End-of-Day Market Manipulations: Winners and Losers

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Abstract

Modern financial markets are impregnated with lightning-fast speed high-frequency trading (HFT). Critics of HFT point out the advantageous speed, which might undermine market fairness. In this paper, we are intrigued to explore and identify ghost HFT manipulations on Euronext. We rely on the rich BEDOFIH AMF - Euronext Paris High-Frequency database for 2017 (33,357 observations). We apply our analysis and detect 412 end-of-day (EOD) manipulations. We find that HFT activities are in tandem with price movements and their aggressive strategies drift the market at day-end. Our results also show that though High-Frequency Traders are the main contributors to extreme price movements (EPM), along with investment banks, they contribute to price reversal on the next day's opening. The study has many implications for regulators, policymakers, and financial markets. It is of particular interest to the data Intelligence department of the French Authority of Financial Markets.

Keywords: market fairness, high-frequency trading, mark the close, high-frequency data

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1 Introduction

The deregulation of the macroeconomic mechanisms of price formation has long been debated in the context of real and financial products. Drastically,

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the last era was marked by many scandals and frauds in the financial markets, leading to investors' distrust and fear. The advent of sophisticated technologies and intricate algorithms have amalgamed HFT strategies and drifted the market to questionable spikes and troughs. Nowadays, algobots are surpassing human brains and artificial intelligence is shaping new concepts through robo advisors (Arnuk and Saluzzi, 2012).

Critics of HFT point out the advantageous speed that might crowd out slower traders. Likewise, HFT firms can afford large amounts of computer processing power, which are unaffordable to many investors. Does this give them an unfair advantage? From one side, HFTs are often blamed for the use of high-speed technology, which allows them to engage in traditional manipulative strategies that seek profit and contribute to price movements away from their fundamental values. On the other side, defenders of HFT state that HFT strategies benefit other market participants, such as reduced trading costs and price accuracy. Yet, the impact of high-frequency trading on market fairness is not a trivial issue. Intrinsically, public policymakers, regulators, analysts, and scholars are intrigued to explore if ghost HFT manipulations exist, or if specific techniques are used to beat the market (Duda *et al.*, 2022). This leads to the dilution of traditional market microstructure concepts and to the introduction of new concepts that prescribe behavioral finance (Gomber *et al.*, 2017).

To emphasize, market manipulation is a trading strategy with the intent to pursue a scheme that undermines economic efficiency both by making prices less accurate as signals for efficient resource allocation and by making markets less liquid for risk transfer (Kyle and Viswanathan, 2008). To wit, the use of trading strategies with the intention of misleading other market participants is called "market manipulation". In this regard, the incidence of illegal price manipulation has long been attributed to market unfairness.

While much prior research has been done particularly on the impact of a market design change on one dimension of market quality, namely market efficiency, little work has been done on market fairness. Previous studies have long reflected a tension between subjective approaches ("the smell test") and more scientific approaches based on economic efficiency. Recently, Kemme *et al.* (2004) considered the Tokyo Stock Exchange (TSE) that implemented Arrowhead Renewal improvements (ARI) in 2015 aiming to reduce latency from about one millisecond to less than 0.5 ms. Effectively, the ARI seems to reduce manipulative trading strategies as it introduces new risk management functions to improve market fairness. The authors reveal an improvement in both market quality dimensions: fairness and efficiency. They find a dramatic improvement in market fairness as proxied by marking-the-close incidents (which declined by 61.19%). In contrast, the improvement in market efficiency is much smaller, as illustrated by a reduction in the effective (quoted) spreads of 6.45% (5.79%). They show that the most dramatic improvement in market quality (fairness and efficiency) was for low-tick-size and high-market-capitalization stocks.

Notwithstanding, Aitken *et al.* (2018) investigate market fairness and pinpoint the positive effect of AT on market fairness in the context of the London Stock Exchange and NYSE Euronext. However, this study covered only the golden era of AT, represented by its explosive growth between 2003 and 2011, a period spanning the installation of the Markets in Financial Instruments Directive (MiFID) in 2007. To our knowledge, very scarce studies have attempted to uncover the identity of manipulators in financial markets. We use the rich BEDOFIH Authorité des Marchés Financiers - Euronext Paris High-Frequency database for 2017 coming before the year of MiFID II implementation, i.e. 2018 and is considered to be a relatively "neutral" year as compared to the previous ones such as 2014 and 2016. Specifically, 2014 was marked by a huge swing of the 10-year government debt that sank and reversed quickly and led to High-Frequency Traders (HFTs) being accused of the high-frequency flipping of treasuries. Also, the year 2016 was marked by the British Pound plunge of 800 points in a few minutes, for which algo traders were blamed. There is a gap in the literature and deeper understanding of the origins and nature of price changes provides a conceptual bridge between the micro-economic mechanics of order matching and the macroeconomic concept of price formation. Thus, our paper aims at revealing the identity of market agents who most benefit from these manipulations and thus, trigger them. Are HFTs still the main market manipulators? Should regulators roll back the technology clock and prohibit algorithmic trading? Or should they also consider carefully another category of traders? Our project contributes to extensive findings. First, access to the 2017 BEDOFIH dataset allows us to develop outstanding expertise in managing such a complex structure and huge-volume database. Second, the exploited database permits the accurate detection of the identity of market actors (HFTs, Mixed HFTs, and non-HFTs) while previous studies to date used proxies to identify them.

