overshooting in the price. Figure 8 focuses on IB-HFT MM only since PURE-HFT MM mostly affect the price with their quoting activity (see Section 4.5) and keep zero inventory across all the stages of the crash.<sup>13</sup>

[Figure 8 about here.]

For non-systematic events, IB-HFT MM do provide liquidity during the crash, albeit it is not sufficient to avoid price over-reaction. However, they do not provide additional liquidity during the recovery, which is left to NON-HFT, most likely due to an attempt to restore the low inventory target level. Nevertheless, when the flash crash affects several stocks simultaneously (systematic events), IB-HFT MM do not provide liquidity on average. Actually, they sell during the crash, contributing to the transient price impact. The order imbalance of systematic flash crashes is again absorbed, especially in the late phase of the crash, by “slow” NON-HFT traders,

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<sup>13</sup>We concentrate on the most active group of traders in this section. Appendix B reports average imbalances for all groups, across all stages of the crash.

who buy at a discount price mostly through limit orders posted far before the crash started. Not only these traders, who do not use extensively algorithmic trading strategies, absorb the selling generated by “sellers” and market makers, but they also mostly contribute to the partial recovery of the price. Thus, IB-HFT OWN appears to generate the crash (through informed selling) and, when crashes are systematic, additional selling by IB-HFT MM precipitates the crash.

To identify the main significant patterns in the behaviour of different traders during flash crashes, for every trader type  $j$ , we estimate the following multivariate panel model:

$$\mathcal{I}_{i,t}^{(j)} = \alpha_0^{(j)} + \sum_{k=1}^5 \beta_k^{(j)} D_{i,t}^k + f_i^{(j)} + \alpha^{(j)} \text{Controls}_{i,t} + \epsilon_{i,t}^{(j)}, \quad (10)$$

where  $\mathcal{I}_{i,t}^{(j)}$  denotes the ten-seconds net trading imbalance of trader  $j$ , computed for the  $t$ -th 10-second interval of the  $i$ -th event day using Equation (9),  $D_{i,t}^k$  are the dummy variables indicating the particular phase of the crash with  $k \in \{pre\text{-}crash, early\text{ }crash, intermediate\text{ }crash, late\text{ }crash, recovery\}$  (for example,  $D_{i,t}^{late\text{ }crash} = 1$  if the  $t$ -th interval of the  $i$ -th event day belong to the period of the late crash and  $D_{i,t}^{late\text{ }crash} = 0$  otherwise),  $\text{Controls}_{i,t}$  is a vector of control variables and  $\epsilon_{i,t}^{(j)}$  is the stochastic error term. The control variables include five lagged values of net trading imbalances (although we do not find significant autocorrelation in their time series), the 10-second stock return, the (log) traded euro volume and the percentage quoted spread. All non-dummy variables are standardized on the stock level, and the regressions are estimated with stock fixed effects and heteroskedasticity robust standard errors, for different sub-samples both in terms of flash-crash type (systematic vs non-systematic) and aggregating different type of traders. Given the 10-second time interval to aggregate the imbalances, some flash-crash are excluded from the regressions (specifically, when their duration is smaller than 100 seconds).

[Table 3 about here.]

Table 3 reports the estimated coefficients of the crash dummies and the corresponding t-statistics for both systematic and non-systematic events, using the model of Equation (10), for the most active group of traders.<sup>14</sup> Panel A shows that for systematic events, the coefficient of

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<sup>14</sup>The estimation of the full model with all trader groups is presented in Appendix B.

*early crash* and *intermediate crash* is negative and statistically significant for IB-HFT OWN, while for the *late crash* and for the *recovery* is negative for IB-HFT MM. These two type of traders, as already shown in the graphical analysis, are the ones that push the price down during the systematic flash crashes. NON-HFT, on the other side, do absorb the selling pressure in all phases of the crash. Panel B instead reports the results of the panel regression for non-systematic events. Even in this case, IB-HFT OWN appears to trigger the selling pressure, followed in a later stage by IB CLIENT. As said before, IB-HFT MM do provide liquidity in all the stages of the crash, but leave the recovery to NON-HFT.

Figure 9 shows the average trading imbalance changes per minute for the two most important trading categories (all trading categories are shown in Appendix F, Figures F.5 and F.6), that is IB-HFT MM and IB-HFT OWN. The intensity of imbalance change is further dissected into initiated buy, initiated sell, supplying buy and supplying sell. A positive value of the average means that the net imbalance is increasing; a negative value means that net imbalance is decreasing.

[Figure 9 about here.]

Panel B and D show that the IB-HFT OWN are, on average, originating crashes, both systematic and non-systematic ones. Their increase in the intensity of selling is strongly correlated with the decline in price, and their selling accelerates till the peak of the crash. They also provide some liquidity (each group consists of several individual traders), but their net effect is strongly negative, especially at the beginning and end of the crash.

Panel A and C point again at the ambivalent behavior of IB-HFT MM. For non-systematic events, they provide liquidity either at the beginning or at the end of the crash. However, a fraction of them starts selling intensely just before the peak of the crash, as indicated in Panel A, thus consuming liquidity instead of providing it. For systematic events, there is no average liquidity provision at the beginning of the crash. Even if some liquidity is provided at the end of the crash, as shown in Panel C, the net effect is strongly negative, and almost as intense as that produced by IB-HFT OWN.

Table 4 provide the estimates of the panel regression in Equation (10) with the aggressive trades (consume liquidity) and the passive trades (provide liquidity) as dependent variables,

instead of net imbalance. These variables assume a positive value when buying a stock, and a negative value when selling it. Looking at the aggressive trades (which are in the direction of return, since the coefficient of Return is positive and significant), IB-HFT OWN have a negative and significant coefficient for the *early crash*, which confirm the graphical intuition that a large selling from this group of traders trigger the subsequent reaction and thus the building-up of the flash crash. For systematic events, the effect on the *intermediate crash* phase is even reinforced, followed in the subsequent phases by IB-HFT MM, which magnify the effect in the late phase of the crash. For the passive trades, which goes in the opposite direction of the return by definition, the estimated coefficients show that IB-HFT MM provides liquidity in non-systematic events in all phases of the flash crash but the recovery, while for IB-HFT OWN the coefficients are never significant, indicating that the selling aggressive pressure dominates the liquidity provision during the crash. For systemic events, as already shown in the previous table, IB-HFT MM provide liquidity only on the selling side (negative sign in front of the coefficients), thus exacerbating the crash especially in the intermediate and late phases of the crash. Overall, the results of these models confirm the graphical assessment discussed before using averages.<sup>15</sup>

[Table 4 about here.]

Figure 10 shows the distribution, across events, of trading imbalances changes of IB-HFT MM and IB-HFT OWN in the different phases of the crash and during recovery (the corresponding Figure F.7 in Appendix F shows the associated results for non-systematic events). The figure highlights that IB-HFT OWN mostly sell at the beginning of the crash, whereas IB-HFT MM start selling immediately after. In particular, IB-HFT MM is always selling in the late phase of the crash.

[Figure 10 about here.]

Why do investment bank DMMs sell when flash crashes affect several stocks, instead of providing liquidity (when it is needed the most) in line with their liquidity provision agreement? Their change in the trading strategy, visible in Panel A of Figure 9, may be motivated by several

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<sup>15</sup>As before, we look at the subset of most active traders for this analysis. The model estimations for all trader groups is presented in Appendix B.

rationales. First, IB-HFT MM carry little to no inventory, so they need to recover their stock to maintain a zero balance. Moreover, market makers face the adverse selection problem that selling may not be motivated by pure immediacy, but it could be informed (as it actually is, on average). Thus, IB-HFT MM may sell opportunistically to profit from the information, as postulated by the backrunning theory of [Yang and Zhu \(2020\)](#) or predatory trading of ([Brunnermeier and Pedersen, 2005](#)). Indeed, we observe a surge in initiated buying from this category immediately before the crash peak, which is consistent with both backrunning and predatory trading. A mixed behavior is to be expected, since market makers do not know a priori if the price is going to recover or not (see also [van Kervel and Menkveld, 2019](#)). An alternative explanation is provided in [Cespa and Vives \(2022\)](#), where lack of transparency leads to additional selling even when prices are below the fundamental value.

[Table 5 about here.]

Table 5 supports the conjecture that IB-HFT MM lose money during crashes. The table reports estimates of the panel regression, akin to Equation (10), for every trader type  $j$ :

$$\text{Profits}_{i,t}^{(j)} = \alpha_0^{(j)} + \beta^{(j)} D_{i,t} + f_i^{(j)} + \alpha^{(j)} \text{Controls}_{i,t} + \epsilon_{i,t}^{(j)}, \quad (11)$$

where now  $\text{Profits}_{i,t}^{(j)}$  are the profits calculated for each 10-second intervals for trader  $j$  at interval  $t$  for the  $i$ -th event, and  $D_{i,t}$  is a dummy which is equal to one for the entire duration of the crash (from the *pre-crash* until the end of the *recovery*). The control variables and lags are as in Equation (10).

The estimation results show that, on average, IB-HFT MM lose a significant amount of money by providing liquidity during non-systematic crashes. On the other side, IB-HFT OWN realize positive and significant profits by selling at a higher price, possibly trading on private information.

Liquidity provision would not compensate IB-HFT MM for these losses. We estimate the average monetary profit they would obtain by providing all the required liquidity to the sellers in the French market to be a meager 28 euros.<sup>16</sup> One may argue that they still do make

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<sup>16</sup>This back-of-the-envelope estimate is obtained by multiplying the total liquidity need, taken from Panel A



profits on average, since providing liquidity in tranquil times should be enough to cover these losses. However, if they have the option to meet the requirements as liquidity providers without penalties, it is rational to not provide liquidity during distress. That is exactly what they appear to do, since Table 5 show that IB-HFT MM avoid losses during systematic events, passing the “hot potato” to slow traders. Our results thus highlight that, even if the behavior of IB-HFT MM is perfectly rational at individual level, in aggregate it exacerbates the transient price impact. Their behavior impairs market efficiency since the traded price overshoots. From a policy angle, our results question the effectiveness of the compensation scheme offered by the exchange.

The last aspect we investigate is whether trader groups change their trading behavior during flash crashes with respect to normal times. We perform this analysis using the methodology of Kirilenko, Kyle, Samadi, and Tuzun (2017), applied to the 148 flash crashes in our sample. The full analysis is detailed in Appendix C. Analyzing multiple crash events, we find that DMMs modify their behavior substantially, contrary to what is found on the single May 6, 2010 event and in line with our previous findings.

Summarizing, our results on trades point out the limited willingness of DMMs to provide liquidity during a flash crash. They provide some liquidity during non-systematic crashes, but during systematic crashes IB-HFT MM are selling in the late phase of the crash. Thus, the role of market makers loses effectiveness exactly when the market mostly needs it, which exacerbates the crash. The role of liquidity providers is instead played by “slow” NON-HFT traders, through passive trades that they posted before the flash crash took place and which were not re-positioned fast enough in the market.

#### 4.4 Who prevents flash crashes under high selling pressure?

In this section, we conduct a counterfactual experiment in order to study what prevents flash crashes when selling pressure is high. To this end, we identify the episodes of extreme sales of similar or larger magnitudes as those observed during our sample of flash crashes. We compare the behavior of DMMs with other traders during these events.

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in Figure 6 to be 1.4 millions of Euro, times the compensation per Euro, taken to be 0.20 bps per Euro (in 2013, this number changed from 0.20 to 0.22 to be back to 0.20). This estimate does not include the standard gain from market making activity, i.e. the bid-ask spread, which is included in the net monetary profit in Table 5.

In order to identify the episodes of extreme sales, for each day and stock in our sample and for each one-minute interval, we compute a multiscale measure of the (instantaneous) selling pressure defined as:

$$\mathcal{SP}_m^{(day,stock)} = \gamma_m^{(stock)} \cdot \min_{u=0,1,\dots,30} \left( \sum_{t \in [m-u,m]} s_t \cdot Q_t \cdot P_t \right), \quad (12)$$

where  $m$  runs over one-minute equispaced partition of a trading day,  $\gamma_m^{(stock)}$  denotes the intraday periodicity adjustment factor, while  $s_t$ ,  $Q_t$  and  $P_t$  are defined as above. That is, for each time instant  $m$ , we compute the signed Euro volume over the previous  $u$  minutes of trading:  $\sum_{t \in [m-u,m]} s_t \cdot Q_t \cdot P_t$ . Since large selling volumes may flow at differing speed and last for differing amounts of time, the signed Euro volume is computed for various intervals ranging from one to 30 minutes. To get a single measure for each time instant, we then take the minimum, e.g. the largest cumulated drawdown in 30 minutes. Finally, the  $\mathcal{SP}_m^{(day,stock)}$  measure is adjusted for intraday periodicity by multiplying it with a factor  $\gamma_m^{(stock)}$  computed as the inverse of the stock-specific average  $\mathcal{SP}_m^{(day,stock)}$ , where the average is taken over all days in the sample for each stock. This ensures that the  $\mathcal{SP}_m^{(day,stock)}$  measure is comparable across time and stocks.

Figure 11 shows the distribution of  $\mathcal{SP}_m^{(day,stock)}$  (black dashed line with dots). We see that during flash crashes the selling pressure is very high. The distribution of  $\mathcal{SP}_m^{(day,stock)}$  conditionally on a flash crash (blue line with circles) is centered at the tail of the unconditional distribution. Thus, extreme values of  $\mathcal{SP}_m^{(day,stock)}$  correspond to episodes of potential crashes.

[Figure 11 about here.]

We extract the 0.1% of events (pooled over all stocks) with the most negative selling pressure, as measured by  $\mathcal{SP}_m^{(day,stock)}$ . For each of these tail events, we compute the changes of the inventory for different traders in the time window  $[m-u, m]$ , which corresponds to the minimum. As a comparison, we juxtapose these inventory changes to the ones during systematic and non-systematic flash crashes. Figure 12 shows the histograms of the inventory changes of different trader groups during high selling pressure intervals excluding flash crashes (Column A) and during systematic and non-systematic crashes (Columns B and C).

[Figure 12 about here.]

It is evident that the main difference between the occurrence and non-occurrence of flash crashes is the behavior of NON-HFT. When they offer liquidity to sellers (Column A) the flash crash does not appear even if selling pressure is high, with some of this emanating from DMMs (which both show a distribution skewed to the left, more prominently so for IB-HFT MM). Also, DMMs do not provide liquidity to large sellers, while NON-HFT do. The cases in which a flash crash occurs (Column B for systematic ones and C for non-systematic), neither NON-HFT nor DMMs provide adequate liquidity. NON-HFT provide some liquidity (as also shown in Panel A of Figure 8) during systematic events, but not enough to avoid a transient price change. Nevertheless, during systematic events NON-HFTs remain the main liquidity providers. These findings indicate that slow traders are preventing the occurrence of flash crashes when selling pressure is high, while when they either leave the order book or their quoting depth is small, a flash crash occurs. This result reinforces the view that DMMs are not incentivized to fully supply liquidity when it is needed the most.

## 4.5 Quoting activity analysis

We finally evaluate the impact of order submissions and cancellations on price changes, in line with the recent literature that suggests quotes play a dominant role for price discovery (Brogaard, Hendershott, and Riordan, 2019). In Figure 13, we look at the average volume of cancelled orders (Panel A) and the average volume of new orders (Panel B), both proxies of the level of activity of the traders, especially for HFTs. The figure is for non-systematic events (the corresponding figure for systematic events is reported in Appendix F, Figure F.4). Cancellations and new orders follow a nearly identical pattern, indicating that limit orders are heavily used to change the positioning of traders in the book. The pattern displays the two-peaks structure of volume intensity in Figure 7. The first peak corresponds to the beginning of the crash. The cancellation volume then declines, only to accelerate again at the end of the crash, whereafter it slowly reverts back to normal. Quote revision is almost exclusively used by HFTs. In particular, PURE-HFT MM cancel and revise most of their orders. This supports the presence of two

distinct phases for a flash crash: an initial one, in which selling pressure is accommodated with a price drop, and an accelerating one which exacerbates the original price decline. The results are also confirmed for systematic events, as documented in Appendix F.

[Figure 13 about here.]

This suggests orders are a primary channel to impact the price for HFTs. To assess the impact of quoting activity on the price, we estimate the impulse responses of mid-price changes on unit shocks in trader group mid-prices, computed as the average between best bid and best ask of each trader group. The impulse-response functions (IRFs) are estimated for each flash crash event in four periods: pre-crash, crash, late crash and recovery. The IRFs are estimated with the local projection method developed by Jordà (2005), which constitutes a robust alternative to standard VAR models (a brief review is available in Appendix D). Figure 14 shows estimated IRFs, averaged across systematic and non-systematic events, of the changes of mid-price on unit shocks in the changes of the average between best bid and best ask of different trader groups. The results are compelling in showing that DMMs (both PURE-HFT and IB-HFT) play a dominant role in determining, through their quote revisions, mid-price changes during crash and recovery. Their role is particularly strong during systematic crashes, and this is especially true for PURE-HFT MM. This suggests market makers are actively moving the market through their quote activity instead of transactions. The role played by other market participants is not visible in the average impact. Further, the impact of PURE-HFT MM is stronger in the late phase of the crash and for systematic events, signaling that they are mostly responsible for the transient price impact with respect to quoting activity.

[Figure 14 about here.]

Taken together, the evidence presented in this section about quoting activity provides statistical support to the main themes of this paper. First, quoting activity follows the pattern observed in trading volume. Second, quoting activity has an impact on prices, most prominently impacted by market makers, in particular PURE-HFT MM. Again, the impact is stronger for systematic events than for non-systematic ones. And, again, the pattern can explain the overshooting associated with the transient price change. Concluding, market efficiency is compromised in the

late phase of the flash crashes due to the combined effect of the quoting activity of PURE-HFT MM and the trading activity of IB-HFT MM, both DMMs in this market.

## 5 Conclusions

This paper shows that DMMs do not necessarily play a beneficial role to market efficiency and liquidity during periods of pronounced market distress. Using a novel econometric methodology proposed by [Christensen, Oomen, and Renò \(2022\)](#) we detect 148 flash crashes in one year (2013) of blue-chip French stocks. The granularity of our database allow us to distinguish different trading groups, including pure HFT firms, which have been largely investigated in the literature, and investment bank HFTs. Our analysis shows that electronic traders, and in particular those of investment banks, play a significant role during flash crashes. IB-HFT OWN push the price down with informed selling at the beginning of the crash; IB CLIENT follow suit to profit opportunistically on this information, especially during non-systematic crashes; IB-HFT MM, who are DMMs in this market, also follow, especially when the crash is systematic; PURE-HFT MM, who are also DMMs, employ intense quote revisions to bring the price down during crashes, contributing to an overshooting in the late phase. The behavior of DMMs in a market turning illiquid can be associated with overshooting and a transitory price impact. Even if DMMs contribute to the price overshooting, especially during systematic crashes, their behavior is rational. When crashes affect several stocks, they sell increasingly as the crash develops to avoid big losses against informed trading. This behavior is very different from what they normally do in “tranquil” times. The main category that stops the crash when there is significant selling pressure and supports recovery after flash crashes is the NON-HFT, who receive a compensation from buying at discount. Our paper thus documents that under severe market distress, traders react rationally but, unfortunately, not in the direction of efficient market functioning. Thus, our empirical findings can be informative for market design, to provide the right incentives or an entirely different market structure (see, e.g., [Budish, Cramton, and Shim, 2015](#)).

Our results have important policy implications. Electronic liquidity providers can indeed recover zero net inventory and provide liquidity on average, but that is not enough to prevent

flash crashes from happening. Our study recommends a deeper evaluation of the recent MiFID II regulation, which recognizes algorithmic liquidity provision as pivotal to the functioning of financial markets. The regulation endorses automatic liquidity provision by electronic market makers, imposing 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, and it should be revised in light of this objective. Possible solutions to this problem are: a change in their compensation scheme; or a change in the mechanism of trading halts, which does not work with flash crashes, since the latter cannot be associated with excess volatility.

## References

- AMF, 2017, “Study of the behaviour of high-frequency traders on Euronext Paris: Risks and Trends,” working paper.
- Anand, A., and K. Venkataraman, 2016, “Market conditions, fragility, and the economics of market making,” *Journal of Financial Economics*, 121(2), 327–349.
- Andersen, T. G., and O. Bondarenko, 2014, “VPIN and the flash crash,” *Journal of Financial Markets*, 17, 1–46.
- Andersen, T. G., O. Bondarenko, A. S. Kyle, and A. A. Obizhaeva, 2015, “Intraday trading invariance in the E-mini S&P 500 futures market,” Working paper, Northwestern University.
- Bandi, F., 2002, “Short-term interest rate dynamics: a spatial approach,” *Journal of Financial Economics*, 65, 73–110.
- Bank for International Settlements, 2017, “The sterling ‘flash event’ of 7 October 2016,” working paper.
- Bank of England, 2019, *Financial Stability Report*.
- Barlevy, G., and P. Veronesi, 2003, “Rational panics and stock market crashes,” *Journal of Economic Theory*, 110(2), 234–263.
- Bellia, M., 2017, “High-Frequency Market Making: Liquidity Provision, Adverse Selection, and Competition,” Working paper.
- Bessembinder, H., J. Hao, and K. Zheng, 2020, “Liquidity provision contracts and market quality: Evidence from the New York Stock Exchange,” *The Review of Financial Studies*, 33(1), 44–74.
- Biais, B., and T. Foucault, 2014, “HFT and market quality,” *Bankers, Markets & Investors*, 128(1), 5–19.
- Brogaard, J., A. Carrion, T. Moyaert, R. Riordan, A. Shkilko, and K. Sokolov, 2018, “High Frequency Trading and Extreme Price Movements,” *Journal of Financial Economics*, 128(2), 253–265.
- Brogaard, J., T. Hendershott, and R. Riordan, 2019, “Price discovery without trading: Evidence from limit orders,” *Journal of Finance*, 74(4), 1621–1658.