Third, our work is of particular interest to the Data Intelligence department of Autorité de Marchés Financiers and regulators to better navigate market regulations and establish more market fairness in an era of exponential changes in technology and infrastructures. The remainder of the paper is structured as follows. Section 2 provides the literature review. Data and methodology are described in Section 3. Section 4 displays the results and discusses the main findings. Section 5 concludes and suggests recommendations and future research directions.

2 Literature Review

The shift from traditional, human-driven financial markets to modern, electronic markets has resulted in notable advancements in areas such as trading costs and liquidity, due in part to the role of information technology. However, this transition has also sparked debate, particularly regarding the significance of speed in today's electronic markets. The global market for algorithmic trading was valued at over $12 billion in 2020 and is expected to reach nearly $31 billion by 2028, with a projected compound annual growth rate of 12.7% between 2021 and 2028.

The introduction of new financial technologies poses a challenge for policymakers as they must determine which innovations benefit society and which harm it. The advent of reasonably liquid stock markets (Ferguson, 2008) has benefited social welfare, whereas others, such as the credit default swaps (Tett, 2009) has diminished social welfare. In this regard, HFTs have been a particularly contentious issue, as it relies on quick algorithms that send orders to various trading venues (Madrigal, 2010; **?**), and has been linked to several market crashes. This has sparked debates about financial regulations and the theories that underlie them. It is crucial to consider how theories can shape the real world and how regulation should be approached. Some argue for a more technocratic approach, while others advocate for an inclusive approach that involves all stakeholders.

Moreover, critics such as Colander *et al.* (2009); Krugman (2009) have argued that theories of financial economics, such as the efficient market hypothesis (Fama, 1970), fueled poor financial regulation, which, in turn, contributed to the 2008 financial crisis (Dymski, 2011; Scherer *et al.*, 2012; Willmott, 2011). Budish *et al.* (2015) defined latency arbitrage as profits gained from exploiting publicly available information, as opposed to private information that is central to classic models of market microstructure (Glosten and Milgrom, 1985; Kyle, 1985). It is important to consider how theories can influence society and how regulation should be approached. The debate over a technocratic or inclusive approach to regulation further complicates current research and highlights the need for reform in financial regulation (Froud *et al.*, 2010; Schneiberg and Bartley).

The emergence of HFTs as new types of mediators and their ability to bypass intermediaries, peruse multiple markets, apply scalping, practice spoofing, perform and cancel orders in nanoseconds cast doubt about their preponderance to deviate the market and circumvent regulatory bodies (Albuquerque *et al.*, 2020; Griffith and Roseman, 2019). In light of the surging technology, many issues are still surrounding such transactions and the discovery of the perfect transaction time, price, and size are highly debatable. Imperfect competition, private information, and market externalities are the roots of such illegal manipulations (Goldstein and Kavajecz, 2000). Notably, some of these manipulations are implemented using high-frequency technology. The common characteristic of HFTs is a co-location principle: traders can put their computers in stock exchange data centers. The co-location respects the principles of procedural fairness, or equal application of the rule, as it is available to everyone on the same terms, offering a speed advantage. However, the other dimension of fairness is distributive and is concerned with equality of outcome.

To date, few studies have quantitatively addressed algo trading (AT)'s impact on market fairness, while studies about market efficiency have exponentially exploded. The need for specific data within a millisecond time-frame and the required reporting infrastructure are the main constraints to conducting studies on market fairness and uncovering illegal manipulations or artificial prices. Relatively, there is little analysis of how we actually define or measure market fairness. Aitken *et al.* (2018) called market fairness the "country cousin" of market efficiency. Consistent with Smith and Krueger (1776) view that actions motivated by self-interest can benefit the common good, the legal system in market economies recognizes that market participants often trade for selfish motives that are socially beneficial, not intrinsically illegal. Somehow, market fairness is highly tied to the imposition of the best rules and regulations that inhibit frauds and violations that undermine the informational and transactional roles of the financial markets. Basically, this stands in sharp opposition to the unsatisfactory definition based on the routine exploitation of market power and private information.

Fairness is a complex moral concept that refers to a wide range of applications and standards. "Fair" can mean a variety of things in different contexts (Boatright, 2010). For instance, the U.S. Congress has frequently used the term "fair markets" in the Dodd-Frank Bill but never defined what "fair" means. As SEC (2020) pointed out, "...continued vigilance in monitoring these advances in technology and trading, and updating of systems and expertise will be necessary to help ensure that our capital markets remain fair, deep, and liquid". Heath (2010) views fairness as "to be treated similarly to others with respect to a rule, agreement, or recognized expectation." Veryzhenko *et al.* (2022) define market fairness as the ability of a market structure and its regulatory framework to guarantee unimpeded competition, while curbing excessive speculation and market manipulation. Shefrin and Statman (1993) identify different notions of market fairness: 1) Equal information (no insider trading); 2) Equal processing power (no disparity in the ability to process information); 3) Efficient prices (prices reflect all the information available in the market). Aitken *et al.* (2018) state that a fair securities market minimizes prohibited behaviors. So, preventing market manipulations is one of the main goals of market regulators and operators, aiming to foster market efficiency and market fairness.

Given the complex features and designs of financial markets, as well as the explosive growth of AT, achieving fairness among market participants seems to be one of the most challenging tasks for regulatory authorities. To promote market fairness, regulators should guarantee fair and unimpeded competition, which can improve the allocation of resources and eliminate opportunistic trades. In corroboration, the mandate of financial markets' regulators is to preserve financial markets' quality and fairness as they play a crucial role in capital allocation to "irrigate" the real economy and generate value for society. Such manipulations undermine the quality of financial markets in the sense that they cause volatility and lead to instability Aitken *et al.* (2018). This increases the magnitude of bubble and crash events, weakens public confidence in financial markets, and undermines proper capital allocation to irrigate the real economy and generate value for society. As most traders aspire to have the same requisites of market fairness: equal opportunity, alike treatment, and relative equality of outcomes, market fairness or integrity surges as a critical component of financial markets' stability. Both fairness and efficiency are crucial considerations in market design and regulation. Since 2015, the SEC has called for market reforms to curb the unfair advantages of algorithmic trading in the world's largest financial markets. Akter and Cumming examine market manipulation's effects on corporate investments. Using a nine-country sample over eight years, they find that market manipulation discourages corporate innovation, highlighting the importance of studying market fairness.

Market manipulation involves creating a false or misleading representation with the will to dislocate the market price (Angel and McCabe, 2013). For instance, illegal price manipulation includes corners and squeezes, pump-and-dump manipulation, and failure to make required disclosures. Chakraborty and Yilmaz (2004) and Mei *et al.* analyzed the pump-and-dump manipulation in a stock market. Allen and Gale (1992) discussed the possibilities of trader-based manipulation and showed that a manipulator could pretend to be informed and mislead the market. Allen and Gorton (1993) showed that the asymmetry between the information associated with buying and selling (i.e., a buy contains more information than a sell) leads the manipulator to buy, causing a higher effect on the price and sell with a lower effect.

More studies find connections between informed trading and dividend signaling (Fuller, 2003), market liquidity and cross-listing (Domowitz *et al.*, 1998; Karolyi, 2003), corporate spinoffs and information asymmetry (Huson and MacKinnon, 2003), stock market liquidity and the decision to repurchase (Brockman *et al.*, 2008), informed trading and CEO's pay-performance sensitivity (Holmström and Tirole, 1993; Kang and Liu, 2008, 2010), and algorithmic trading and firm value (Hatch *et al.*, 2021).

Furthermore, existing literature examined the behavior of such informed trading on the market dimensions, more particularly on market liquidity. Degryse *et al.* (2021) discover the phenomenon known as "Ghost Liquidity" (GL) in modern fragmented equity markets. GL occurs when traders place duplicate limit orders on multiple venues with the intention of only one order executing and the other being cancelled. Using data from 2013 for 91 stocks trading on primary exchanges and alternative platforms, the study finds that measured liquidity exceeds true liquidity due to GL. The greatest GL is found among HFTs who mostly act as liquidity takers on heavily traded and less volatile stocks across alternative platforms. Boussetta *et al.* (2017, 2020) analyze the behavior of market players based on the speed and nature of their orders (proprietary, agency, or market-making) in the pre-opening of Euronext Paris, BATS, and Chi-X platforms. The authors use a dataset of stocks cross-traded on these platforms. They show that the pre-opening activity of slow brokers is closely related to the price discovery process across trading venues. While the tentative clearing prices of the pre-open contain information, there is reversal in the next 15 minutes across the different platforms, reflecting price pressure and liquidity issues around the open on both Euronext and Chi-X.