- Brunnermeier, M., and L. Pedersen, 2005, “Predatory trading,” *The Journal of Finance*, 60(4), 1825–1863.
- Budish, E., P. Cramton, and J. Shim, 2015, “The high-frequency trading arms race: Frequent batch auctions as a market design response,” *The Quarterly Journal of Economics*, 130(4), 1547–1621.
- Cespa, G., and T. Foucault, 2014, “Illiquidity contagion and liquidity crashes,” *Review of Financial Studies*, 27(6), 1615–1660.
- Cespa, G., and X. Vives, 2022, “Market opacity and fragility,” Working paper.
- Chaboud, A. P., B. Chiquoine, E. Hjalmarsson, and C. Vega, 2014, “Rise of the machines: Algorithmic trading in the foreign exchange market,” *The Journal of Finance*, 69(5), 2045–2084.
- Chong, Y., O. Jordà, and A. M. Taylor, 2012, “The Harrod-Balassa-Samuelson hypothesis: real exchange rates and their long-run equilibrium,” *International Economic Review*, 53(2), 609–634.
- Christensen, K., R. C. A. Oomen, and R. Renò, 2022, “The drift burst hypothesis,” *Journal of Econometrics*, 227(2), 461–497.
- Clark-Joseph, A. D., M. Ye, and C. Zi, 2017, “Designated market makers still matter: Evidence from two natural experiments,” *Journal of Financial Economics*, 126(3), 652–667.
- Easley, D., M. M. L. de Prado, and M. O’Hara, 2011, “The microstructure of the “flash crash”: Flow toxicity, liquidity crashes and the probability of informed trading,” *Journal of Portfolio Management*, 37(2), 118–128.
- ESMA, 2021, “MiFID II Review Report,” MiFID II/MiFIR review report on Algorithmic Trading.
- Euronext, 2014, “Euronext Rule Book - Book I: Harmonised Rules,” working paper.
- Glosten, L. R., 1987, “Components of the bid-ask spread and the statistical properties of transaction prices,” *The Journal of Finance*, 42(5), 1293–1307.
- Golub, A., J. Keane, and S.-H. Poon, 2017, “High Frequency Trading and Mini Flash Crashes,” Working paper.
- Grossman, S., and M. Miller, 1988, “Liquidity and market structure,” *Journal of Finance*, 43(3),



617–633.

Hautsch, N., M. Noè, and S. S. Zhang, 2017, “The Ambivalent Role of High-Frequency Trading in Turbulent Market Periods,” Working paper.

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

Huang, J., and J. Wang, 2009, “Liquidity and market crashes,” *Review of Financial Studies*, 22(7), 2607.

Jacod, J., Y. Li, P. A. Mykland, M. Podolskij, and M. Vetter, 2009, “Microstructure noise in the continuous case: The pre-averaging approach,” *Stochastic Processes and their Applications*, 119(7), 2249–2276.

Jones, C. M., 2013, “What do we know about high-frequency trading?,” Columbia Business School Research Paper 13-11.

Jordà, O., 2005, “Estimation and Inference of Impulse Responses by Local Projections,” *American Economic Review*, 95(1), 161–182.

Kirilenko, A., A. S. Kyle, M. Samadi, and T. Tuzun, 2017, “The Flash Crash: High frequency trading in an electronic market,” *Journal of Finance*, 3, 967–998.

Korajczyk, R. A., and D. Murphy, 2019, “High-frequency market making to large institutional trades,” *The Review of Financial Studies*, 32(3), 1034–1067.

Kristensen, D., 2010, “Nonparametric filtering of the realised spot volatility: A kernel-based approach,” *Econometric Theory*, 26(1), 60–93.

Madhavan, A. N., 2012, “Exchange-traded funds, market structure and the Flash Crash,” *Financial Analysts Journal*, 68(4), 20–35.

Megarbane, N., P. Saliba, C.-A. Lehalle, and M. Rosenbaum, 2018, “The Behaviour of High-Frequency Traders Under Different Market Stress Scenarios,” *Market Microstructure and Liquidity*, 3(3-4).

Menkveld, A. J., and B. Z. Yueshen, 2019, “The Flash Crash: A cautionary tale about highly fragmented markets,” *Management Science*, 10(10), 4470–4488.

NYSE-Euronext, 2012, “Euronext Cash Market, Info Flash of 26 March 2012,” working paper.

SEC, 2014, “Equity market structure literature review Part II: High frequency trading,” *US*

*Security and Exchange Commission, Staff of the Division of Trading and Markets.*

van Kervel, V., and A. J. Menkveld, 2019, “High-Frequency Trading around Large Institutional Orders,” *The Journal of Finance*, 74(3), 1091–1137.

Yang, L., and H. Zhu, 2020, “Back-running: Seeking and hiding fundamental information in order flows,” *The Review of Financial Studies*, 33(4), 1484–1533.

**Table 1 Summary statistics of Flash Crash events**

	Mean	Std	Min	Max	Quantile(0.1)	Quantile(0.5)	Quantile(0.9)
<b>Return</b>	-1.35	0.80	-5.18	-0.37	-2.42	-1.11	-0.62
<b>Duration (min)</b>	9.53	8.45	0.07	41.60	2.12	7.32	19.34
<b>Duration (%)</b>	1.87	1.66	0.01	8.16	0.42	1.44	3.81
<b>N. trades during crash</b>	582.10	442.32	89.00	2612.00	182.90	452.50	1191.70
<b>N. trades daily</b>	10337.07	5710.67	2501.00	44264.00	5258.50	8823.00	19025.90
<b>N. trades during crash (%)</b>	5.99	4.29	1.07	35.98	2.46	5.01	9.66
<b>Signed volume during crash</b>	-1276.37	1347.86	-9291.14	1722.17	-2942.18	-1049.13	-19.78
<b>Signed volume daily</b>	-4848.60	15259.88	-128877.88	42409.70	-16296.97	-3218.63	4980.44
<b>Signed volume during crash (%)</b>	21.07	182.75	-667.12	1592.26	-58.15	9.19	64.44
<b>Trading volume during crash</b>	4598.60	3789.11	537.53	18268.03	1210.75	3521.45	9530.02
<b>Trading volume daily</b>	93943.52	69076.44	16946.98	435185.60	34809.38	75966.21	183647.23
<b>Trading volume during crash (%)</b>	5.43	4.06	0.71	34.71	2.02	4.50	9.03

*Note.* This table reports summary statistics of the price drop during Flash Crashes, flash crash duration and trading activity for the stocks in which flash crashes occur: returns during the crash (per cent), duration of crashes in minutes and as a fraction of length of the trading session, number of trades, signed and total trading volume (in thousands of euros) over the whole trading session and during the crash period in the same units and relative to the whole trading day (per cent). The database is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data, with trader group and account flags, are from BEDOFIH.

**Table 2 Liquidity measures during non-systematic flash crashes**

	pre-crash	early crash	intermediate crash	late crash	recovery
Signed Volume (millions of Euro)					
Mean	-0.01	-0.49	-0.71	-1.05	-1.52
Median	-0.04	-0.45	-0.68	-0.89	-1.45
s.e. (mean)	0.57	0.58	0.59	0.61	0.66
Bid-ask spread (%)					
Mean	1.59	1.79	1.97	1.79	1.97
Median	1.22	1.31	1.35	1.35	1.42
s.e. (mean)	0.12	0.17	0.33	0.14	0.18
Market depth change (%)					
Mean	4.14	-1.96	-2.40	-7.79	-8.44
Median	1.81	-2.44	-4.06	-9.94	-10.53
s.e. (mean)	1.18	1.99	2.11	2.55	2.49
Executed order age (seconds)					
Mean	2.05	6.47	11.47	15.40	3.50
Median	0.42	2.35	5.35	12.53	0.61
s.e. (mean)	0.39	0.87	1.27	1.11	0.58

*Note.* This table reports the cross-sectional average, median and standard error of the mean of the average quantities displayed in Figure 6 in the five different periods of the crash described in Figure 4. The standard error of the mean is computed assuming independence across different events. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

**Table 3 Trading imbalances during flash crashes**

<b>Panel A: Systematic flash crashes</b>				
	IB-HFT MM	IB-HFT OWN	IB CLIENTS	NON-HFT
Pre-crash	-0.010 (-0.46)	-0.024 (-1.23)	0.019 (1.14)	0.017 (1.02)
Early crash	0.002 (0.02)	-0.155** (-2.15)	0.049 (0.56)	0.183** (2.74)
Intermediate crash	-0.183 (-1.59)	-0.364*** (-3.82)	0.141 (1.15)	0.480** (2.78)
Late crash	-0.395*** (-2.66)	-0.089 (-0.92)	-0.003 (-0.04)	0.559*** (3.72)
Recovery	-0.043** (-2.27)	0.027 (1.33)	-0.015 (-0.83)	0.016 (1.25)
Perc. Spread	-0.007 (-0.57)	-0.004 (-0.69)	0.003 (0.31)	0.003 (0.46)
Volume (log)	-0.143*** (-11.19)	-0.022 (-1.34)	0.047*** (3.04)	0.103*** (4.82)
Return	-0.075*** (-3.76)	0.007 (0.65)	0.030* (1.97)	-0.034*** (-3.38)
Observations	79404	79404	79404	79404
Adj $R^2$	0.067	0.020	0.029	0.036

<b>Panel B: NON-Systematic flash crashes</b>				
	IB-HFT MM	IB-HFT OWN	IB CLIENTS	NON-HFT
Pre-crash	0.031** (2.69)	-0.011 (-1.17)	-0.019 (-1.53)	0.015 (1.31)
Early crash	0.294*** (3.37)	-0.136** (-2.41)	-0.018 (-0.49)	-0.036 (-0.71)
Intermediate crash	0.186*** (4.30)	-0.047 (-1.19)	-0.087* (-1.90)	-0.027 (-0.69)
Late crash	0.241*** (3.31)	0.012 (0.15)	-0.267*** (-3.95)	-0.004 (-0.07)
Recovery	-0.009 (-0.54)	-0.017 (-0.82)	-0.017 (-0.91)	0.042** (2.52)
Perc. Spread	0.006 (1.18)	-0.009* (-1.81)	0.001 (0.16)	-0.002 (-0.43)
Volume (log)	0.025* (1.94)	0.008 (0.57)	-0.026* (-1.78)	0.011 (0.75)
Return	-0.188*** (-11.01)	0.012 (1.16)	0.031*** (3.78)	0.016 (1.43)
Observations	342032	342032	342032	342032
Adj $R^2$	0.055	0.023	0.038	0.019

*Note.* This table presents the estimates of the coefficients  $\beta_k^{(j)}$  of the crash phase dummies from the regression equation 10 estimated for different trader groups separately for systematic and non-systematic events. *Perc. Spread* is the percentage quoted spread, *Volume* is the log of the total trading volume, *Return* is the stock return calculated for each 10-second interval. Non-dummy variables are standardized at stock level. Coefficients of lagged variables are not reported for brevity. The panel regressions are estimated with stock fixed effects and robust standard errors. *t*-statistics are in parenthesis. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

**Table 4 Trading imbalances during flash crashes: aggressive and passive trades**

**Panel A: Systematic flash crashes**

	Aggressive trades		Passive trades	
	IB-HFT MM	IB-HFT OWN	IB-HFT MM	IB-HFT OWN
Pre-crash	0.041*** (3.04)	0.023 (1.51)	-0.047* (-1.74)	-0.055* (-2.03)
Early crash	0.075 (0.73)	-0.184* (-2.02)	-0.062 (-1.69)	-0.008 (-0.12)
Intermediate crash	-0.055 (-0.45)	-0.353*** (-3.70)	-0.177** (-2.31)	-0.055 (-1.27)
Late crash	-0.306** (-2.22)	-0.071 (-0.92)	-0.308** (-2.65)	-0.025 (-0.28)
Recovery	-0.074*** (-4.32)	-0.032** (-2.56)	-0.010 (-0.48)	0.080** (2.75)
Perc. Spread	0.010 (0.94)	0.010* (1.88)	-0.015 (-1.32)	-0.020*** (-3.61)
Volume (log)	-0.108*** (-9.62)	-0.065*** (-3.75)	-0.089*** (-7.59)	0.049*** (2.95)
Return	0.179*** (10.79)	0.118*** (11.23)	-0.226*** (-11.96)	-0.134*** (-11.30)
Observations	79404	79404	79404	79404
Adj $R^2$	0.081	0.039	0.088	0.054

**Panel B: NON-Systematic flash crashes**

	Aggressive trades		Passive trades	
	IB-HFT MM	IB-HFT OWN	IB-HFT MM	IB-HFT OWN
Pre-crash	0.004 (0.43)	-0.017* (-2.03)	0.033** (2.70)	0.004 (0.42)
Early crash	-0.032 (-1.06)	-0.160*** (-2.87)	0.352*** (4.11)	0.004 (0.13)
Intermediate crash	0.042 (1.13)	-0.053 (-1.53)	0.194*** (4.40)	0.012 (0.39)
Late crash	0.027 (0.50)	-0.052 (-0.71)	0.242*** (3.27)	0.089 (1.47)
Recovery	-0.012 (-0.95)	-0.036* (-1.89)	-0.006 (-0.35)	0.013 (0.60)
Perc. Spread	0.006 (1.24)	-0.006 (-1.02)	0.003 (0.63)	-0.003 (-0.57)
Volume (log)	-0.012 (-1.51)	-0.015* (-1.78)	0.036*** (3.09)	0.024** (2.15)
Return	0.142*** (11.92)	0.199*** (24.08)	-0.311*** (-28.41)	-0.207*** (-20.93)
Observations	342032	342032	342032	342032
Adj $R^2$	0.028	0.049	0.104	0.058

*Note.* This table presents the estimates of the coefficients  $\beta_k^{(j)}$  of the crash phase dummies from the regression equation 10 estimated for different trader groups separately for systematic and non-systematic events. In this case, the dependent variables are the Aggressive trades (trades initiated) and the passive trades (liquidity provision). *Perc. Spread* is the percentage quoted spread, *Volume* is the log of the total trading volume, *Return* is the stock return calculated for each 10-second interval. Non-dummy variables are standardized at stock level. Coefficients of lagged variables are not reported for brevity. The panel regressions are estimated with stock fixed effects and robust standard errors. *t*-statistics are in parenthesis. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

**Table 5 Profits during flash crashes**

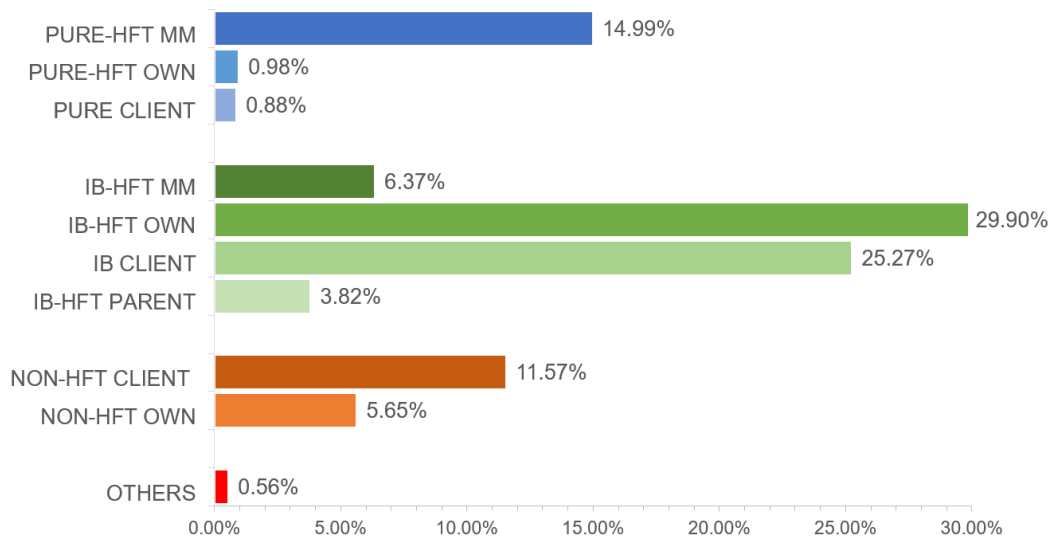
<b>Panel A: Systematic flash crashes - Profits</b>									
	PURE CLIENT	PURE- HFT OWN	PURE- HFT MM	IB-HFT MM	IB CLIENTS	IB-HFT OWN	IB-HFT PARENT	NON- HFT CLIENT	NON- HFT OWN
Crash	-0.054 (-0.93)	-0.021 (-0.52)	0.343 (1.09)	0.331* (1.96)	-0.418** (-2.36)	0.878*** (3.15)	0.521** (2.18)	-0.882** (-2.69)	-0.467 (-1.46)
Perc. Spread	0.018 (1.30)	-0.025 (-0.86)	-0.010 (-0.13)	-0.054 (-0.61)	0.259* (1.83)	0.225** (2.72)	0.056 (0.95)	-0.235* (-2.00)	-0.201* (-1.81)
Volume (log)	-0.008 (-0.92)	-0.031 (-1.08)	1.050*** (4.50)	-0.029 (-0.28)	0.057 (0.44)	-0.069 (-0.44)	0.283*** (5.12)	-0.705*** (-3.95)	-0.469** (-2.61)
Return	0.032 (1.22)	-0.018 (-1.21)	-0.001 (-0.00)	-1.092*** (-5.15)	0.070 (0.45)	0.196 (0.74)	-0.662*** (-5.67)	0.759*** (4.04)	0.715*** (5.25)
Observations	79404	79404	79404	79404	79404	79404	79404	79404	79404
Adj $R^2$	0.001	0.000	0.010	0.022	0.002	0.002	0.021	0.015	0.010

<b>Panel B: NON-Systematic flash crashes - Profits</b>									
	PURE CLIENT	PURE- HFT OWN	PURE- HFT MM	IB-HFT MM	IB CLIENTS	IB-HFT OWN	IB-HFT PARENT	NON- HFT CLIENT	NON- HFT OWN
Crash	-0.008 (-0.26)	0.055 (0.70)	0.042 (0.60)	-0.367** (-2.66)	0.138 (1.05)	0.410** (2.28)	-0.094** (-2.06)	-0.355** (-2.51)	0.171 (1.38)
Perc. Spread	-0.040** (-2.17)	0.105 (1.32)	0.354* (1.72)	-0.028 (-0.26)	-0.029 (-0.17)	0.016 (0.07)	0.002 (0.05)	-0.159 (-0.84)	-0.218 (-1.48)
Volume (log)	-0.004 (-0.47)	0.055 (1.24)	0.476*** (4.03)	-0.114 (-1.67)	-0.019 (-0.19)	0.159* (1.73)	0.066*** (2.86)	-0.655*** (-3.75)	0.034 (0.36)
Return	0.009 (0.19)	-0.019 (-0.11)	0.071 (0.36)	0.076 (0.36)	-0.390 (-1.19)	0.058 (0.16)	0.017 (0.14)	0.372 (1.09)	-0.194 (-0.92)
Observations	342032	342032	342032	342032	342032	342032	342032	342032	342032
Adj $R^2$	0.001	0.001	0.006	0.003	0.002	0.001	0.002	0.003	0.001

*Note.* This table presents the estimates of the coefficients  $\beta_k^{(j)}$  from the regression equation 10 estimated for different trader groups separately for systematic and non-systematic events. In this case, the dummy variable *crash* assumes the value of one for the entire duration of the crash (from the pre-crash until the end of the recovery). In this case, the dependent variable is the profit calculated for each 10-second interval, gross of fees and rebates. *Perc. Spread* is the percentage quoted spread, *Volume* is the log of the total trading volume, *Return* is the stock return calculated for each 10-second interval. Non-dummy variables are standardized at stock level. Coefficients of lagged variables are not reported for brevity. The panel regressions are estimated with stock fixed effects and robust standard errors. *t*-statistics are in parenthesis. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

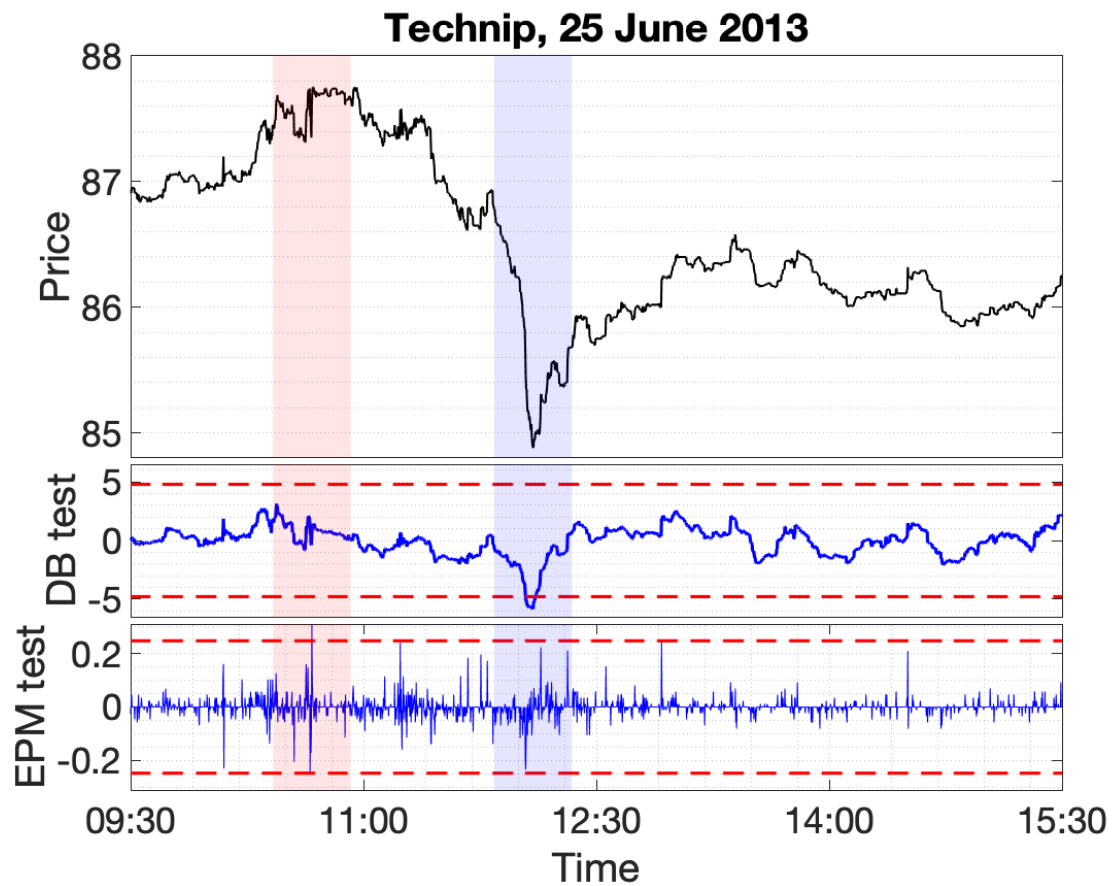
**Figure 1. Trading Activity by trader category**



*Note.* This figure displays the percentage of total double-counted volume (buy plus sell) averaged across stocks, for each trader group, using the AMF flag for HFT and the account flag from the exchange. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

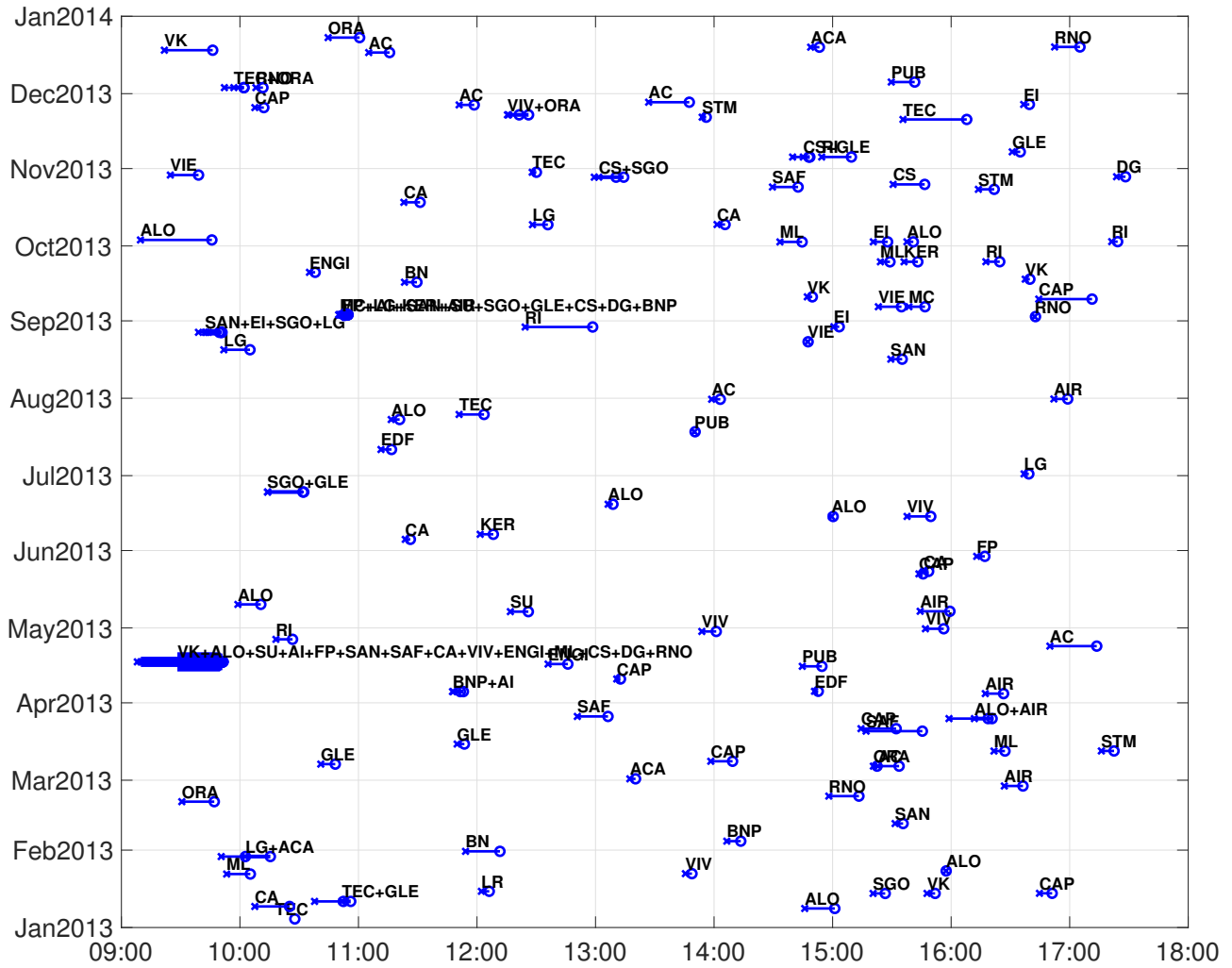


Figure 2. An example of a crash event



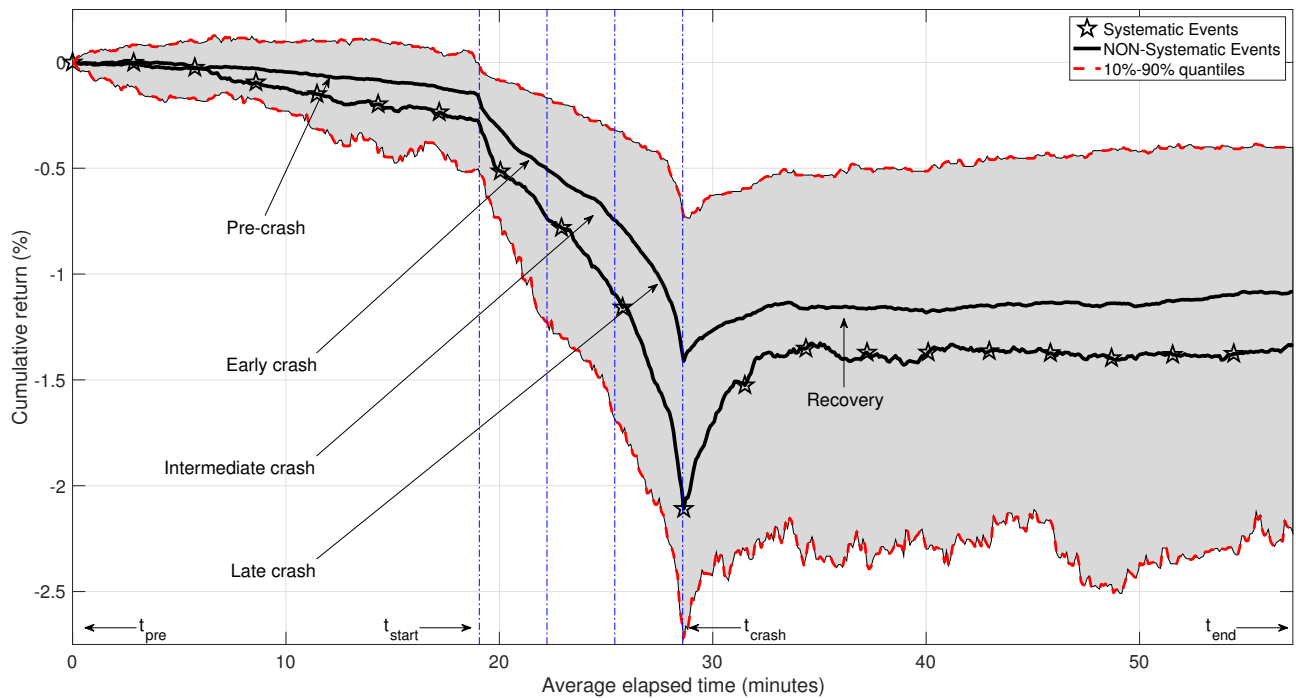
*Note.* This figure reports the evolution of the price of Technip over a flash crash events on June 25, 2013, which is detected using the methodology of [Christensen, Oomen, and Renò \(2022\)](#), but not detected by the extreme price movement approach of [Brogaard et al. \(2018\)](#). The upper panel reports the time-series traded price sampled at the 10-seconds grid. The middle panel reports the drift burst (DB) test statistics we use to detect flash crashes in our sample. The lower panel shows the basic test used to detect extreme price movement (EPM), that is 10-second returns. Dashed-red lines in the figure represent 99.9% confidence bands.

Figure 3. Temporal distribution of crash events in the data



Note. This figure presents, for each of the 148 crash events which are analyzed in the empirical application, on the  $x$  axis, the time of the crash start  $t_0$  (with a cross) and the time of the crash end  $t_1$  (with a circle) connected by a segment. The  $y$  axis report the day of the year. For each crash, the ticker of the corresponding stock is also reported. Tickers are connected by a “+” sign when the crash is simultaneous. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

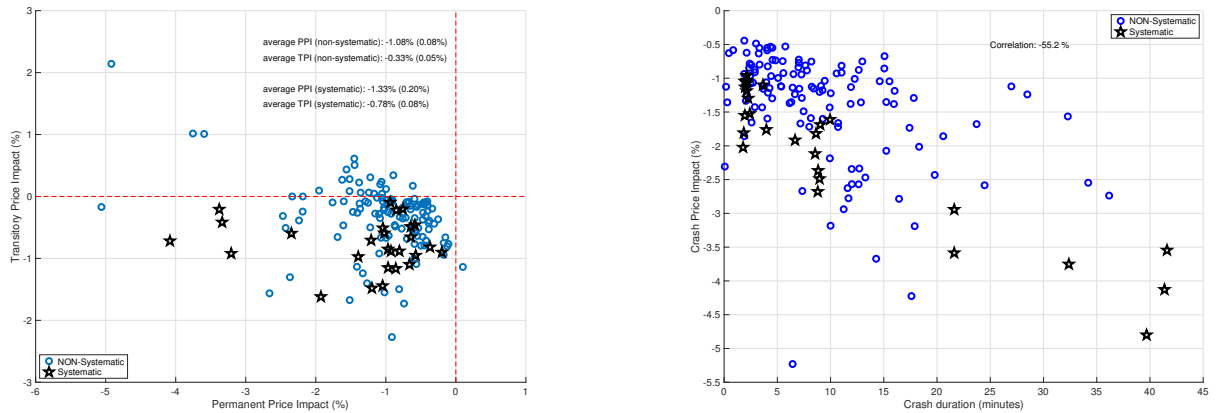
Figure 4. Average cumulative return dynamics during a crash event



*Note.* This figure reports the average of the price evolution over systematic and non-systematic flash crash events, as well as the 10-90% quantiles for all the 148 events. The vertical lines separate the different periods in the evolution of the crash as labelled in the figure and described in the text. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

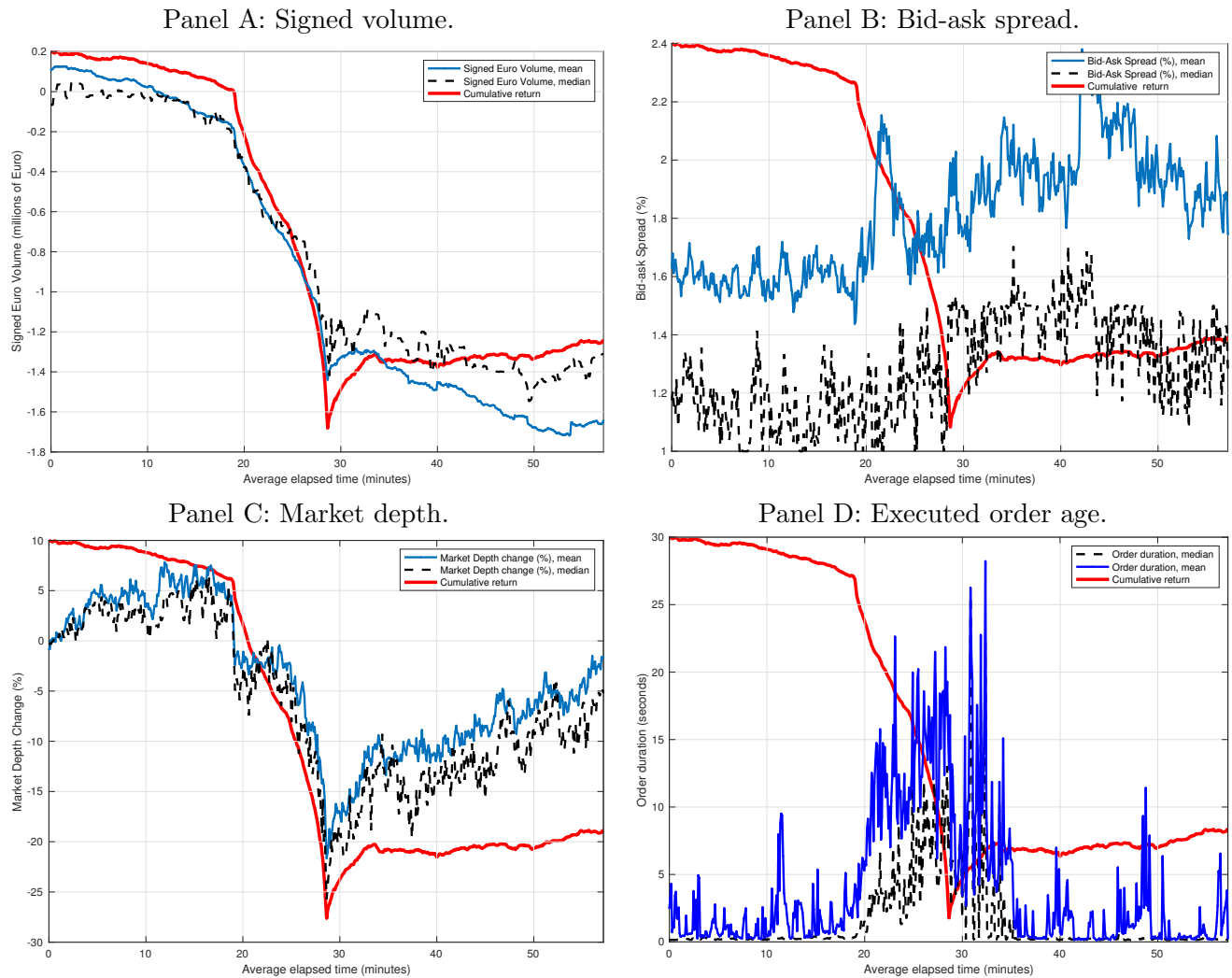
**Figure 5. Average cumulative return dynamics during a Flash Crash**

Panel A: Permanent vs. Transitory price impact    Panel B: Crash price impact vs crash duration



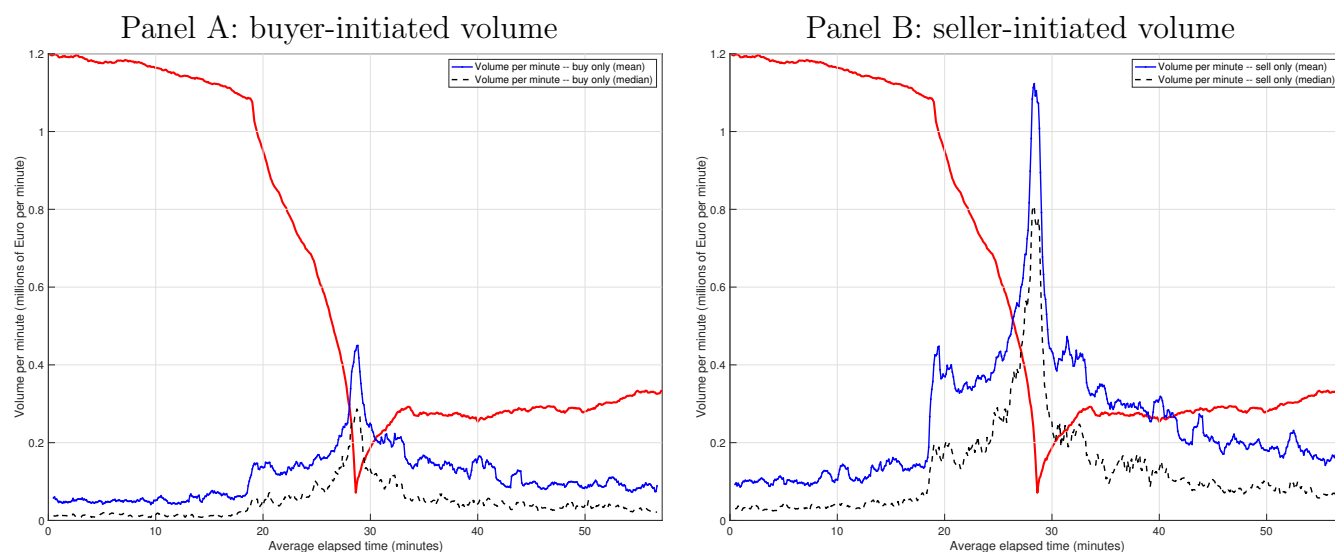
*Note.* This figure presents the permanent and transitory price impact. Panel A reports the scatter plot of the Transient Price Impact (negative log-return from peak to end) with the Permanent Price Impact (log-return from beginning to end). Means and standard deviations (in parenthesis) are reported for both systematic and non-systematic events. Panel B reports the scatter plot of the Crash Price Impact (log-return from beginning to peak) with the duration of the crash. A longer duration implies a deeper crash. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

Figure 6. Liquidity measures during non-systematic flash crashes



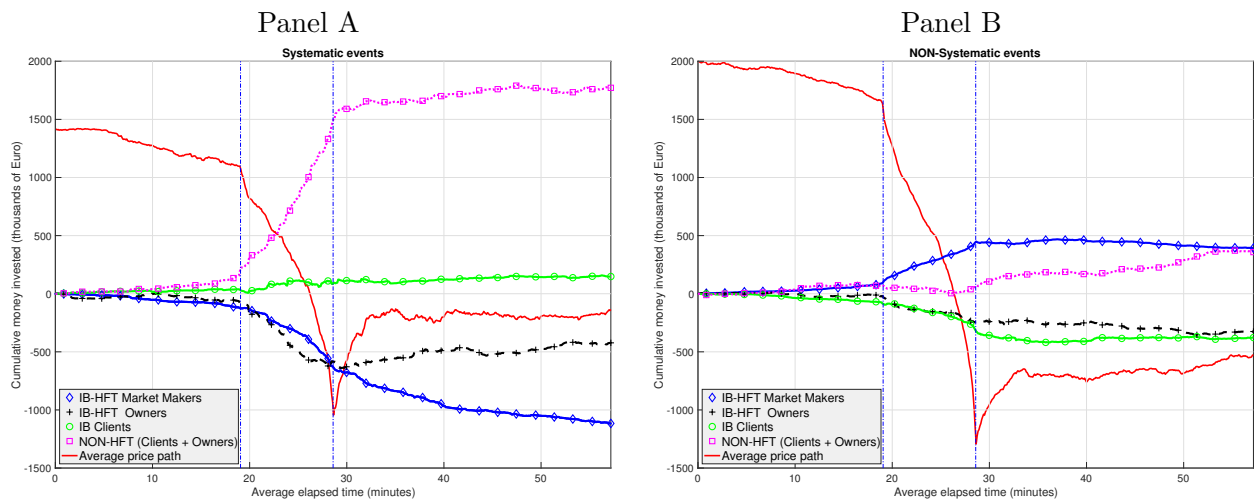
*Note.* This figure reports four measures of liquidity averaged across non-systematic flash crash events considered in this study. Panel A: cumulative signed monetary volume (negative volume = sell). Panel B: bid-ask spread. Panel C: market depth (difference from beginning). Panel D: the age of the executed orders (we exclude orders with age less than 0.1 seconds and those coming from the previous day). On each panel, we superimpose the average price evolution for visual comparison. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

**Figure 7. Volume per minute for initiated buyer and initiated seller trades (non-systematic)**



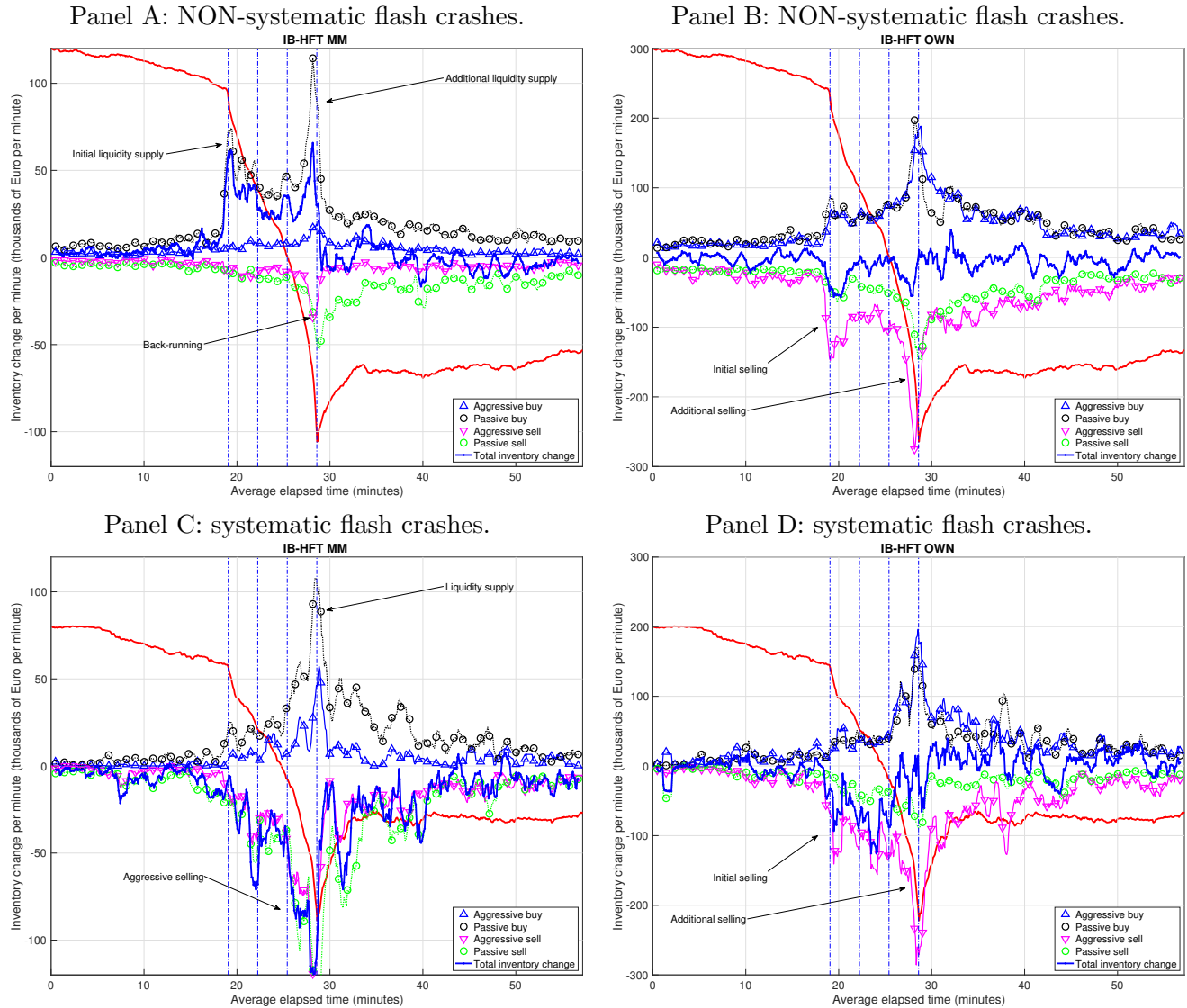
*Note.* This figure depicts the average euro volume traded per minute during crash events, separated in buyer-initiated trades (Panel A) and seller-initiated trades (Panel B). On each panel, we superimpose the average price evolution for visual comparison. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