3 Data Analysis

3.1 Data Description

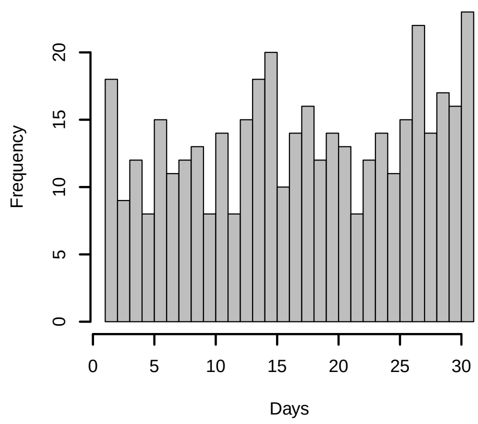
We use the rich BEDOFIH AMF - Euronext Paris High-Frequency database for 2017, a source not previously exploited in fairness examinations. All companies listed on Euronext in 2017 are included in our study. This source includes all the messages received by the market operator over a trading session, indicating high-frequency traders' complex behavior and the effect on market fairness. Such data enables us to distinguish the effects of activities among different categories of traders on price efficiency during a trading session. To ensure consistent analysis, we require a stock to have at least 500 trades each day. We have analyzed 943,245 files to select 33,357 (ISIN x days) observations. Over 255 days, 135 ISIN codes are concerned by such events (small cap and blue chip, all together). It would be interesting to check the relationship between the market capitalization and occurrence of EPM.

Figure 1 shows quite strong calendar dependence of market manipulations. The frequency of the end-of-day market manipulations increase at the end of the month. The manipulations are less frequent during summertime. This probability increases at the end of the year. End-of-day market manipulations are the most frequent in November.

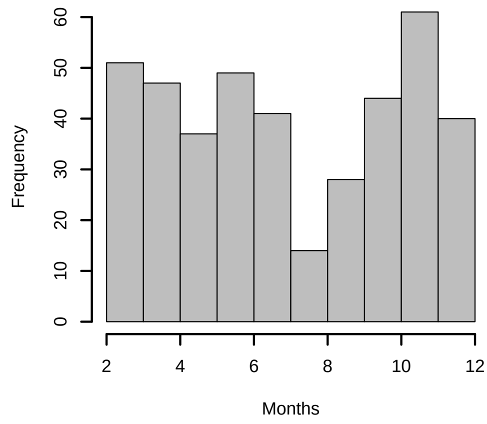
3.2 Methodology and Variables

3.2.1 Market fairness measures

Similar to Veryzhenko *et al.* (2022), we link market fairness to the ability of a market structure and its regulatory framework to guarantee unimpeded competition and curb market manipulation. Accordingly, we identify three dimensions or measures of fairness 1) less market manipulation, 2) in-



(a) Manipulation frequency within the month



(b) Manipulation frequency during the year

Figure 1: Calendar distribution of manipulations

sider trading, and 3) broker-agency conflict. Normally, we use two main proxies, one for information leakage due to insider trading and one for the dislocation of the closing price with end-of-day (EOD) manipulation also called ramping manipulation attempts to mark the close (MTC). The data about the broker-agency conflict started to be available in Australia in July 28, 2014, as brokers are seldom required to add a condition code identifying whether the order/trade is as principal or as agent. However, there is a $1 million fine for providing access to the data outside a regulatory or exchange inquiry.

In the present study, we only use MTC as our proxy for market fairness. MTC is the purchase or sale of securities at or near the close to change the closing price without a change in the securities' fundamental values. Manipulation is suspected following two simultaneous conditions: (1) EOD percentage price change exceeds three standard deviations above or below the mean of 30-day prior observations, and (2) followed by other extreme price movement in the opposite direction in the first 15 min of the next day.

Thus, we define MTC as a dummy variable that equals 1 if the price change for the given day matches both criteria. All selected "doubtful" manipulative episodes are screened against Reuters News feed to detect the abnormal market reactions that can be explained by the specific announcements for each company. When choosing the time window that allows traders to manipulate EOD prices, we follow previous literature (Aitken *et al.*, 2018; Akter and Cumming) and use 15 min. The trading speed of market participants has become much higher. However, it is still very difficult to manipulate security prices in a very short time because of the circuit breaker rules in the stock exchanges.

According to Aitken *et al.* (2018), potential motivations for manipulating closing prices may include modifying the value of managed funds at the end of reporting periods, making profit from derivatives positions in the underlying stock, obtaining a favorable price in pre-arranged off-market trades, maintaining the listing of a stock on an exchange with minimum price requirements, ensuring inclusion in an index near stock index rebalancing days, avoiding margin calls, and many other reasons. Obviously, we cannot confirm that all abnormal end-of-day (EOD) prices are the result of illegal manipulative trading strategies. Stock prices may naturally close at levels that appear statistically abnormal from the expected level for many reasons. These include 1/the unwillingness of some market actors to hold inventory overnight, which leads them to liquidate at the close, 2/the brokers with a mandate to establish certain stock positions or who guarantee VWAP at the close being forced to become aggressive at the end of the trading day, 3/ HFT/ATs seeking to go flat at the closing and mimicking one another generating positively correlated trading patterns that create a false impression that markets are being manipulated at the end of the trading day (Aitken *et al.*, 2018).