**Figure 8. Average trading imbalance of different trading categories during a flash crash**



*Note.* The figure reports the average monetary net imbalance (negative corresponding to selling, positive corresponding to buying) of Investment Bank HFT Market Makers, IB CLIENT, IB-HFT OWN, and the sum of NON-HFT CLIENT and NON-HFT OWN. We superimpose the average cumulative return during the events for visual comparison. In Panel A, the average is applied to 121 standalone, non-systematic events. In Panel B, the average is applied to the remaining 27 systematic events of April, 17 and September 3. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

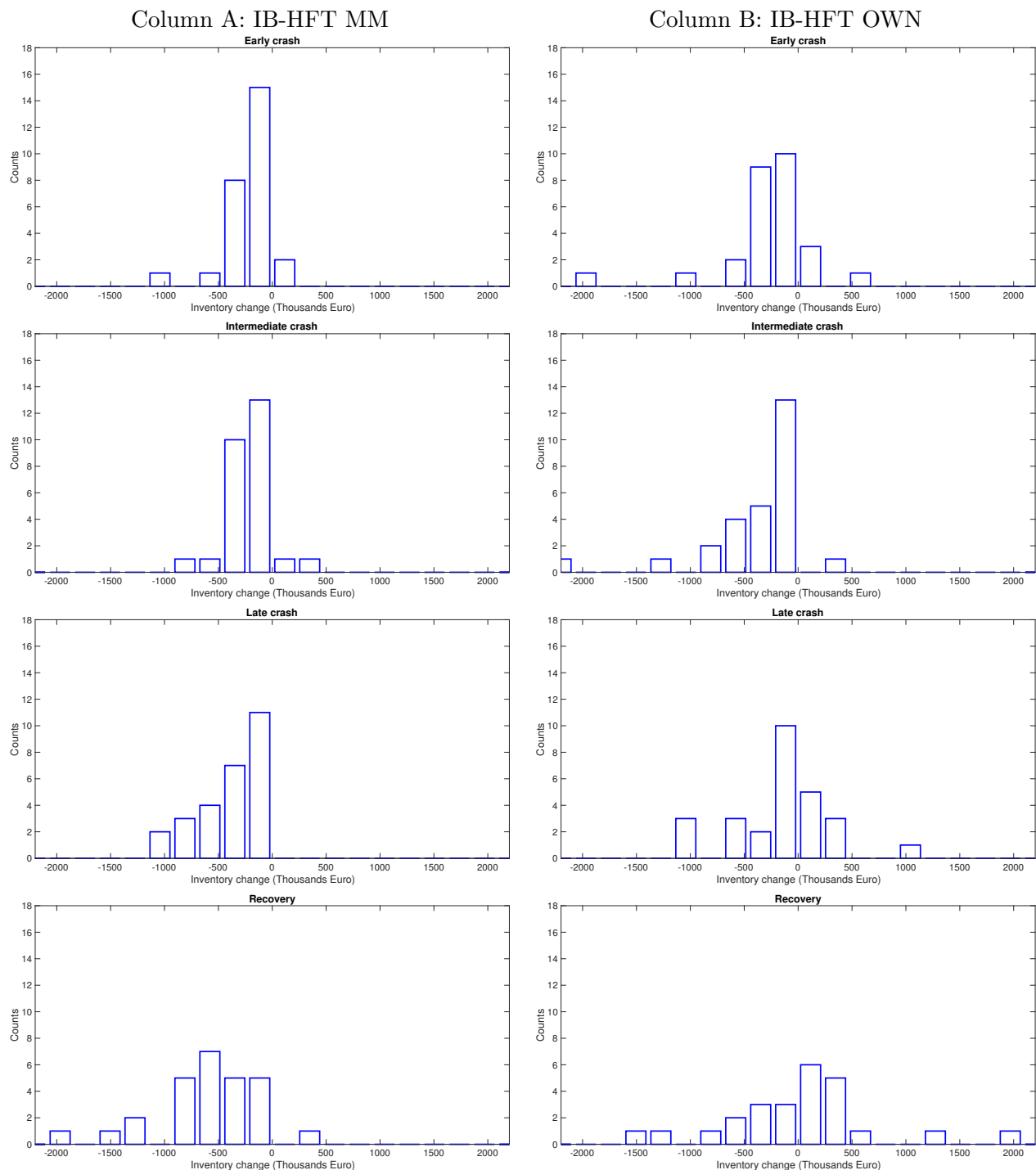
Figure 9. Average trading imbalance changes per minute



Note. The figure displays the trading imbalance change per minute for IB-HFT Market Makers and IB-HFT Owners. separated in buyer initiated, seller initiated, buyer passive and seller passive trades. Only non-systematic events are averaged. Panel A and B report averages for non-systematic flash crashes. Panel C and D report averages for systematic flash crashes. The y-units are not uniform across different trader categories. Back-running in Panel A refers to the theory of Yang and Zhu (2020). The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

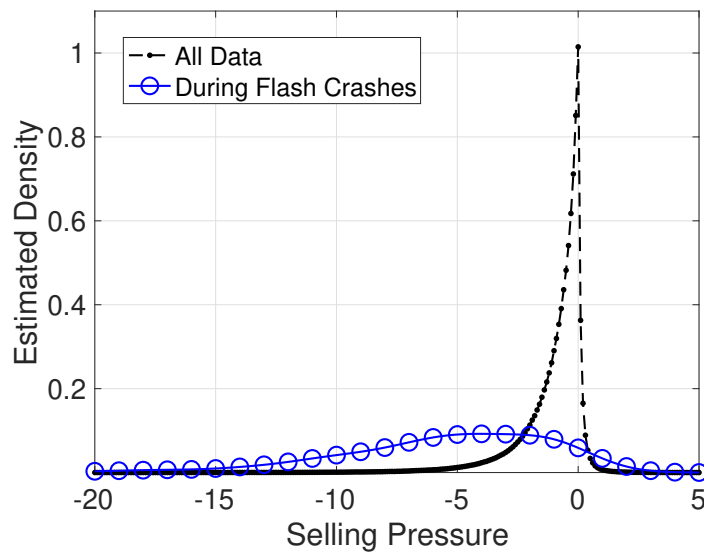


**Figure 10. Monetary net imbalances changes per minute of systematic events**



*Note.* The figure depicts the empirical distribution of monetary net imbalances for IB-HFT MM and IB-HFT OWN at different stages of the crash for systematic events. Column A is for IB-HFT MM. Column B is for IB-HFT OWN. We can see that IB-HFT MM sell more intensely as price declines. In particular, during the late phase of the crash, they are always selling. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

Figure 11. The distribution of selling pressure.



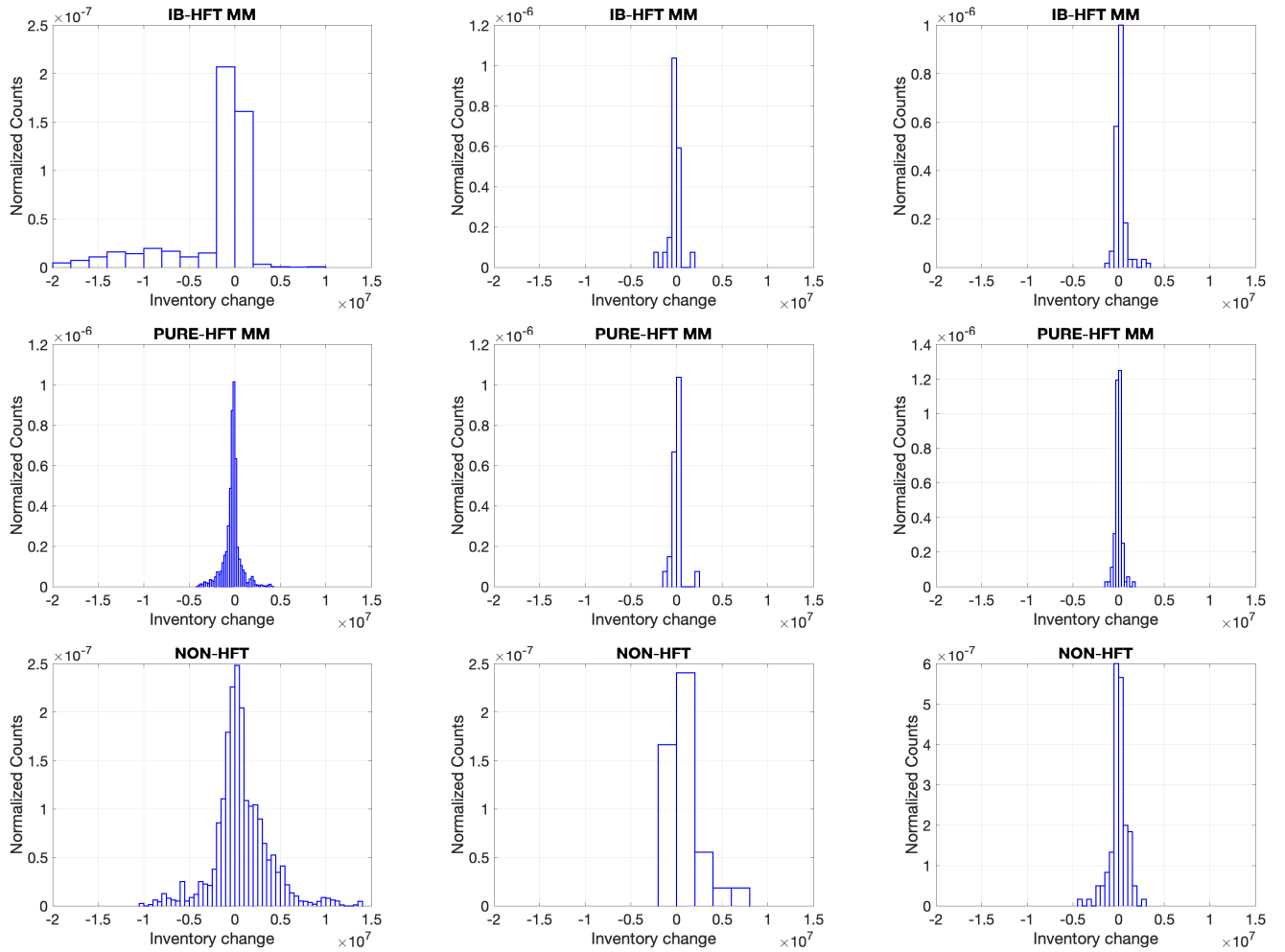
*Note.* Kernel smooth densities of  $\mathcal{SP}_m^{(day,stock)}$  based on the pooled (over all days stocks and one-minute grid-points) data and based on the measures corresponding to the grid-points which belong to a crash period (pooled over all days stocks and flash crashes).

Figure 12. Inventory changes during flash crashes and high selling pressure episodes.

Column A: High selling pressure,  
no flash crashes

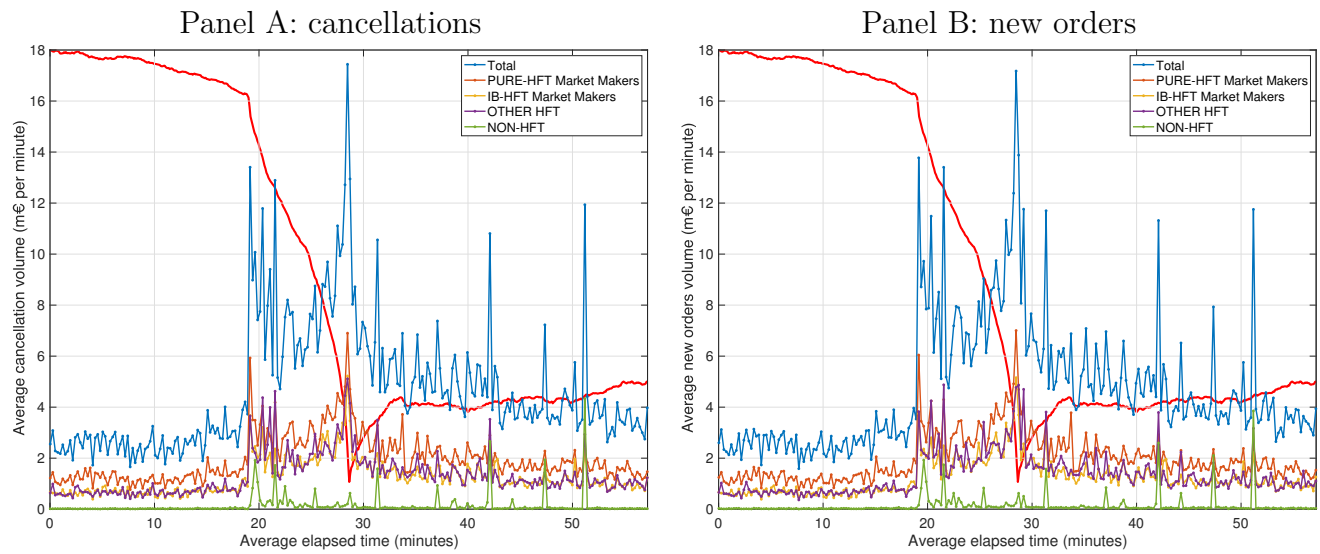
Column B: Systematic  
flash crashes

Column C: Non-systematic  
flash crashes



*Note.* Distribution of the inventory changes of NON-HFT, IB-HFT MM and PURE-HFT MM during high selling pressure episodes. Column A shows the the distribution conditional on the absence a flash crash. Columns B and C corresponds to the intervals of high selling pressure coinciding with respectively systematic and non-systematic flash crashes.

**Figure 13.** Cancellations and new orders volume by trader category (non-systematic)

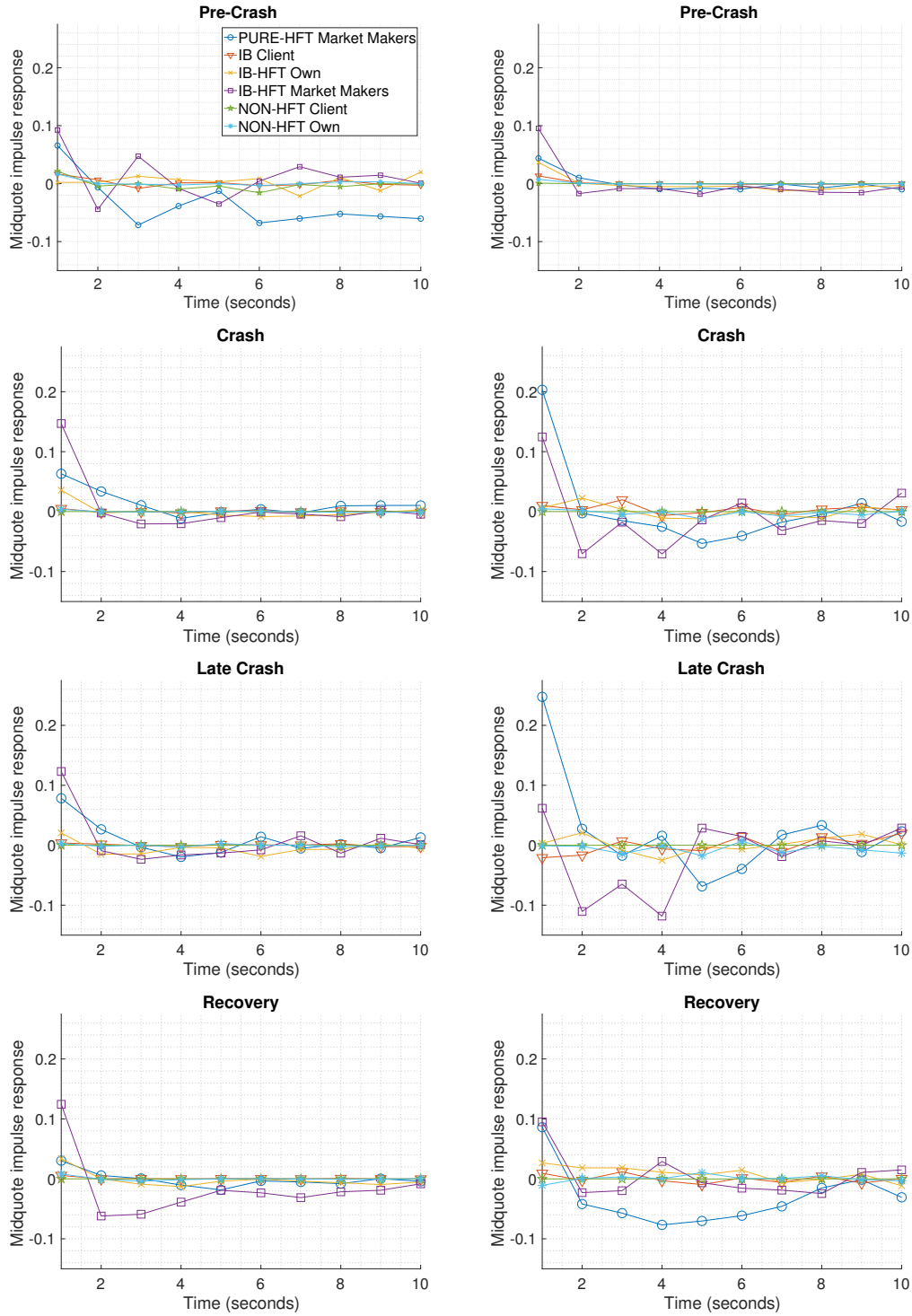


*Note.* This figure displays the average per minute euro volume of cancelled orders (Panel A) and new orders (Panel B). On each panel, we superimpose the average price evolution for visual comparison. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

Figure 14. Average Estimated Impulse Response Functions

Column A: NON-systematic flash crashes

Column B: Systematic flash crashes.



Note. The figure shows impulse response functions of the changes of mid-price on unit shocks in the changes of the average between best bid and best ask of different trader groups, for non-systematic (Column A) and systematic (Column B) events, in four different phases of the crash/recovery. Impulse response functions are estimated using the local projection methodology developed by Jordà (2005).

# Appendix

## A A comparison with the EPM method

In [Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov \(2018\)](#), distress events are mainly identified using Extreme Price Movements (EPMs). EPMs are detected with one of the following methods. The first method simply labels all 10-second intervals that belong to the 99.9th percentile of 10-second absolute midpoint returns for each stock as EPMs. The second method identifies EPMs based on the residuals from the return autoregression. We apply the same methodology to our data set.

Table [A.1](#) compares the identified (negative) EPMs with the flash crashes detected using our methodology. On average, for each stock, both EPM detection methods label 0.05% of 10-second intervals as EPMs. However, only a little fraction of our flash crashes is identified as EPMs: the first method detects roughly 26.35% of flash crashes, while the second one – only 18.92%. The pure power of the EPM approach is rather natural, as the typical flash crash episodes are not exhausted by a few large price movements, but represent a “dense” series of different magnitude price changes leaning to the same direction. On the other hand, EPM approach exhibit a large number of false-positives due to oversampling periods of high volatility, as also admitted by the authors. Summarizing, we compute that the overlap between flash crashes and EPMs is limited, and thus that our distressed sample is different from that analyzed by [Brogaard et al. \(2018\)](#).

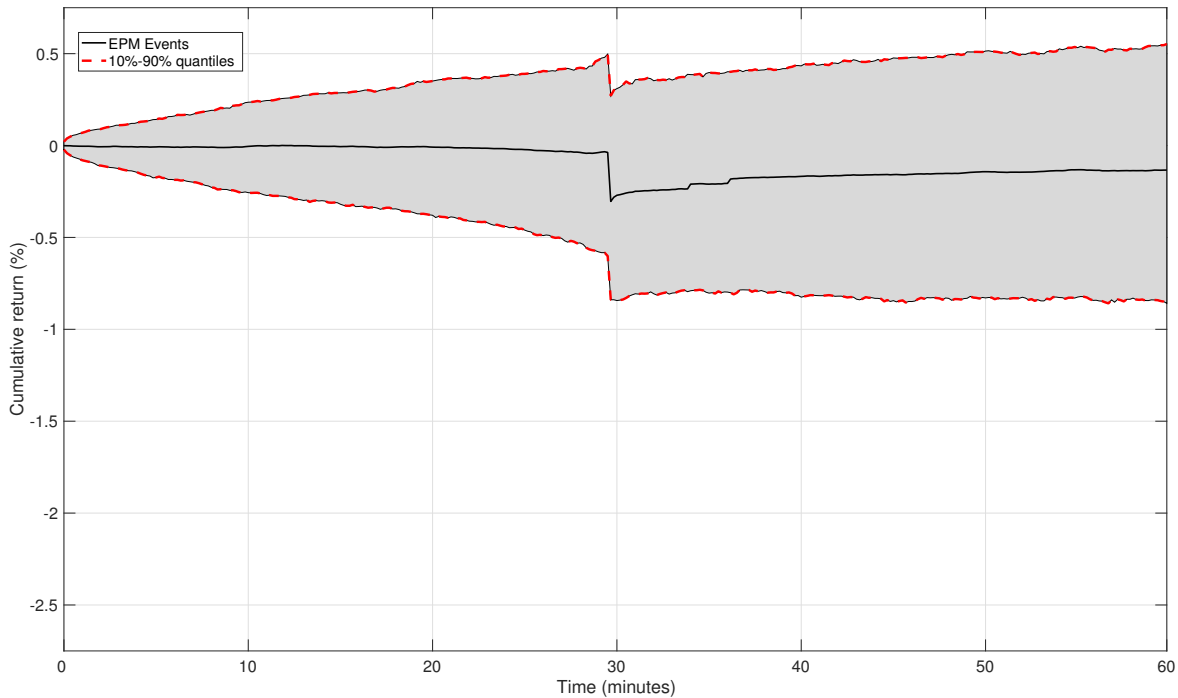
Figure [A.1](#) is the same as Figure [4](#), now computed with events identified with EPMs. While there is a slight evidence of extreme price movement, on average, it is clear that EPMs are not capturing the V-shapes of a flash crash. The Figure makes clear that EPMs look more at “volatility”-induced price changes, while our methodology looks more at “drift”-induced price changes. This explains why the two samples identified by EPMs and the flash crash test of [Christensen, Oomen, and Renò \(2022\)](#) are substantially different.

**Table A.1 Compares detected EPMS and flash crashes**

	# of EPMS per stock	Detected flash crashes
<i>First method</i>	286.48 (0.05%)	39 (26.35%)
<i>Second method</i>	282.19 (0.05%)	28 (18.92%)

*Note.* This table reports in the first column the average (across stocks) number of EPMS detected in a single stock in absolute value and as a fraction (per cent) of the total number of the 10-second returns in our sample. The second column reports the number of our flash crashes episodes identified as EPMS according to the methodology presented by Brogaard, Carrion, Moyaert, Riordan, Shkilko, and Sokolov (2018). The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

**Figure A.1. Average cumulative return dynamics around an Extreme Price Movement.**



*Note.* This figure reports the average of the price evolution around extreme price movements (EPMS), as well as the 10-90% quantiles for all the events. The EPMS are detected by labelling the 10-second intervals that belong to the 99.9th percentile of 10-second absolute midpoint returns for each stock as EPMS over the full year for each stock.

## B Supplementary statistical assessment and robustness checks

This section contains additional statistical assessments of the trading behavior of all trading categories during a flash crash. Having 148 different crash events allows us to assess whether what we observe is statistically significant, i.e. that the observed trading behavior are precise trading strategies which are constantly implemented, and not the artifact of statistical fluctuations.

Table B.1 reports the cross-sectional average and standard deviation of net trade imbalances  $\mathcal{I}_{\text{period}}^{(j)}$  in the five different periods of a flash crash, for the trading categories for which this number is non-negligible and divided into systematic and non-systematic flash crashes. 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 ( $\mathcal{I}_{\text{period}}^{(i),\text{init}}$  and  $\mathcal{I}_{\text{period}}^{(j),\text{liq}}$ , 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). To add information with respect to Table B.1, we now report net imbalance per minute, to measure the intensity of accumulated inventory. This also allows to compare fairly among periods with different duration.

Substantial heterogeneity emerges in the behavior of trader groups. PURE-HFTs do not accumulate any significant inventory during the crash, which is consistent with their trading mandate. The only exception is the liquidity they provide to recovery for non-systematic events. However, they do not stop trading, as concluded in Kirilenko, Kyle, Samadi, and Tuzun (2017) by looking at the Flash Crash of May 6, 2010 only. This result also complements the findings in Bellia (2017), who instead shows that in “normal” market periods, PURE-HFT MM activity improves market liquidity significantly. This conclusion does not hold anymore in distressed times.

Regarding the remaining HFT categories, IB-HFTs, we observe more heterogeneity. The imbalance of IB-HFT OWN is largely negative across the whole crash, consistent with their role of big sellers, and selling is particularly massive and prolonged during non-systematic events.



IB CLIENT are also net sellers, but they follow IB-HFT OWN and mostly sell in the late crash for non-systematic events, while their net inventory is non-significant during systematic events. This shows that informed trading seems to originate from the IB-HFT OWN, and then propagates to the IB CLIENT. The attempt of clients to profit from the information coming from owners generates the big part of the second wave of selling which, in a liquidity deprived market, contributes to the transient price impact crash.

Regarding IB-HFT MM, the table shows that they do provide significant liquidity during the price drop and (mildly) during price recovery, but only for non-systematic events. However, the liquidity they provide is not sufficient to prevent the transitory price impact. For systematic events, they are significant big sellers along all stages. They also increase their net inventory as the IB-HFT OWN decrease their selling pressure. In the late phase of the crash and during recovery, they are the largest sellers. This is the main result of the paper and is shown here to be strongly statistically significant. IB-HFT Parents are also particularly active in becoming big sellers in the late phase of the crash. Analyzing the flash crash of May 6, 2010, [Menkveld and Yueshen \(2019\)](#) argue that it has been caused by large investors. However, they do not provide information on whether large investors employ HFTs or NON-HFTs for placing their orders, whether they split their orders or not, the reason why large investors sell, and whether large investors are the investment banks or the clients on their accounts, nor they clarify the role of market makers in providing liquidity during the crash. Our analysis supplies this information.

Importantly, Table [B.1](#) also shows that NON-HFTs play an important role in reducing the negative effects of the crash and in helping the price recovery afterwards. The trade imbalance of NON-HFT CLIENT is positive and highly significant during both price drop and recovery, and especially for systematic events, where they play the role of liquidity providers in place of the market makers. Their net inventory becomes increasingly positive as the crash develops and then price recovers. NON-HFT OWN instead contribute mildly to the non-systematic crashes, while they also become significant net liquidity providers in the late phase of systematic crash.

Table [B.2](#) provides the estimates of the panel regression model [10](#) for all trader groups. The results, which integrates Table [3](#) are qualitatively similar to the one presented in Table [B.1](#).

Table [B.3](#) reports the estimation of the panel model using the aggressive trades only as

dependend variable ( $\mathcal{I}_{\text{period}}^{(i),\text{init}}$ ) by different trader categories at different stages of a flash crash, divided for systematic and non-systematic crashes. In addition to what has been presented in Section 4.3, we highlight that for systematic events, PURE-HFT MM (in the initial stage) and IB-HFT PARENT (in the intermediate stage) are contributing to the build-up of the flash crash, while for NON-systematic also NON-HFTs plays a role, together with IB CLIENTS.

Table B.4 complements Table B.3 by showing the liquidity provision trades, which is the flip side of the aggressive order. NON-HFT Clients are the big liquidity suppliers, especially in the late crash phase and especially for systematic crashes. The fact that they provide liquidity is always significant. The second-best liquidity supplier during the late phase of systematic crashes are NON-HFT OWN. IB-HFT MM provide significant liquidity only for non-systematic events. They are the first liquidity providers in the initial phase of the crash, which is in line with their contractual role. As the crash develops, their relative role as liquidity providers declines, and in the late phase of non-systematic crash they are even surpassed by NON-HFT CLIENT. As said, they do not provide any liquidity through limit orders during systematic crashes. PURE-HFT MM are mildly significant as liquidity providers for NON-systematic events, but the net amount is small compared to other trader groups. Overall, Table B.4 confirms and complements the previous finding on categorized traders activity during flash crashes.

**Table B.1 Average trade imbalances (k€).**

**Panel A: Systematic flash crashes.**

	pre-crash	early crash	intermediate crash	late crash	recovery
PURE CLIENT	-1.11 (1.11)	0.00 (0.00)	6.17 (5.80)	10.90 (10.90)	13.12 (8.83)
PURE-HFT MM	44.55 (31.31)	-4.67 (31.34)	-26.43 (28.10)	-17.27 (34.33)	137.12 (84.56)
PURE-HFT OWN	-20.02 (14.97)	3.34 (2.57)	18.98 (12.33)	4.46 (9.26)	-3.83 (7.36)
IB CLIENT	28.58 (32.60)	52.73 (72.55)	27.81 (46.09)	-24.47 (72.98)	63.41 (63.21)
IB-HFT MM	-127.32*** (34.88)	-105.36** (44.97)	-117.98*** (39.24)	-274.55*** (49.16)	-491.03*** (94.87)
IB-HFT OWN	-94.98 (67.02)	-168.84* (88.80)	-265.59*** (90.44)	-59.06 (85.93)	165.76 (206.97)
IB-HFT PARENT	-53.57** (23.23)	-1.52 (19.36)	-86.08*** (31.48)	-224.09*** (60.60)	-197.01*** (56.69)
NON-HFT CLIENT	195.74** (91.39)	226.00*** (74.38)	308.02*** (72.49)	372.75*** (83.01)	74.32 (85.02)
NON-HFT OWN	28.09 (39.45)	27.46 (35.85)	134.87* (74.83)	209.58*** (65.23)	194.80** (97.68)

**Panel B: NON-systematic flash crashes.**

	pre-crash	early crash	intermediate crash	late crash	recovery
PURE CLIENT	5.93 (8.49)	-4.80 (8.14)	15.44** (7.20)	4.38 (11.07)	-1.44 (19.64)
PURE-HFT MM	-37.96 (23.72)	27.01 (17.03)	-12.64 (13.15)	-0.80 (20.07)	-108.51*** (29.86)
PURE-HFT OWN	-28.41 (30.68)	2.55 (5.31)	5.27 (4.20)	4.91 (4.62)	27.89 (18.84)
IB CLIENT	-84.77** (35.12)	-39.52* (22.36)	-58.51*** (20.48)	-137.66*** (36.75)	-57.33 (88.78)
IB-HFT MM	93.29*** (24.16)	143.54*** (29.56)	85.04*** (16.29)	127.89*** (20.01)	-55.14 (42.87)
IB-HFT OWN	-16.27 (53.84)	-117.70** (49.69)	-31.21 (30.65)	-73.52 (52.83)	-86.56 (132.57)
IB-HFT PARENT	3.79 (14.37)	13.85 (9.29)	19.17** (9.35)	42.87*** (10.67)	-20.73 (52.54)
NON-HFT CLIENT	87.81* (50.25)	38.79** (19.62)	31.60* (19.00)	107.58*** (35.08)	309.31*** (104.48)
NON-HFT OWN	-23.45 (25.18)	-63.92** (28.09)	-54.14** (27.34)	-73.83*** (28.41)	-1.02 (58.19)

*Note.* This table reports the cross-sectional average, and standard errors in brackets, of the trade imbalances measured in k€, in the five different periods of the crash described in Figure 4. Panel A: reports averages on the 27 flash crashes which happen in several stocks on April 17 and September 3, 2013. Panel B: reports averages on all the other flash crashes. The significance of the mean is evaluated with a standard *t*-test. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ . The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

**Table B.2 Trading imbalances during flash crashes - All trader groups**

<b>Panel A: Systematic flash crashes</b>									
	PURE CLIENT	PURE- HFT OWN	PURE- HFT MM	IB-HFT MM	IB CLIENTS	IB-HFT OWN	IB-HFT PARENT	NON- HFT CLIENT	NON- HFT OWN
Pre-crash	-0.005 (-0.91)	-0.017 (-0.94)	0.016 (0.89)	-0.010 (-0.46)	0.019 (1.14)	-0.024 (-1.23)	-0.010 (-0.56)	0.039* (1.95)	-0.017 (-1.09)
Early crash	0.001 (0.14)	0.012 (0.78)	-0.053 (-1.16)	0.002 (0.02)	0.049 (0.56)	-0.155** (-2.15)	0.022 (0.31)	0.303*** (3.37)	-0.139 (-1.03)
Interm. crash	0.061 (1.27)	0.132* (1.98)	-0.108** (-2.73)	-0.183 (-1.59)	0.141 (1.15)	-0.364*** (-3.82)	-0.254* (-1.91)	0.460*** (2.94)	0.151 (0.90)
Late crash	0.131 (1.04)	0.155 (1.62)	-0.047 (-0.65)	-0.395** (-2.66)	-0.003 (-0.04)	-0.089 (-0.92)	-0.705*** (-4.49)	0.505*** (3.08)	0.221** (2.76)
Recovery	0.017 (1.65)	-0.010 (-0.83)	0.017 (0.70)	-0.043** (-2.27)	-0.015 (-0.83)	0.027 (1.33)	-0.045** (-2.65)	0.018 (1.68)	0.010 (0.53)
Perc. Spread	-0.004 (-1.12)	0.005 (0.79)	0.007 (0.70)	-0.007 (-0.57)	0.003 (0.31)	-0.004 (-0.69)	0.003 (0.46)	-0.006 (-0.79)	0.012 (1.68)
Volume (log)	0.011** (2.42)	0.006 (1.30)	-0.022 (-1.29)	-0.143*** (-11.19)	0.047*** (3.04)	-0.022 (-1.34)	-0.102*** (-8.23)	0.061** (2.54)	0.074*** (2.92)
Return	-0.000 (-0.00)	0.018*** (3.52)	0.031 (1.18)	-0.075*** (-3.76)	0.030* (1.97)	0.007 (0.65)	0.055*** (5.20)	-0.028** (-2.73)	-0.019* (-1.97)
Observations	79404	79404	79404	79404	79404	79404	79404	79404	79404
Adj $R^2$	0.032	0.003	0.005	0.067	0.029	0.020	0.025	0.029	0.030

<b>Panel B: NON-Systematic flash crashes</b>									
	PURE CLIENT	PURE- HFT OWN	PURE- HFT MM	IB-HFT MM	IB CLIENTS	IB-HFT OWN	IB-HFT PARENT	NON- HFT CLIENT	NON- HFT OWN
Pre-crash	0.022 (1.25)	0.006 (0.44)	-0.008 (-0.89)	0.031** (2.69)	-0.019 (-1.53)	-0.011 (-1.17)	0.014** (2.18)	0.027 (1.66)	-0.009 (-0.72)
Early crash	0.004 (0.07)	0.073*** (3.03)	0.071 (1.37)	0.294*** (3.37)	-0.018 (-0.49)	-0.136** (-2.41)	0.075** (2.16)	0.043 (1.13)	-0.104* (-1.73)
Interm. crash	0.199*** (2.84)	0.020 (0.54)	-0.034 (-0.88)	0.186*** (4.30)	-0.087* (-1.90)	-0.047 (-1.19)	0.112*** (4.47)	0.012 (0.29)	-0.046 (-1.08)
Late crash	0.122 (1.26)	0.028 (0.57)	0.002 (0.04)	0.241*** (3.31)	-0.267*** (-3.95)	0.012 (0.15)	0.220*** (5.30)	0.106 (1.62)	-0.142*** (-2.76)
Recovery	0.007 (0.48)	0.015 (1.35)	-0.025** (-2.46)	-0.009 (-0.54)	-0.017 (-0.91)	-0.017 (-0.82)	0.005 (0.40)	0.054*** (3.32)	-0.009 (-0.61)
Perc. Spread	0.005 (0.92)	0.013** (2.58)	0.002 (0.48)	0.006 (1.18)	0.001 (0.16)	-0.009* (-1.81)	0.005 (0.97)	-0.003 (-0.60)	-0.001 (-0.15)
Volume (log)	0.008 (1.18)	0.004 (0.61)	-0.018** (-2.50)	0.025* (1.94)	-0.026* (-1.78)	0.008 (0.57)	-0.019*** (-2.95)	0.016 (0.93)	-0.005 (-0.45)
Return	0.012 (1.49)	0.012 (1.28)	0.021 (1.42)	-0.188*** (-11.01)	0.031*** (3.78)	0.012 (1.16)	0.023** (2.52)	0.002 (0.18)	0.024*** (3.06)
Observations	342032	342032	342032	342032	342032	342032	342032	342032	342032
Adj $R^2$	0.008	0.005	0.002	0.055	0.038	0.023	0.014	0.02	0.023

*Note.* This table presents the estimates of the coefficients  $\beta_k^{(j)}$  of the crash phase dummies from the regression equation 10 estimated for different trader groups separately for systematic and non-systematic events. *Perc. Spread* is the percentage quoted spread, *Volume* is the log of the total trading volume, *Return* is the stock return calculated for each 10-second interval. Non-dummy variables are standardized at stock level. Coefficients of lagged variables are not reported for brevity. The panel regressions are estimated with stock fixed effects and robust standard errors. *t*-statistics are in parenthesis. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

Table B.3 Trading imbalances during flash crashes - Aggressive trades

Panel A: Systematic flash crashes - Aggressive trades									
	PURE CLIENT	PURE- HFT OWN	PURE- HFT MM	IB-HFT MM	IB CLIENTS	IB-HFT OWN	IB-HFT PARENT	NON- HFT CLIENT	NON- HFT OWN
Pre-crash	0.018* (1.96)	-0.000 (-0.03)	0.045** (2.36)	0.041*** (3.04)	0.030 (1.49)	0.023 (1.51)	-0.002 (-0.14)	0.036** (2.32)	0.010 (0.66)
Early crash	-0.006 (-0.23)	0.007 (0.24)	-0.083* (-1.95)	0.075 (0.73)	-0.072 (-0.96)	-0.184* (-2.02)	0.010 (0.15)	0.106*** (3.08)	-0.161 (-1.06)
Interm. crash	0.063 (1.22)	0.098* (1.84)	-0.060 (-1.64)	-0.055 (-0.45)	-0.023 (-0.54)	-0.353*** (-3.70)	-0.285** (-2.13)	0.068 (1.08)	-0.036 (-0.46)
Late crash	0.118*** (3.98)	0.201*** (2.87)	0.192** (2.79)	-0.306** (-2.22)	-0.118 (-1.43)	-0.071 (-0.92)	-0.507*** (-3.34)	0.072 (0.94)	0.216*** (3.12)
Recovery	-0.022 (-1.42)	-0.023* (-1.75)	0.014 (0.53)	-0.074*** (-4.32)	-0.038** (-2.69)	-0.032** (-2.56)	-0.046** (-2.83)	-0.010 (-0.61)	-0.029 (-1.27)
Perc. Spread	0.001 (0.19)	0.002 (0.26)	0.018* (1.88)	0.010 (0.94)	0.007 (0.61)	0.010* (1.88)	0.009 (1.21)	-0.010 (-1.22)	0.021** (2.46)
Volume (log)	0.005 (1.16)	-0.000 (-0.04)	-0.010 (-0.73)	-0.108*** (-9.62)	-0.003 (-0.24)	-0.065*** (-9.75)	-0.086*** (-9.53)	0.005 (0.30)	0.043*** (3.33)
Return	0.073*** (8.77)	0.075*** (10.13)	0.248*** (16.07)	0.179*** (10.79)	0.125*** (5.98)	0.118*** (11.23)	0.116*** (12.26)	0.088*** (9.18)	0.065*** (8.67)
Observations	79404	79404	79404	79404	79404	79404	79404	79404	79404
Adj $R^2$	0.010	0.012	0.086	0.081	0.041	0.039	0.036	0.017	0.017

Panel B: NON Systematic flash crashes - Aggressive trades									
	PURE CLIENT	PURE- HFT OWN	PURE- HFT MM	IB-HFT MM	IB CLIENTS	IB-HFT OWN	IB-HFT PARENT	NON- HFT CLIENT	NON- HFT OWN
Pre-crash	-0.003 (-0.30)	-0.005 (-0.38)	-0.007 (-0.69)	0.004 (0.43)	-0.024** (-2.22)	-0.017* (-2.03)	0.005 (0.59)	-0.008 (-0.86)	-0.006 (-1.02)
Early crash	-0.013 (-0.30)	0.039 (1.49)	0.023 (0.50)	-0.032 (-1.06)	-0.080* (-1.95)	-0.160*** (-2.87)	0.059 (1.64)	-0.063** (-2.05)	-0.110** (-2.18)
Interm. crash	0.060* (1.76)	0.003 (0.11)	0.010 (0.23)	0.042 (1.13)	-0.118** (-2.25)	-0.053 (-1.53)	0.090*** (2.91)	-0.055* (-1.89)	-0.055 (-1.29)
Late crash	0.022 (0.57)	0.048 (1.26)	0.052 (1.10)	0.027 (0.50)	-0.342*** (-4.76)	-0.052 (-0.71)	0.203*** (4.73)	-0.187*** (-3.35)	-0.165*** (-3.45)
Recovery	0.009 (0.59)	0.010 (0.82)	-0.015 (-1.40)	-0.012 (-0.95)	-0.024 (-1.46)	-0.036* (-1.89)	0.001 (0.05)	0.037* (1.93)	-0.003 (-0.27)
Perc. Spread	0.005 (1.17)	0.010* (1.86)	0.001 (0.18)	0.006 (1.24)	0.008 (1.22)	-0.006 (-1.02)	0.009* (1.89)	-0.007 (-1.16)	0.004 (0.53)
Volume (log)	-0.007 (-1.06)	-0.009 (-1.53)	-0.021*** (-3.33)	-0.012 (-1.51)	-0.033*** (-2.86)	-0.015* (-1.78)	-0.020*** (-3.62)	-0.015 (-1.36)	-0.014 (-1.47)
Return	0.087*** (13.03)	0.091*** (9.21)	0.238*** (22.62)	0.142*** (11.92)	0.161*** (19.21)	0.199*** (24.08)	0.113*** (18.24)	0.173*** (25.79)	0.117*** (14.44)
Observations	342032	342032	342032	342032	342032	342032	342032	342032	342032
Adj $R^2$	0.008	0.010	0.054	0.028	0.048	0.049	0.018	0.034	0.028

Note. This table presents the estimates of the coefficients  $\beta_k^{(j)}$  of the crash phase dummies from the regression equation 10 estimated for different trader groups separately for systematic and non-systematic events. For these models, the dependent variables are the aggressive trades only (trades that take liquidity from the market) *Perc. Spread* is the percentage quoted spread, *Volume* is the log of the total trading volume, *Return* is the stock return calculated for each 10-second interval. Non-dummy variables are standardized at stock level. Coefficients of lagged variables are not reported for brevity. The panel regressions are estimated with stock fixed effects and robust standard errors. *t*-statistics are in parenthesis. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

**Table B.4 Trading imbalances during flash crashes - Passive trades**

**Panel B: Systematic flash crashes - Passive trades**

	PURE CLIENT	PURE- HFT OWN	PURE- HFT MM	IB-HFT MM	IB CLIENTS	IB-HFT OWN	IB-HFT PARENT	NON- HFT CLIENT	NON- HFT OWN
Pre-crash	-0.028** (-2.46)	-0.036* (-1.97)	-0.032** (-2.27)	-0.047* (-1.74)	-0.006 (-0.38)	-0.055* (-2.03)	-0.010 (-0.91)	0.026 (1.19)	-0.030 (-1.45)
Early crash	-0.002 (-0.06)	0.005 (0.15)	0.020 (0.50)	-0.062 (-1.69)	0.073 (0.82)	-0.008 (-0.12)	0.039 (1.27)	0.300** (2.71)	-0.013 (-0.34)
Interm. crash	-0.023 (-0.39)	0.073 (0.76)	-0.090* (-1.75)	-0.177** (-2.31)	0.166 (1.09)	-0.055 (-1.27)	-0.022 (-0.45)	0.518*** (3.13)	0.258 (1.40)
Late crash	-0.029 (-0.26)	-0.133*** (-3.75)	-0.298*** (-3.67)	-0.308** (-2.65)	0.053 (0.57)	-0.025 (-0.28)	-0.350*** (-3.91)	0.559*** (2.97)	0.140 (1.47)
Recovery	0.029* (1.81)	0.012 (0.67)	0.005 (0.56)	-0.010 (-0.48)	0.005 (0.22)	0.080** (2.75)	-0.015 (-0.96)	0.033** (2.36)	0.036** (2.23)
Perc. Spread	-0.001 (-0.12)	0.000 (0.01)	-0.012 (-1.34)	-0.015 (-1.32)	-0.003 (-0.89)	-0.020*** (-3.61)	-0.009* (-1.99)	0.002 (0.26)	-0.001 (-0.15)
Volume (log)	0.001 (0.18)	0.010 (1.28)	-0.017* (-1.74)	-0.089*** (-7.59)	0.066*** (3.90)	0.049*** (2.95)	-0.042** (-2.62)	0.069*** (3.36)	0.061** (2.34)
Return	-0.084*** (-10.46)	-0.073*** (-8.06)	-0.266*** (-14.00)	-0.226*** (-11.96)	-0.077*** (-9.11)	-0.134*** (-11.30)	-0.076*** (-8.21)	-0.099*** (-8.10)	-0.073*** (-6.47)
Observations	79404	79404	79404	79404	79404	79404	79404	79404	79404
Adj $R^2$	0.010	0.012	0.086	0.081	0.041	0.039	0.036	0.017	0.017