3.2.2 HFT/Algorithmic trading

While previous studies report the cumulative effect of trading or quoting activities on price efficiency, our rich dataset allows us a more nuanced and detailed view of different trading activity behaviors and their effects on price efficiency discovery, both of which affect our market fairness metrics. We investigate the behavior and activities of the main categories of traders during such extreme market events. We focus on trading (trade-based) activities and quotation (order submission) activities, as any extreme price variation results from a prior liquidity dislocation in the order book. Activities of different categories of traders are measured by the number of limit orders they send, the traded dollar volume, the market-to-limit ratio, and the number of canceled/modified orders within a 0.5-second time span divided by the number of sent limit orders. We compute all these measures over five-minute time intervals.

3.2.3 Market mechanism

We successfully reconstruct the total depth of the order book (order book print screens) in event-driven manner. We "take a picture" of the state of the order book as fat as it is updated. For this purpose we use We use an ArTificial Open Market (ATOM) (Brandouy *et al.*, 2013) which is a highly flexible simulation platform that allows a perfect reconstruction of the trading session with a complete order book record on average in 8 seconds. We begging by order accumulation pre-opening phase: all pending orders and newly submitted orders are simply collected in the order book without any transaction being executed. Transactions are not carried out before the market opening. Then, at 9 hours and few seconds (that varies every day within a 30-second time span), equilibrium opening price is computed. This price satisfies the greatest volume of buyers and sellers match. At continuous trading phase from 9h to 17h30, a submission of a new order may lead to a new transaction if the trade conditions are satisfied (best bid $\geq$ best ask). At 17h30 a new order accumulation period or pre-closing phase begins. The purpose of this period is to accumulate the orders without giving rise to trades. At 17h35 the closing price is determined. In such a way investors may manage the over-night risk. To stress the importance of the work realized, we would like to provide the volume of received data. All print screens of the total depth of the bid/ask sides of the central order book recorded as a row text represents 40 Gbts for one security per day.

A reconstruction of the total depth of the order book (order book print screens) at the 1/10 second time grain, which allows us to analyze the strategic order placement for different categories of traders (at top 5-, 10- and 20-best limits). Figure 2 shows an intraday dynamic of the volume provision (%) at the top 5 level in the order book. This information is extremely important as these orders define the future price trends. Our results witness an active participation of non-HFT traders during opening session and first hours. At the same time, they decrease their participation during the day and at market closing. During these sessions pure-HFTs and mix-HFTs dominate the order book at the top 20-level. Figures 2, 3, 4: Liquidity provision of different categories of traders at the top 5, 10, 20 best limit level of the order book. (to add after).

End-of-day EPM (end-of-day)			EPM at opening		
mean	median	sd	mean	median	sd
0.0046864	0.0037000	0.0033896	0.0063354	0.0047000	0.0049060

Table 1: Descriptive statistics of the end-of-day extreme price movements and their corrections at the market opening.

3.2.4 Identity of the manipulator

We run a t-test to measure significant changes in the behavior of various categories of traders between normal periods and extreme events. We pursue a thorough analysis to uncover the identity of the main manipulator. There are three types of traders: pure High-Frequency Traders (HFTs), traders operating both high frequency and non-high-frequency (MIXED HFTs - investment banks), and non-high-frequency traders (Non-HFTs). Once a trader is classified, it is immutable.

3.2.5 Summary statistics

We have detected 412 EPM (manipulations). Over the studied period, the number of negative EPM (216) is higher than the number of positive EPM (196) which implies a downward tendency in price movement. Moreover, the statistics of the absolute value of EPM show that the magnitude of the reversal of extreme price movement on the next day is higher than at the end of the previous day. All three metrics (mean, median, standard deviation) of the next-day reversals are higher than those of the last 15-mn of the previous day. This indicates the higher tendency to correct last day manipulations which validate our doubt about potential EOD. Table 1 reports these results.

4 Results and discussion

To study the changes in liquidity provision and consumption of different categories of traders during particular turbulent periods, we use monetary net trade imbalance, which is the difference between the funds invested in buy-transactions and funds gained as a result of sell-transactions. Negative net imbalance of a trading category during a crash indicates that it contributes to price drop while a positive net imbalance during a crash indicates that it contributes to a market stabilization and price recovery.