**Panel B: NON-Systematic flash crashes - Passive trades**

	PURE CLIENT	PURE- HFT OWN	PURE- HFT MM	IB-HFT MM	IB CLIENTS	IB-HFT OWN	IB-HFT PARENT	NON- HFT CLIENT	NON- HFT OWN
Pre-crash	0.022 (1.17)	0.004 (0.25)	-0.008 (-0.77)	0.033** (2.70)	-0.010 (-0.79)	0.004 (0.42)	0.018*** (2.81)	0.037** (2.17)	-0.011 (-0.74)
Early crash	0.007 (0.19)	0.026 (1.30)	0.084** (2.20)	0.352*** (4.11)	0.059 (1.57)	0.004 (0.13)	0.042 (1.21)	0.086** (2.26)	-0.039 (-0.90)
Interm. crash	0.150* (1.92)	0.004 (0.15)	-0.068** (-2.56)	0.194*** (4.40)	-0.030 (-0.94)	0.012 (0.39)	0.064* (1.80)	0.049 (0.99)	-0.013 (-0.43)
Late crash	0.055 (0.81)	-0.015 (-0.59)	-0.077* (-1.81)	0.242*** (3.27)	-0.017 (-0.37)	0.089 (1.47)	0.077*** (3.19)	0.251*** (3.59)	-0.034 (-0.61)
Recovery	-0.005 (-0.68)	0.007 (0.65)	-0.023*** (-2.81)	-0.006 (-0.35)	-0.009 (-0.49)	0.013 (0.60)	0.012 (1.37)	0.039*** (2.76)	-0.006 (-0.43)
Perc. Spread	-0.004 (-1.07)	0.004 (0.85)	0.001 (0.11)	0.003 (0.63)	-0.006 (-0.98)	-0.003 (-0.57)	-0.003 (-0.49)	0.003 (0.62)	-0.007 (-1.25)
Volume (log)	0.014** (2.59)	0.013** (2.07)	-0.002 (-0.24)	0.036*** (3.09)	-0.000 (-0.00)	0.024** (2.15)	-0.008 (-0.89)	0.034** (2.36)	0.008 (0.87)
Return	-0.082*** (-12.32)	-0.086*** (-7.54)	-0.299*** (-27.19)	-0.311*** (-28.41)	-0.111*** (-10.32)	-0.207*** (-20.93)	-0.117*** (-11.69)	-0.129*** (-11.15)	-0.077*** (-10.14)
Observations	342032	342032	342032	342032	342032	342032	342032	342032	342032
Adj $R^2$	0.008	0.009	0.081	0.104	0.034	0.058	0.021	0.040	0.021

*Note.* This table presents the estimates of the coefficients  $\beta_k^{(j)}$  of the crash phase dummies from the regression equation 10 estimated for different trader groups separately for systematic and non-systematic events. For these models, the dependent variables are the passive trades only (trades that provide liquidity to the market) *Perc. Spread* is the percentage quoted spread, *Volume* is the log of the total trading volume, *Return* is the stock return calculated for each 10-second interval. Non-dummy variables are standardized at stock level. The panel regressions are estimated with stock fixed effects and robust standard errors. *t*-statistics are in parenthesis. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

## C Change of trading behavior

This section addresses the question of whether HFTs change their trading behavior during flash crashes by estimating the Kirilenko, Kyle, Samadi, and Tuzun (2017) model for inventory changes of different trader groups. Kirilenko, Kyle, Samadi, and Tuzun (2017) answered in the negative by using data from the flash crash of May 6, 2010 only. We instead answer in the positive, and this is made possible by the fact that we analyze 148 crashes instead of a single one.

The model reads:

$$\begin{aligned} \Delta y_t = & \alpha + \phi \Delta y_{t-1} + \delta y_{t-1} + \sum_{i=0}^3 \beta_i (\Delta \log p)_{t-i} \\ & + D^D \left( \alpha^D + \phi^D \Delta y_{t-1} + \delta^D y_{t-1} + \sum_{i=0}^3 \beta_i^D (\Delta \log p)_{t-i} \right) \\ & + D^U \left( \alpha^U + \phi^U \Delta y_{t-1} + \delta^U y_{t-1} + \sum_{i=0}^3 \beta_i^U (\Delta \log p)_{t-i} \right) + \varepsilon_t, \end{aligned} \quad (13)$$

where  $D^D$  is a dummy which is activated during the crash period (from  $t_{\text{start}}$  to  $t_{\text{crash}}$ , according to our definitions),  $D^U$  is a dummy which is activated during the recovery period (from  $t_{\text{crash}}$  to  $t_{\text{end}}$ ),  $y_t$  is the net inventory of each category (measured in million euros and starting at the beginning of each day) at time  $t$ , and  $\Delta y_t$  is the change in inventory over the period from  $t-1$  to  $t$ ;  $(\Delta \log p)_t$  is the logarithmic return of mid-prices from  $t-1$  to  $t$ .<sup>17</sup> We estimate model (13) for each day in which one of the 148 crash events occurs, and for each trading category separately. The inventories and prices are recorded on grids of 10 seconds. Significance of the variables associated with the crash (recovery period) would imply a different trading behavior during that phase. Average coefficients, together with their associated t-statistic (robustified to account for heteroskedasticity using the White correction) are reported in Table C.1 for non-systematic flash crashes, and Table C.2 for systematic flash crashes.<sup>18</sup>

<sup>17</sup>The model here is slightly modified with respect to Kirilenko, Kyle, Samadi, and Tuzun (2017). Specifically, we use 3 ten-seconds lags (instead of 20 one-second lags) and we regress on logarithmic returns instead of price changes, since we consider different stocks and days and we need to guarantee uniformity across different price levels.

<sup>18</sup>To compute the t-statistic on average coefficients, we assume that coefficient estimates are independent across

Table C.1 Non-systematic flash crashes

	PURE-HFT MM	PURE-HFT OWN	IB-HFT MM	IB-HFT OWN	IB CLIENT	NONHFT CLIENT	NONHFT OWN
constant	-0.000*** (-4.62)	0.000 (0.73)	0.000* (1.74)	0.000 (1.09)	-0.000*** (-4.85)	0.000 (1.22)	0.000 (1.34)
$\Delta y_{t-1}$	0.004 (1.15)	0.029*** (3.73)	0.065*** (15.01)	0.091*** (19.59)	0.099*** (13.81)	0.081*** (14.70)	0.080*** (8.35)
$y_{t-1}$	-0.002*** (-13.82)	-0.001 (-1.37)	0.000 (0.91)	0.000 (1.12)	-0.000 (-0.77)	-0.001*** (-7.44)	-0.000 (-1.55)
$\Delta p_t$	0.181*** (11.34)	0.002 (0.13)	-0.227*** (-14.12)	-0.064** (-2.37)	0.050 (1.60)	-0.107*** (-3.99)	0.061*** (2.61)
$\Delta p_{t-1}$	-0.086*** (-9.13)	-0.020** (-2.22)	0.030*** (3.82)	0.097*** (5.24)	0.018 (1.39)	-0.054*** (-2.88)	0.020 (1.20)
$\Delta p_{t-2}$	-0.041*** (-4.79)	-0.008 (-1.06)	-0.011* (-1.75)	0.003 (0.13)	0.039*** (3.81)	-0.004 (-0.20)	0.004 (0.28)
$\Delta p_{t-3}$	-0.050*** (-5.84)	-0.003 (-0.49)	-0.011* (-1.74)	0.045*** (2.93)	0.025** (2.34)	-0.012 (-0.73)	-0.006 (-0.30)
$D^D$ *constant	-0.000 (-0.26)	0.000 (0.27)	0.001*** (4.47)	0.001 (0.81)	0.003 (0.86)	0.006*** (2.90)	-0.000 (-0.21)
$D^D \Delta y_{t-1}$	-0.029* (-1.87)	-0.063** (-2.08)	-0.076*** (-4.37)	-0.051*** (-3.04)	-0.040* (-1.85)	-0.061*** (-3.85)	-0.032 (-1.37)
$D^D y_{t-1}$	-0.092*** (-9.86)	-0.047*** (-3.22)	-0.040*** (-7.38)	-0.061*** (-7.68)	-0.035*** (-4.35)	-0.027*** (-3.73)	-0.036*** (-4.88)
$D^D \Delta p_t$	0.045 (0.47)	0.012 (0.14)	-0.676*** (-7.47)	1.034*** (7.04)	0.076 (0.63)	-0.834*** (-4.45)	0.205* (1.91)
$D^D \Delta p_{t-1}$	-0.063 (-0.91)	0.068 (1.40)	-0.088 (-1.40)	-0.282** (-2.36)	0.148 (1.48)	0.001 (0.00)	0.307*** (2.70)
$D^D \Delta p_{t-2}$	0.014 (0.25)	0.059 (1.49)	0.040 (0.79)	0.085 (0.80)	0.095 (1.06)	0.030 (0.28)	-0.084 (-1.07)
$D^D \Delta p_{t-3}$	0.054 (0.91)	0.025 (0.60)	-0.113*** (-2.20)	-0.164* (-1.74)	0.046 (0.59)	-0.045 (-0.48)	0.127* (1.73)
$D^U$ *constant	-0.001* (-1.78)	-0.001* (-1.94)	0.003*** (6.70)	0.001 (0.82)	-0.003** (-2.35)	0.003*** (2.96)	-0.001*** (-3.68)
$D^U \Delta y_{t-1}$	-0.019 (-1.60)	0.042* (1.66)	-0.043*** (-3.05)	-0.037*** (-2.83)	-0.013 (-0.82)	-0.022 (-1.59)	-0.029 (-1.27)
$D^U y_{t-1}$	-0.052*** (-12.37)	-0.071*** (-5.59)	-0.054*** (-9.18)	-0.047*** (-11.21)	-0.033*** (-9.89)	-0.036*** (-8.67)	-0.037*** (-6.37)
$D^U \Delta p_t$	-0.303*** (-4.99)	0.226** (2.10)	-0.222*** (-4.30)	0.167* (1.84)	-0.107 (-1.40)	0.424*** (3.67)	-0.101 (-1.45)
$D^U \Delta p_{t-1}$	0.090** (2.31)	0.023 (0.24)	-0.058* (-1.74)	-0.129* (-1.85)	-0.017 (-0.26)	-0.024 (-0.37)	0.006 (0.12)
$D^U \Delta p_{t-2}$	0.010 (0.31)	0.205* (1.89)	0.023 (0.81)	-0.061 (-1.10)	0.123** (2.14)	-0.052 (-0.89)	-0.071 (-1.45)
$D^U \Delta p_{t-3}$	0.086** (2.02)	0.167 (1.29)	-0.017 (-0.52)	0.015 (0.25)	-0.069 (-1.32)	-0.004 (-0.05)	0.027 (0.50)

Note. The significance of the mean is evaluated with a standard  $t$ -test, adjusted for heteroskedasticity. One star denotes 90% significance, two stars 95% significance and three stars 99% significance. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

The first thing we immediately notice is that, in the crash and recovery periods, the regression model yields significant differences in many instances, for both systematic and non-systematic different events.



Table C.2 Systematic flash crashes

	PURE-HFT MM	PURE-HFT OWN	IB-HFT MM	IB-HFT OWN	IB CLIENT	NONHFT CLIENT	NONHFT OWN
constant	-0.000*** (-4.11)	-0.000 (-1.11)	0.000 (0.46)	0.000** (2.17)	0.000 (1.51)	0.000 (1.18)	-0.000 (-0.13)
$\Delta y_{t-1}$	-0.006 (-0.73)	0.011 (1.21)	0.060*** (5.60)	0.083*** (6.23)	0.037* (1.93)	0.058*** (5.98)	0.097*** (4.29)
$y_{t-1}$	-0.005*** (-8.43)	0.000 (0.20)	0.000*** (5.16)	0.000 (0.08)	0.000 (1.56)	-0.000 (-1.06)	0.000 (1.34)
$\Delta p_t$	-0.036 (-1.19)	0.006 (0.69)	-0.038* (-1.87)	0.021 (0.43)	0.081*** (3.78)	0.025 (0.59)	-0.072** (-2.35)
$\Delta p_{t-1}$	-0.067*** (-4.35)	-0.004 (-0.97)	0.040*** (3.95)	0.050** (1.97)	0.010 (0.52)	-0.005 (-0.46)	-0.030* (-1.92)
$\Delta p_{t-2}$	-0.048*** (-3.73)	-0.003 (-1.17)	0.012 (1.29)	0.007 (0.34)	0.029*** (2.64)	0.019 (1.64)	0.003 (0.14)
$\Delta p_{t-3}$	-0.038*** (-2.82)	0.001 (0.23)	0.014 (1.47)	-0.006 (-0.27)	0.022* (1.70)	0.009 (0.66)	0.026 (1.24)
$D^D$ *constant	0.000 (1.02)	-0.000 (-0.99)	0.000 (0.19)	0.000 (0.06)	-0.000* (-1.89)	0.001*** (2.71)	0.000 (1.53)
$D^D \Delta y_{t-1}$	-0.039 (-1.06)	-0.043 (-1.19)	-0.075* (-1.77)	-0.020 (-0.64)	0.045 (1.17)	-0.048 (-1.48)	-0.010 (-0.19)
$D^D y_{t-1}$	-0.089*** (-5.14)	-0.055*** (-2.71)	0.006 (0.48)	-0.060*** (-3.25)	-0.032*** (-2.71)	-0.025*** (-2.67)	-0.017 (-1.51)
$D^D \Delta p_t$	0.341*** (3.50)	0.036 (0.90)	0.119** (2.05)	-0.019 (-0.11)	0.029 (0.25)	-0.652*** (-4.45)	-0.397* (-1.65)
$D^D \Delta p_{t-1}$	-0.095 (-1.27)	0.016* (1.76)	0.079* (1.88)	0.128 (1.07)	-0.080 (-1.10)	-0.138* (-1.88)	0.032 (0.24)
$D^D \Delta p_{t-2}$	-0.052 (-0.79)	0.020 (1.22)	-0.008 (-0.17)	0.016 (0.09)	0.050 (0.61)	-0.118 (-1.24)	0.198 (1.28)
$D^D \Delta p_{t-3}$	-0.038 (-0.74)	0.010 (0.98)	-0.061 (-1.44)	0.211* (1.85)	-0.033 (-0.59)	-0.039 (-0.56)	-0.037 (-0.53)
$D^U$ *constant	-0.001*** (-4.67)	-0.000** (-2.45)	-0.001*** (-4.46)	0.001 (1.12)	0.000 (0.52)	0.001 (0.77)	0.005*** (6.50)
$D^U \Delta y_{t-1}$	-0.001 (-0.03)	-0.013 (-0.52)	-0.068*** (-2.59)	-0.021 (-0.81)	0.002 (0.05)	-0.037 (-1.20)	-0.037 (-1.14)
$D^U y_{t-1}$	-0.085*** (-6.42)	-0.036*** (-3.91)	-0.023*** (-4.55)	-0.050*** (-4.61)	-0.059*** (-4.59)	-0.016** (-2.09)	-0.119*** (-10.76)
$D^U \Delta p_t$	0.153*** (2.70)	-0.006 (-0.60)	-0.052 (-1.27)	-0.072 (-0.68)	-0.089 (-1.47)	-0.062 (-0.82)	-0.010 (-0.14)
$D^U \Delta p_{t-1}$	-0.000 (-0.00)	0.010* (1.90)	0.078*** (2.64)	-0.055 (-0.67)	0.007 (0.13)	0.082 (1.35)	-0.101 (-1.18)
$D^U \Delta p_{t-2}$	0.073** (2.00)	0.011** (2.22)	0.016 (0.66)	0.012 (0.15)	0.007 (0.19)	0.014 (0.26)	-0.056 (-1.18)
$D^U \Delta p_{t-3}$	0.089** (2.38)	0.002 (0.38)	0.074*** (2.62)	-0.077 (-0.73)	0.033 (0.87)	-0.004 (-0.08)	-0.147** (-2.10)

*Note.* The significance of the mean is evaluated with a standard  $t$ -test, adjusted for heteroskedasticity. One star denotes 90% significance, two stars 95% significance and three stars 99% significance. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

events. For example, Kirilenko, Kyle, Samadi, and Tuzun (2017) report a significant negative coefficient on the lagged inventory level in the pre-crash period (and interpret this as an in-

dication of mean-reversion), but no significant changes in the crash and recovery period. We instead see that mean-reversion is much stronger for all categories during crash and recovery, with respect to the pre-crash and post-recovery period. There is only one exception to this regularity: the positive (but insignificant) coefficient of IB-HFT MM during the crash period (and normal periods, in this case significant) for systematic events, denoting lack of mean reversion for these traders which, instead, should hold a capacity limit. This is consistent with their reported behavior during systematic events, see Figure 8, panel A.

In Kirilenko, Kyle, Samadi, and Tuzun (2017), HFT inventory changes are positively related to contemporaneous and lagged price changes for the first few seconds, then they become negatively correlated, while Market Makers are negatively related to contemporaneous price changes and positively to lagged ones. We broadly confirm this finding, which has just to be specialized to our trader groups. For example, IB-HFT MM and IB-HFT OWN inventory changes behave like the Market Makers of Kirilenko, Kyle, Samadi, and Tuzun (2017), while PURE-HFT MM behave like the HFTs of Kirilenko, Kyle, Samadi, and Tuzun (2017). The main difference with their finding is the significant changes for the price/inventory coefficients during the crash and recovery period. For example, while IB-HFT Market Makers become more significantly negatively correlated to contemporaneous price changes during non-systematic crashes (signalling more inventory absorption), the opposite holds for systematic crashes, since they become net sellers (see again Figure 8). Slow traders (NON-HFT CLIENT and NON-HFT OWN) turn the correlation of their inventory changes with contemporaneous price changes to negative during systematic crashes, consistent with the fact they have been shown to be the main liquidity providers for these events.

Summarizing, the analysis of the regression model (13) yields two conclusions. The first one is to provide further statistical significance on the results on net inventories, by showing significant changes in inventory management of different traders during flash crashes at an alternative frequency and with a fully blown statistical model. The second conclusion is that the significant change in the management of net inventory is robust to the interaction with prices: when price changes are added to the model, the behavior of the traders is still different during flash crashes with respect to normal times, and in line with what shown in the previous sections. In particular,

the estimated model parameters confirm that IB-HFT MM consume liquidity during systematic crashes, and the role of liquidity providers is left to slow traders, who buy at a discount with respect to the fundamental price.

## D The local projection methodology

Let  $y_t$  be a  $(7 \times 1)$ -vector with the first component being the mid-price at time  $t$ , and the other components representing the averages between best bid and best ask for the six trader groups: PURE HFT MM, IB CLIENT, IB-HFT OWN, IB-HFT MM, NON-HFT CLIENT and NON-HFT OWN.  $y_t$  is a non-stationary vector with cointegrated components, where cointegrating equation represent the long-run equilibrium between “mid-prices” of different trader group (the presence of cointegration is revealed using Johansen’s methodology). Hence,  $\Delta y_t$  is a stationary process following a vector error correction model of the form:

$$\Delta y_{t+1} = \Psi_1 \Delta y_t + \dots + \Psi_p \Delta y_{t-p+1} + \Psi_0 y_t + \epsilon_{t+1}, \quad (14)$$

where  $\Psi_1, \dots, \Psi_p$  are the parameter matrices,  $\Psi_0 = -\Phi(1)$ , with  $\Phi(1)$  being a reduced-rank (with rank 1 as we have single cointegrating relation) matrix which can be expressed as  $\Phi(1) = BA'$ , where  $B$  is an  $(7 \times 1)$  parameter matrix and  $z_t = A'y_t$  is a stationary variable representing cointegrating relationship. Equation (14) can be rewritten in the state space form:

$$\begin{bmatrix} z_{t+1} \\ \Delta y_{t+1} \\ \Delta y_t \\ \vdots \\ \Delta y_{t-p+1} \end{bmatrix} = \begin{bmatrix} I - A'B & A'\Psi_1 & \dots & A'\Psi_{p-2} & A'\Psi_{p-1} \\ -B & \Psi_1 & \dots & \Psi_{p-2} & \Psi_{p-1} \\ 0 & I & \dots & 0 & 0 \\ \vdots & \vdots & \dots & \vdots & \vdots \\ 0 & 0 & \dots & I & 0 \end{bmatrix} \begin{bmatrix} z_t \\ \Delta y_t \\ \Delta y_{t-1} \\ \vdots \\ \Delta y_{t-p+2} \end{bmatrix} + \begin{bmatrix} A'\epsilon_{t+1} \\ \epsilon_{t+1} \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad (15)$$

or more compactly, as

$$\xi_{t+1} = G\xi_t + \tilde{\epsilon}_{t+1}. \quad (16)$$

Notice that the state-space representation implies that, for for  $h = 1, \dots, H$ , linear forecasts of  $\Delta y_{t+h}$  can be computed as:

$$\begin{cases} \Delta y_{t+h} &= G_{[2,1]}^h z_t + G_{[2,2]}^h \Delta y_t + \sum_{j=3}^{p-2} G_{[2,j]}^h \Delta y_{t-j+2} + v_{t+h}, \\ v_{t+h} &= \epsilon_{t+h} + C_1 \epsilon_{t+h-1} + \dots + C_{h-1} \epsilon_{t+1}, \end{cases} \quad (17)$$

where  $G_{[i,j]}^h$  denotes the  $[i, j]$  block of the matrix  $G$  raised to the  $h$ -th power and  $C_1, \dots, C_{h-1}$  are  $(7 \times 7)$  matrices from the Wold representation  $\Delta y_t = \sum_{j=0}^{\infty} C_j \epsilon_{t-j}$ . This implies that the impulse response at lag  $h$  of  $\Delta y_t$  on a shock  $\epsilon_t = \delta$  can be calculated as:

$$IR(\Delta y_{t+h}, \delta) = \mathbf{E}(\Delta y_{t+h} | \epsilon_t = \delta; y_{t-1}, \dots) - \mathbf{E}(\Delta y_{t+h} | \epsilon_t = 0; y_{t-1}, \dots) = G_{[2,1]}^h A' \delta + G_{[2,2]}^h \delta. \quad (18)$$

Following [Jordà \(2005\)](#) and [Chong, Jordà, and Taylor \(2012\)](#) we first estimate the cointegration equation by OLS and then directly estimate the impulse responses as:

$$\widehat{IR}(\Delta y_{t+h}, \delta) = \widehat{G}_{[2,1]}^h A' \delta + \widehat{G}_{[2,2]}^h \delta, \quad (19)$$

with

$$\begin{pmatrix} \widehat{G}_{[2,1]}^1 & \widehat{G}_{[2,2]}^1 \\ \vdots & \vdots \\ \widehat{G}_{[2,1]}^H & \widehat{G}_{[2,2]}^H \end{pmatrix} = Y_H' M_W X (X' M_W X)^{-1}, \quad (20)$$

where the matrices  $Z_H$ ,  $Y_H$ ,  $X$  and  $W$  collect respectively the observations  $\{z'_{t+1}, \dots, z'_{t+H}\}$ ,  $\{\Delta y'_{t+1}, \dots, \Delta y'_{t+H}\}$ ,  $\{z'_t, \Delta y'_t\}$  and  $\{1, \Delta y'_{t-1}, \dots, \Delta y'_{t-p+2}\}$ , with  $t = p+1, \dots, T-H$ , and  $M_W = I - W(W'W)^{-1}W'$ . We use  $p = 2$  and take  $\delta = \delta_j$  to be a vector with unit  $j$ -th element and the other elements being zero, for  $j = 2, \dots, 7$ .

## E Additional tables

Tables [E.1](#) and [E.2](#) provides the detailed list of the 148 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 [E.3](#) 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 E.1 Flash Crash Events constituting the distressed sample (i)

Date	Isin	Company	Time Begin	Time Peak	Duration (min:sec)	Date	Isin	Company	Time Begin	Time Peak	Duration (min:sec)
4-Jan	FR0000131708	Technip	10:19:27	10:29:29	0:10:01	10-Apr	FR0000125338	Cap Gemini	13:11:55	13:13:52	0:01:57
8-Jan	FR0010220475	Alstom	14:47:54	15:03:40	0:15:46	15-Apr	FR0000130577	Publicis Groupe SA	14:46:08	14:56:04	0:09:56
9-Jan	FR0000120172	Carrefour	10:07:42	10:25:18	0:17:36	16-Apr	FR0010208488	ENGIE	12:36:04	12:47:55	0:11:51
11-Jan	FR0000130809	Société Générale	10:53:06	10:57:35	0:04:30	17-Apr	FR0000131906	Renault	9:30:08	9:51:45	0:21:37
11-Jan	FR0000131708	Technip	10:39:28	10:54:05	0:14:37	17-Apr	FR0010220475	Alstom	9:30:01	9:51:26	0:21:24
14-Jan	FR0000125338	Cap Gemini	16:45:52	16:52:20	0:06:28	17-Apr	FR0010208488	ENGIE	9:44:54	9:51:34	0:06:41
14-Jan	FR0000125007	Saint-Gobain	15:21:35	15:27:45	0:06:10	17-Apr	FR0000073272	Safran	9:29:55	9:51:56	0:22:00
14-Jan	FR0000120354	Vallourec	15:48:07	15:52:15	0:04:08	17-Apr	FR0000127771	Vivendi Universal	9:42:54	9:51:24	0:08:30
15-Jan	FR0010307819	Legrand	12:04:25	12:08:24	0:03:58	17-Apr	FR0000125486	Vinci	9:30:09	9:51:45	0:21:36
22-Jan	FR0000127771	Vivendi Universal	13:46:51	13:50:10	0:03:19	17-Apr	FR0000120628	Axa	9:42:50	9:51:45	0:08:56
22-Jan	FR0000121261	Michelin	9:54:07	10:06:05	0:11:58	17-Apr	FR0000120354	Vallourec	9:30:02	9:51:25	0:21:23
23-Jan	FR0010220475	Alstom	15:59:27	15:59:30	0:00:04	17-Apr	FR0000120578	Sanofi Synthelabo	9:42:55	9:51:30	0:08:35
29-Jan	FR0000120537	Lafarge	9:52:51	10:05:06	0:12:15	17-Apr	FR0000120172	Carrefour	9:42:34	9:51:29	0:08:55
29-Jan	FR0000045072	Credit Agricole	10:02:42	10:15:25	0:12:43	17-Apr	FR0000120073	Air Liquide	9:41:34	9:51:30	0:09:56
31-Jan	FR0000120644	Danone	11:54:52	12:12:21	0:17:28	17-Apr	FR0000121261	Michelin	9:42:50	9:51:40	0:08:50
4-Feb	FR0000131104	BNP	14:08:05	14:15:11	0:07:06	17-Apr	FR0000120271	Total	9:30:09	9:51:34	0:21:26
11-Feb	FR0000120578	Sanofi Synthelabo	15:31:45	15:36:10	0:04:25	17-Apr	FR0000121972	Schneider	9:30:00	9:51:29	0:21:29
20-Feb	FR0000133308	Orange	9:32:28	9:49:00	0:16:33	23-Apr	FR0000120404	Accor	16:50:24	17:14:07	0:23:43
22-Feb	FR0000131906	Renault	14:59:51	15:15:05	0:15:14	26-Apr	FR0000120693	Pernod Ricard	10:18:56	10:27:19	0:08:23
26-Feb	NL0000235190	EADS	16:29:03	16:38:35	0:09:32	29-Apr	FR0000127771	Vivendi Universal	13:55:11	14:02:29	0:07:19
1-Mar	FR0000045072	Credit Agricole	13:17:21	13:20:15	0:02:54	30-Apr	FR0000127771	Vivendi Universal	15:48:25	15:57:40	0:09:15
6-Mar	FR0000133308	Orange	15:22:29	15:24:25	0:01:56	7-May	NL0000235190	EADS	15:46:36	16:01:39	0:15:03
6-Mar	FR0000120404	Accor	15:23:22	15:34:03	0:10:41	7-May	FR0000121972	Schneider	12:17:56	12:27:00	0:09:04
7-Mar	FR0000130809	Société Générale	10:42:26	10:49:45	0:07:19	10-May	FR0010220475	Alstom	10:01:03	10:12:20	0:11:17
8-Mar	FR0000125338	Cap Gemini	13:59:34	14:10:35	0:11:01	22-May	FR0000125338	Cap Gemini	15:44:54	15:47:05	0:02:11
12-Mar	NL0000226223	STMicroelectronics	17:18:25	17:24:55	0:06:30	23-May	FR0000120172	Carrefour	15:46:17	15:48:51	0:02:34
12-Mar	FR0000121261	Michelin	16:22:32	16:28:04	0:05:33	29-May	FR0000120271	Total	16:13:10	16:17:20	0:04:10
15-Mar	FR0000130809	Société Générale	11:51:19	11:55:10	0:03:52	5-Jun	FR0000120172	Carrefour	11:23:47	11:26:35	0:02:48
20-Mar	FR0000073272	Safran	15:17:00	15:45:28	0:28:28	7-Jun	FR0000121485	Kering	12:02:29	12:09:09	0:06:41
21-Mar	FR0000125338	Cap Gemini	15:15:37	15:33:26	0:17:49	14-Jun	FR0010220475	Alstom	15:01:31	15:02:23	0:00:52
25-Mar	FR0010220475	Alstom	16:00:55	16:20:45	0:19:49	14-Jun	FR0000127771	Vivendi Universal	15:39:05	15:51:09	0:12:05
25-Mar	NL0000235190	EADS	16:14:00	16:23:06	0:09:05	19-Jun	FR0010220475	Alstom	13:08:27	13:10:54	0:02:27
26-Mar	FR0000073272	Safran	12:50:52	13:06:22	0:15:30	24-Jun	FR0000130809	Société Générale	10:15:26	10:33:25	0:17:59
4-Apr	NL0000235190	EADS	16:19:32	16:29:26	0:09:54	24-Jun	FR0000125007	Saint-Gobain	10:15:02	10:33:25	0:18:23
5-Apr	FR0000131104	BNP	11:49:35	11:53:15	0:03:39	1-Jul	FR0000120537	Lafarge	16:39:15	16:41:45	0:02:30
5-Apr	FR0010242511	EDF	14:53:00	14:54:55	0:01:55	11-Jul	FR0010242511	EDF	11:13:35	11:18:55	0:05:20
5-Apr	FR0000120073	Air Liquide	11:47:43	11:53:20	0:05:37	18-Jul	FR0000130577	Publicis Groupe SA	13:51:35	13:51:56	0:00:21

*Note.* The table reports the detailed list of the 148 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. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

Table E.2 Flash Crash Events constituting the distressed sample (ii)

Date	Isin	Company	Time Begin	Time Peak	Duration (min:sec)	Date	Isin	Company	Time Begin	Time Peak	Duration (min:sec)
23-Jul	FR0010220475	Alstom	11:18:39	11:22:57	0:04:18	2-Oct	FR0000121261	Michelin	14:34:11	14:45:30	0:11:19
25-Jul	FR0000131708	Technip	11:52:35	12:05:16	0:12:41	2-Oct	FR0000120693	Pernod Ricard	17:21:58	17:25:05	0:03:08
31-Jul	FR0000120404	Accor	13:59:14	14:03:35	0:04:21	2-Oct	FR0010220475	Alstom	15:39:45	15:43:00	0:03:15
31-Jul	NL0000235190	EADS	16:54:15	17:01:15	0:07:00	2-Oct	FR0000121667	Essilor International	15:21:32	15:28:50	0:07:18
16-Aug	FR0000120578	Sanofi Synthelabo	15:30:00	15:35:45	0:05:45	3-Oct	FR0010220475	Alstom	9:29:40	9:48:00	0:18:20
20-Aug	FR0000120537	Lafarge	9:54:11	10:07:20	0:13:09	9-Oct	FR0000120172	Carrefour	14:01:46	14:05:45	0:04:00
23-Aug	FR0000124141	Veolia Environnement	14:48:18	14:48:39	0:00:21	9-Oct	FR0000120537	Lafarge	12:30:21	12:38:28	0:08:07
27-Aug	FR0000120578	Sanofi Synthelabo	9:39:30	9:51:30	0:12:00	18-Oct	FR0000120172	Carrefour	11:23:12	11:34:48	0:11:35
27-Aug	FR0000125007	Saint-Gobain	9:44:07	9:51:35	0:07:28	23-Oct	NL0000226223	STMicroelectronics	16:16:06	16:24:16	0:08:10
27-Aug	FR0000120537	Lafarge	9:44:47	9:51:56	0:07:09	24-Oct	FR0000073272	Safran	14:29:39	14:42:41	0:13:02
27-Aug	FR0000121667	Essilor International	9:44:59	9:51:29	0:06:30	25-Oct	FR0000120628	Axa	15:31:14	15:47:16	0:16:02
29-Aug	FR0000120693	Pernod Ricard	12:25:04	12:59:15	0:34:12	28-Oct	FR0000120628	Axa	13:00:01	13:11:11	0:11:11
29-Aug	FR0000121667	Essilor International	15:01:36	15:04:20	0:02:44	28-Oct	FR0000125486	Vinci	17:25:06	17:29:35	0:04:29
2-Sep	FR0000131906	Renault	16:44:04	16:44:31	0:00:26	28-Oct	FR0000125007	Saint-Gobain	13:02:45	13:15:25	0:12:39
3-Sep	FR0000121485	Kering	10:52:46	10:54:56	0:02:10	29-Oct	FR0000124141	Veolia Environnement	9:29:59	9:40:05	0:10:06
3-Sep	FR0000121014	Lvmh Moet	10:52:45	10:54:54	0:02:09	30-Oct	FR0000131708	Technip	12:29:41	12:31:48	0:02:07
3-Sep	FR0000131104	BNP	10:53:21	10:55:15	0:01:55	5-Nov	FR0000120693	Pernod Ricard	14:55:14	15:10:07	0:14:53
3-Sep	FR0000130809	Société Générale	10:53:18	10:55:10	0:01:52	5-Nov	FR0000130809	Société Générale	14:46:45	14:50:15	0:03:30
3-Sep	FR0000120628	Axa	10:53:09	10:55:10	0:02:01	5-Nov	FR0000120628	Axa	14:40:25	14:48:38	0:08:13
3-Sep	FR0000125486	Vinci	10:52:56	10:55:14	0:02:18	7-Nov	FR0000130809	Société Générale	16:32:20	16:36:35	0:04:15
3-Sep	FR0000120073	Air Liquide	10:51:15	10:54:55	0:03:40	20-Nov	FR0000131708	Technip	15:37:23	16:09:40	0:32:17
3-Sep	FR0000120578	Sanofi Synthelabo	10:52:54	10:54:55	0:02:01	21-Nov	NL0000226223	STMicroelectronics	13:56:25	13:58:30	0:02:06
3-Sep	FR0000120271	Total	10:53:00	10:54:55	0:01:55	22-Nov	FR0000133308	Orange	12:17:19	12:27:59	0:10:41
3-Sep	FR0000125007	Saint-Gobain	10:51:03	10:55:04	0:04:01	22-Nov	FR0000127771	Vivendi Universal	12:16:49	12:22:49	0:06:00
3-Sep	NL0000235190	EADS	10:52:56	10:54:55	0:01:59	25-Nov	FR0000125338	Cap Gemini	10:08:52	10:13:24	0:04:32
3-Sep	FR0000120537	Lafarge	10:52:40	10:54:59	0:02:19	26-Nov	FR0000120404	Accor	11:49:31	11:59:05	0:09:34
3-Sep	FR0000121972	Schneider	10:52:38	10:55:07	0:02:29	26-Nov	FR0000121667	Essilor International	16:37:43	16:41:02	0:03:18
6-Sep	FR0000121014	Lvmh Moet	15:39:26	15:47:35	0:08:09	27-Nov	FR0000120404	Accor	13:27:19	13:47:55	0:20:36
6-Sep	FR0000124141	Veolia Environnement	15:24:16	15:43:00	0:18:44	3-Dec	FR0000133308	Orange	9:58:45	10:03:55	0:05:10
9-Sep	FR0000125338	Cap Gemini	16:45:34	17:12:40	0:27:07	3-Dec	FR0000131906	Renault	10:09:54	10:13:25	0:03:30
10-Sep	FR0000120354	Vallourec	14:47:32	14:50:04	0:02:32	3-Dec	FR0000131708	Technip	9:53:52	10:03:48	0:09:56
16-Sep	FR0000120644	Danone	11:23:54	11:30:20	0:06:26	5-Dec	FR0000130577	Publicis Groupe SA	15:31:10	15:43:04	0:11:55
17-Sep	FR0000120354	Vallourec	16:37:51	16:40:15	0:02:24	17-Dec	FR0000120404	Accor	11:05:41	11:16:16	0:10:35
20-Sep	FR0010208488	ENGIE	10:37:10	10:40:05	0:02:55	18-Dec	FR0000120354	Vallourec	9:30:00	9:46:41	0:16:41
24-Sep	FR0000121485	Kering	15:37:05	15:44:04	0:06:58	19-Dec	FR0000045072	Credit Agricole	14:48:57	14:53:20	0:04:23
24-Sep	FR0000121261	Michelin	15:25:05	15:30:00	0:04:55	19-Dec	FR0000131906	Renault	16:54:09	17:07:10	0:13:01
24-Sep	FR0000120693	Pernod Ricard	16:18:15	16:25:20	0:07:05	23-Dec	FR0000133308	Orange	10:46:27	11:02:27	0:16:00

*Note.* The table reports the detailed list of the 148 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 E.3 Summary of Flash Crashes grouped by stocks**

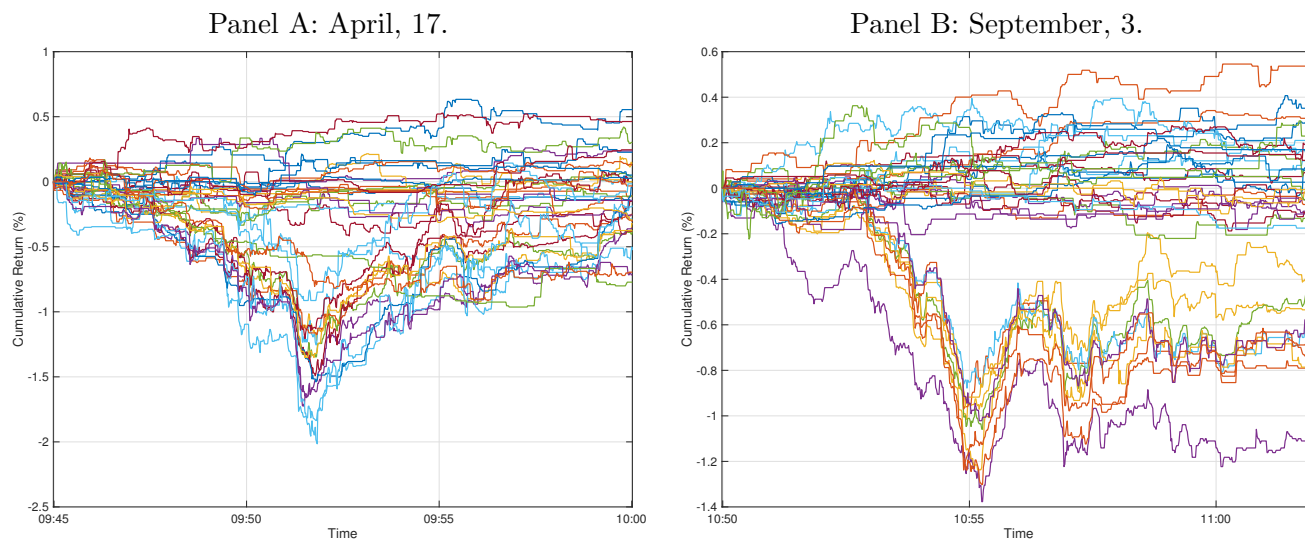
Isin	Name	Market Cap (M Euro)	Average daily trading (N. trades)	Average daily volume (M Euro)	No. DBs	Mean return	Median return	Std return	Mean Dura- tion	Median Dura- tion	Std Du- ration
FR0000045072	Credit Agricole	23'221	12'774	88	3	-1.13	-0.89	0.47	0:06:40	0:04:23	0:05:17
FR0000073272	Safran	21'064	8'569	60	4	-1.11	-0.98	0.53	0:19:45	0:18:45	0:06:56
FR0000120073	Air Liquide	32'047	12'821	128	3	-0.99	-0.99	0.30	0:06:24	0:05:37	0:03:12
FR0000120172	Carrefour	20'858	13'152	116	6	-1.53	-1.57	0.74	0:07:55	0:06:27	0:05:58
FR0000120271	Total	145'995	26'025	348	3	-1.23	-1.01	0.49	0:09:10	0:04:10	0:10:40
FR0000120354	Vallourec	5'035	9'902	51	5	-1.18	-0.78	0.60	0:09:26	0:04:08	0:08:57
FR0000120404	Accor	7'822	7'872	49	6	-1.10	-1.07	0.48	0:13:15	0:10:38	0:07:21
FR0000120537	Lafarge	15'652	11'512	76	6	-1.12	-0.97	0.40	0:07:35	0:07:38	0:04:37
FR0000120578	Sanofi Synthélabo	101'851	27'238	400	5	-0.94	-0.87	0.57	0:06:33	0:05:45	0:03:52
FR0000120628	Axa	48'784	19'042	200	5	-1.24	-1.02	0.71	0:09:16	0:08:56	0:05:05
FR0000120644	Danone	30'688	14'526	176	2	-1.40	-1.40	0.02	0:11:57	0:11:57	0:07:49
FR0000120693	Pernod Ricard	21'799	10'385	96	5	-0.88	-0.69	0.59	0:13:32	0:08:23	0:12:18
FR0000121014	LVMH Moët Henessy	66'353	13'133	200	2	-1.27	-1.27	0.33	0:05:09	0:05:09	0:04:14
FR0000121261	Michelin B	14'350	12'618	99	5	-1.50	-1.77	0.72	0:08:31	0:08:50	0:03:13
FR0000121485	Kering	19'395	6'899	83	3	-0.89	-0.84	0.29	0:05:16	0:06:41	0:02:42
FR0000121667	Essilor International	16'592	10'950	86	4	-0.98	-0.93	0.15	0:04:58	0:04:54	0:02:17
FR0000121972	Schneider	35'628	16'767	164	3	-1.79	-1.43	1.15	0:11:01	0:09:04	0:09:39
FR0000124141	Veolia Environnement	6'338	10'989	68	3	-2.46	-2.79	1.21	0:09:44	0:10:06	0:09:12
FR0000125007	Saint-Gobain	22'193	13'639	116	5	-1.36	-1.34	0.33	0:09:44	0:07:28	0:05:47
FR0000125338	Cap Gemini	7'876	9'677	61	7	-0.87	-0.87	0.28	0:10:09	0:06:28	0:09:20
FR0000125486	Vinci	28'713	14'361	124	3	-1.25	-1.18	0.79	0:09:28	0:04:29	0:10:34
FR0000127771	Vivendi Universal	25'660	13'320	143	6	-1.39	-1.34	0.66	0:07:45	0:07:54	0:02:59
FR0000121667	Essilor International	16'592	10'950	86	3	-1.52	-1.26	0.54	0:07:24	0:09:56	0:06:11
FR0000130809	Société Générale	33'722	32'204	317	7	-1.62	-1.52	0.83	0:06:11	0:04:15	0:05:27
FR0000131104	BNP	70'354	33'015	364	3	-1.14	-1.03	0.28	0:04:13	0:03:39	0:02:38
FR0000131708	Technip	7'942	10'665	75	6	-1.17	-1.08	0.48	0:13:36	0:11:21	0:10:06
FR0000131906	Renault	17'064	14'722	118	5	-1.57	-1.33	0.88	0:10:46	0:13:01	0:08:41
FR0000133308	Orange	23'630	21'114	167	5	-1.47	-1.25	0.82	0:10:04	0:10:41	0:06:28
FR0010208488	ENGIE	40'349	13'831	148	3	-2.02	-1.68	0.81	0:07:09	0:06:41	0:04:29
FR0010220475	Alstom	8'126	11'838	81	10	-1.45	-1.47	0.67	0:09:45	0:07:47	0:08:29
FR0010242511	EDF	47'729	9'368	64	2	-1.40	-1.40	0.67	0:03:37	0:03:37	0:02:25
FR0010307819	Legrand	10'633	6'387	45	1	-1.08	-1.08	0.00	0:03:58	0:03:58	0:00:00
NL0000226223	STMicroelectronics	7'098	8'668	44	3	-2.60	-1.41	2.16	0:05:35	0:06:30	0:03:08
NL0000235190	EADS	43'550	20'886	212	6	-0.88	-0.96	0.25	0:08:46	0:09:19	0:04:15

*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. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH. Market capitalizations are from Bloomberg.