	5 minutes before "+" EPM at **closing**			5 minutes before "-" EPM at **closing**		
	mean	median	sd	mean	median	sd
HFT	-1301.562	-2150.495	138891.71	11503.97	0.000	248986.2
MIX	-7511.558	1758.115	168991.99	-20837.64	-114.565	227855.0
NON	8813.119	0.000	81992.39	9333.67	0.000	135800.9
	during "+" EPM at **closing**			during "-" EPM at **closing**		
	mean	median	sd	mean	median	sd
HFT	26604.632	343.315	176343.0	-58738.7213	-5217.93	354618.5
MIX	-33610.225	-1841.815	216738.1	59576.1315	5588.83	349873.1
NON	7005.593	0.000	158559.7	-837.4102	0.00	174050.1

Table 2: This table reports average net trading positions of different categories of traders during and just before extreme price movements. Net Positions = buy volume consumed + buy volume provided - dollar sell volume consumed - sell volume provided. "+" EPM means positive extreme price movement (a strong price increase). "-" EPM means negative price movement (a strong downward trend). Pure high frequency traders create a strong pressure in the direction of positive and negative extreme price movement. They actively consume the liquidity provided by mix high frequency traders. Non-HFTs contribute only marginally at end-of-day extreme market movement. However, they are the key actors at extreme price movements opening. They are the main liquidity providers at the opening. Pure-HFTs and Mixed HFTs create the strongest pressure into the direction of EPM.

Non-HFTs mainly trade in the opposite direction of the extreme price movement.

As market manipulation is proxied through MTC following two simultaneous conditions that are conditional on the EOD percentage price change and next day EOD reversion, we proceed our analysis based on 412 manipulations to uncover the identity of the main manipulators. The previous studies have long attributed the market drift to HFT strategies and harmful strategies. Thus, we pursue our work to validate prior findings and uncover the most aggressive manipulator in four different period tranches. Table 2 presents statistical data on the average net trading positions of different categories of traders during two different periods at *the day-close*: 5 minutes before the negative ("+") or positive ("-") EPM, and during the "+" or "-" EPM. Furthermore, Table 3 presents statistical data on the average net trading positions of different categories of traders during two different periods at *the next-day opening*: 5 minutes before "+" or "-" EPM, and during "+" or "-" EPM. Net positions are calculated as the sum of buy volume consumed, buy volume provided, sell volume consumed, and sell volume provided. "+" EPM refers to positive extreme price movements, while "-" EPM refers to negative extreme price movements.

We also perform an order-flow based analysis (Table 4). We find that 5 minutes before the closing, during the closing, and under both cases

	5 minutes before "+" EPM at **opening**			5 minutes before "-" EPM at **opening**		
	mean	median	sd	mean	median	sd
HFT	16898.35	391.510	159022.0	-2164.776	-487.605	119678.6
MIX	33796.14	2881.125	402329.4	-4984.816	-1021.845	225419.5
NON	-50694.49	-2974.210	448770.0	7149.592	0.000	177864.8
	during "+" EPM at **opening**			during "-" EPM at **opening**		
	mean	median	sd	mean	median	sd
HFT	1953.513	1414.865	264939.4	-10987.0200	-3412.985	149790.1
MIX	53102.608	8317.480	331164.4	-476.1677	-1917.135	275248.5
NON	-55056.121	-4420.075	326788.4	11463.1877	3825.420	183046.7

Table 3: This table reports average net trading positions of different categories of traders during and just before extreme price movements. Net Positions = buy volume consumed + buy volume provided - dollar sell volume consumed - sell volume provided. "+" EPM means positive extreme price movement (a strong price increase). "-" EPM means negative price movement (a strong downward trend). Pure high frequency traders create a strong pressure in the direction of positive and negative extreme price movement. They actively consume the liquidity provided by mix high frequency traders. Non-HFTs contribute only marginally at end-of-day extreme market movement. However, they are the key actors at extreme price movements opening. They are the main liquidity providers at the opening. Pure-HFTs and Mixed HFTs create the strongest pressure into the direction of EPM.

("+" EPM and "-" EPM), the mean values for the number of limit orders bought and the number of limit orders sold are highest for the HFT group followed by the Mix. Non- HFT group has a very "shy" activity. The standard deviation is highest for the HFT group, followed by the MIX group and then the non-HFT group. In addition, the mean values for the number of canceled orders are highest for the HFT group, followed by the Mix and non-HFT groups. The standard deviation is also the highest for the HFT group, followed by the MIX group and then the non-HFT group. These findings are consistent with the ratio of the number of canceled/modified orders within a 0.5-second time span divided by the number of sent limit orders, where the mean values for the number of canceled orders are highest for the HFT group, followed by the Mix, and non- HFT group.