## F Additional figures

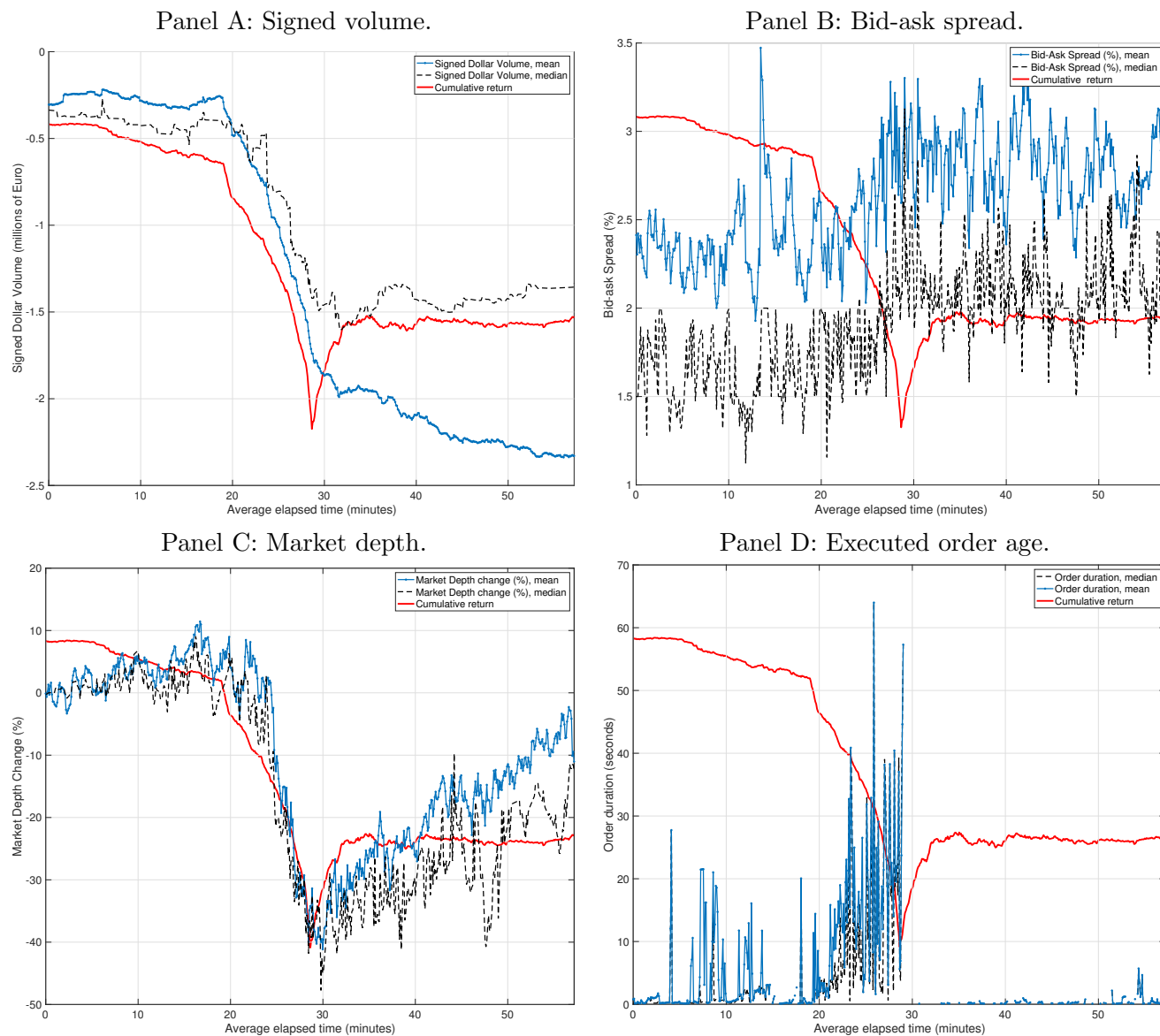
This section presents additional figures which complement the analysis in the main text.

**Figure F.1. Price evolution during systematic flash crashes.**



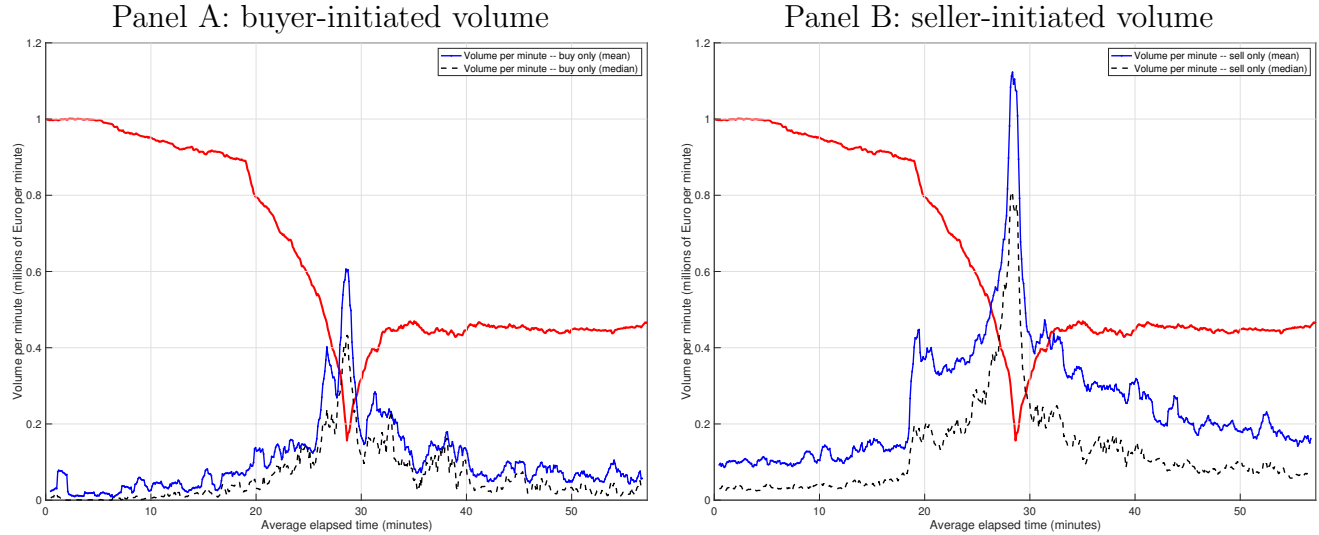
*Note.* This figure shows the price evolution of the 37 blue-chips French stocks during the systematic flash crashes of April 17, 2013 (Panel A) and September 3, 2013 (Panel B). [6](#) for systematic events. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

Figure F.2. Liquidity measures during systematic flash crashes.



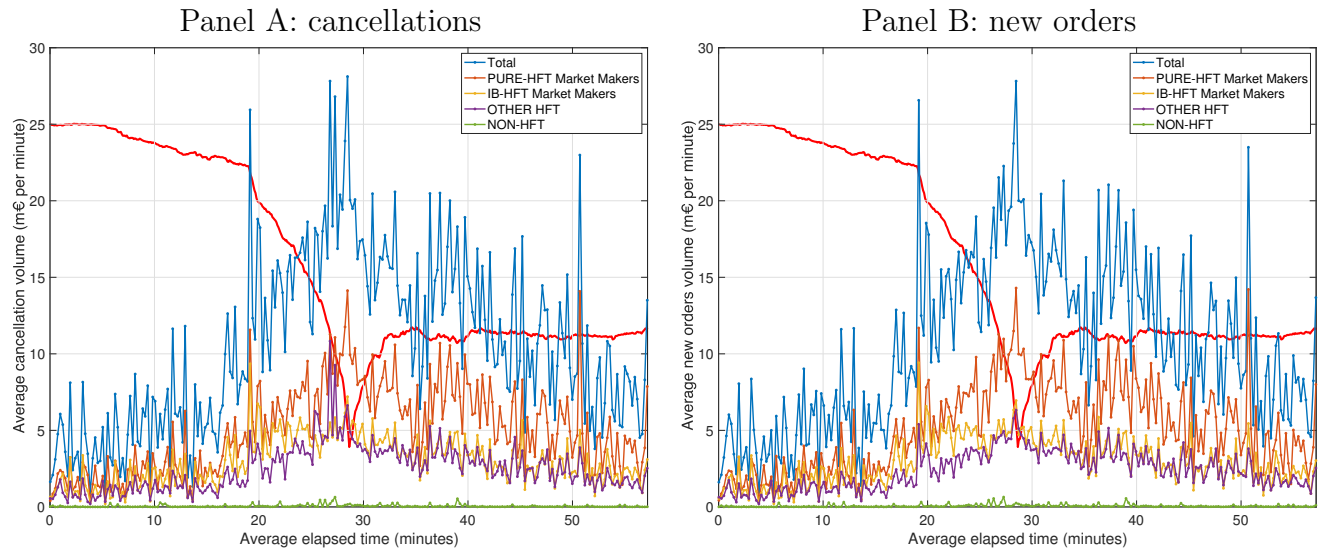
*Note.* This figure reports four measures of liquidity averaged across the systematic flash crash events (compared to Figure 6 for non-systematic events). Panel A: cumulative signed monetary volume (negative volume = sell). Panel B: bid-ask spread. Panel C: market depth (difference from beginning). Panel D: the age of the executed orders (we exclude orders with age less than 0.1 seconds and those coming from the previous day). On each panel, we superimpose the average price evolution for visual comparison. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

**Figure F.3. Volume per minute for initiated buyer and initiated seller trades (systematic).**



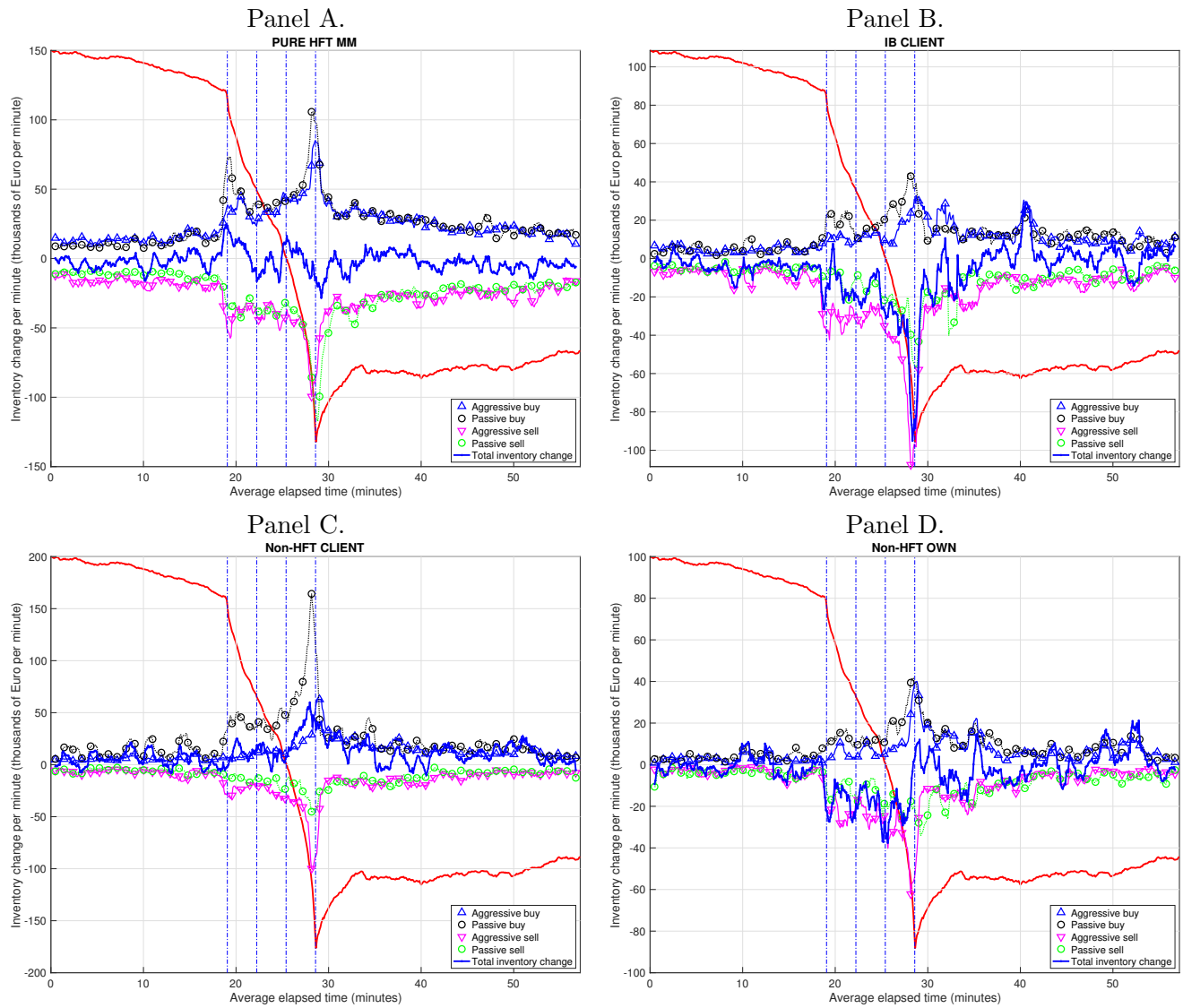
*Note.* This figure shows the average euro volume traded per minute during crash events, separated in buyer-initiated trades (Panel A) and seller-initiated trades (Panel B) only for systematic events (compared to Figure 7 for non-systematic events) The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

**Figure F.4. Cancellations and new orders volume by trader category (systematic).**



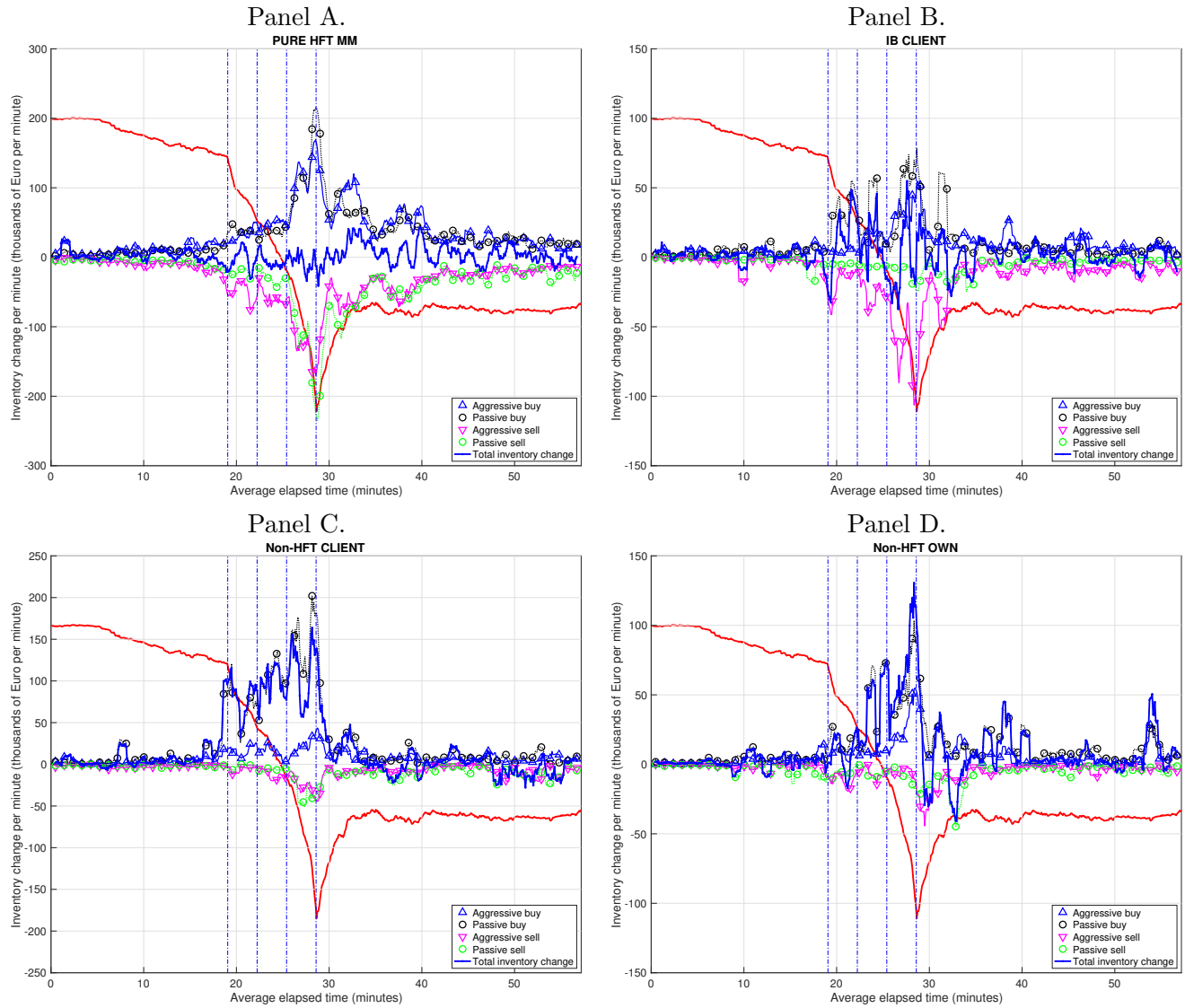
*Note.* This figure display the average per minute euro volume of cancelled orders (Panel A) and new orders (Panel B) only for systematic events. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

**Figure F.5. Cumulative net trading imbalances per minute of different trader groups (non-systematic).**



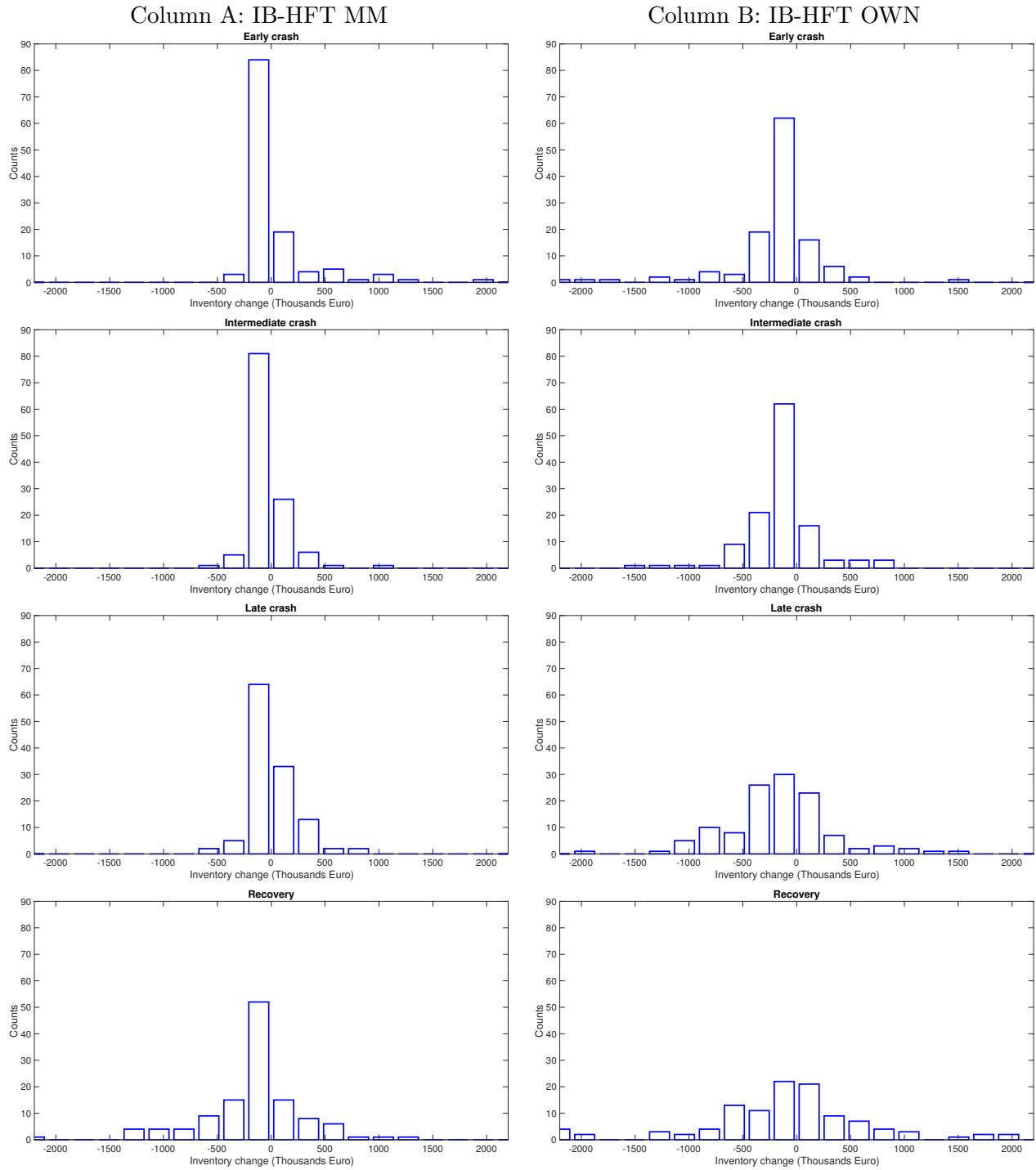
*Note.* This figure reports inventory change per minute for the most active trading categories not considered in Table 9 during non-systematic events, separated in buyer initiated, seller initiated, buyer passive and seller passive trades. The y-units are not uniform across panels. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

**Figure F.6. Cumulative net trading imbalances per minute of different trader groups (systematic).**



*Note.* This figure reports inventory change per minute for the most active trading categories not considered in Table 9 during systematic events, separated in buyer initiated, seller initiated, buyer passive and seller passive trades. The y-units are not uniform across panels. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow and trade data are from BEDOFIH.

Figure F.7. Monetary net imbalances per minute of non-systematic events.



Note. Same as Figure 10 for non-systematic events.

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