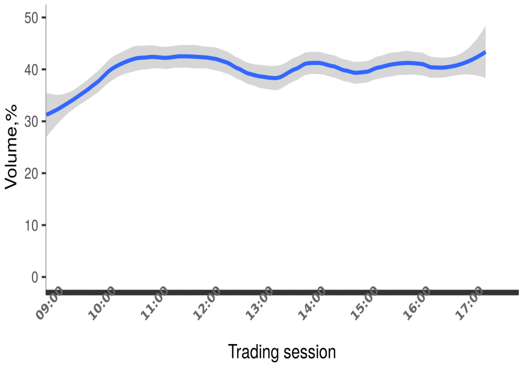
Furthermore, when exploring the period of 5 minutes before the opening of the next day and under both cases ("+" EPM and "-" EPM), we find that the mean values for the number of limit orders bought and the number of limit orders sold are highest for the Mix followed by HFT and non- HFT. Yet, the mean values for the number of canceled orders are highest for the Mix, followed by HFT and non- HFT under "+" EPM. Under "-" EPM, we notice that the HFT group has the highest mean of canceling orders. Again, the means values of the ratio of the number of canceled/modified orders within a 0.5-second time span divided by the number of sent limit orders are the highest for the HFT group, followed by the Mix and non- HFT group.

Finally, during the 5 minutes of the opening session of the next trading day and under both cases ("+" EPM and "-" EPM), the mean values for the number of limit orders bought and the number of limit orders sold are highest for the HFT group, followed by the Mix, and non- HFT. The standard deviation is highest for the HFT group followed by the MIX group and then the non-HFT group. In addition, the mean values for the number of canceled orders are highest for the HFT group, followed by the Mix and non-HFT groups. The standard deviation is also the highest for the HFT group, followed by the MIX group and then the non-HFT group. These findings are consistent with the ratio of the number of canceled/modified orders within a 0.5-second time span divided by the number of sent limit orders, where the mean values for the number of canceled orders are highest for the HFT group, followed by the Mix, and non-HFT group.

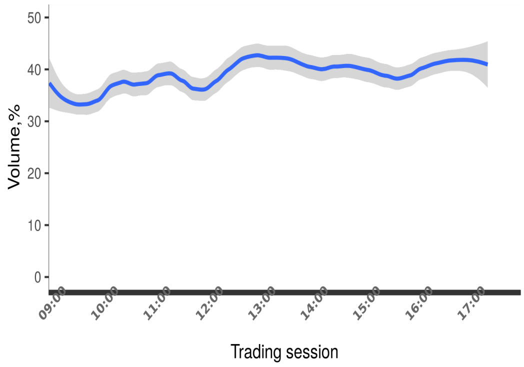
To the best of our knowledge, we are the first to closely examine the limit order book and the activity of market players accurately identified at the closing session and the very next opening session of the next trading day. The scarce studies that used proxies to identify market players based on the speed and nature of their orders (proprietary, agency, or market-making) also show that non-HFTs are more present in the opening. Boussetta *et al.* (2020) find that slow brokers activity in the pre-opening session is closely related to price discovery process across the trading venues they covered (Euronext, BATS, and Chi-X). They also confirm that while the clearing prices of pre-opening session contains information, there is a reversal in the next 15 minutes across the different platforms, reflecting price pressure and liquidity issues around the open.

Our results also show that though HFTs are the main contributors to extreme price movements (EPM), they actively consume the available liquidity provided by mixed HFTs, who in their turn, actively cancel their pending orders to manage the adverse selection risks. Then, they place the orders in the direction of the price trend. Mixed HFTs contribute to the price movement amplification. As a result, mixed HFTs create the strongest selling pressure on the order book during a typical price crash. These findings are in line with Degryse *et al.* (2021) who identify a GL phenomenon in modern fragmented equity markets and state that measured liquidity exceeds true liquidity due to GL. Not surprisingly, the authors confirm that the greatest GL is found among HFTs who mostly act as liquidity takers on heavily traded and less volatile stocks across alternative platforms.

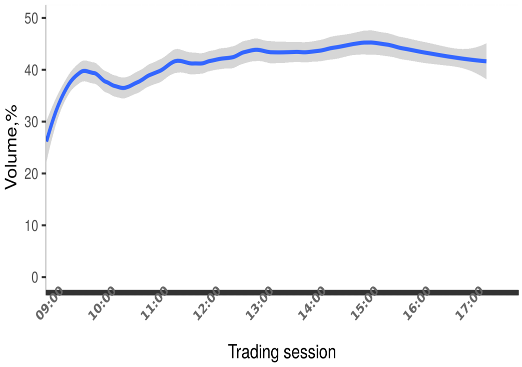
We examine data on the activity levels of different trader types during regular market conditions (Table 5). This information is used to identify significant changes in trader behavior during extraordinary market events. At the end of the trading day (17h15-17h30), it is shown that Mix traders are more active than HFTs and Non-HFTs, as evidenced by their higher means for limit order buys and sells (108.7288 and 105.4963) and greater variability (228.193 & 105.0307). Additionally, the ratio of market orders to limit orders is highest for Mix traders. The number of cancelled orders is also highest for Mix traders, however, the ratio of canceled orders to limit orders is higher for HFTs, indicating that HFTs tend to cancel a larger proportion of their orders even under normal conditions. The dollar Volume Net Positions show that the non-HFTs are aggressively selling the last 15 minutes at the end of the day, followed by HFTs while Mix keep on buying more than selling. At the opening of the next trading day (9h-9h15), HFTs appear more active as the means of their activities (limit buy & limit set) are the highest (173.8595 & 197.194). The number of cancelled orders and, the ratio of cancelled orders to limit orders are also highest for HFT traders. The dollar Volume Net Positions show that the HFTs are aggressively buying at the first 15 mns of the next day, followed by HFTs while non-HFTs have a very shy activity.



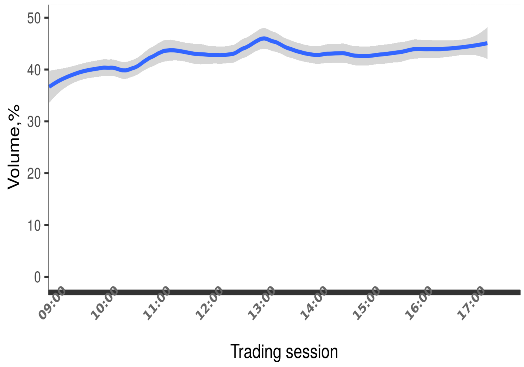
(a) Bid side, HFT, top 5 best limits



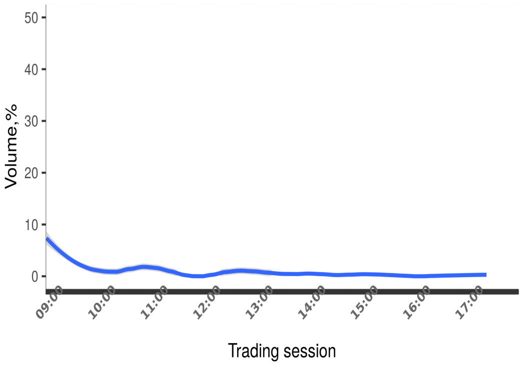
(b) Ask side, HFT, top 5 best limits



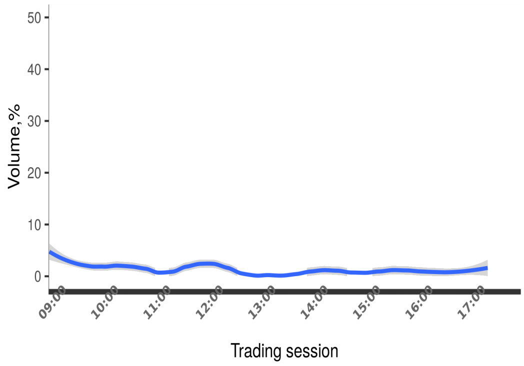
(c) Bid side, MIX, top 5 best limits



(d) Ask side, MIX, top 5 best limits

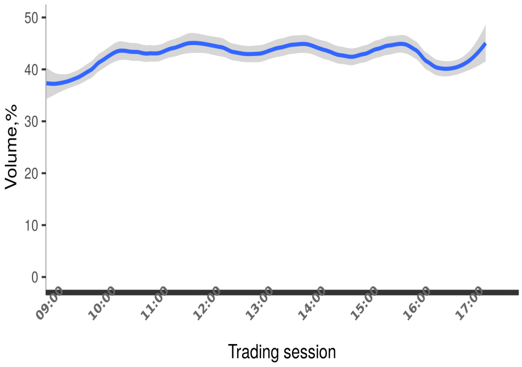


(e) Bid side, NON, top 5 best limits

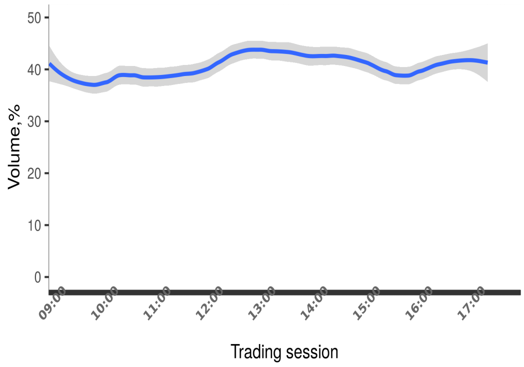


(f) Ask side, NON, top 5 best limits

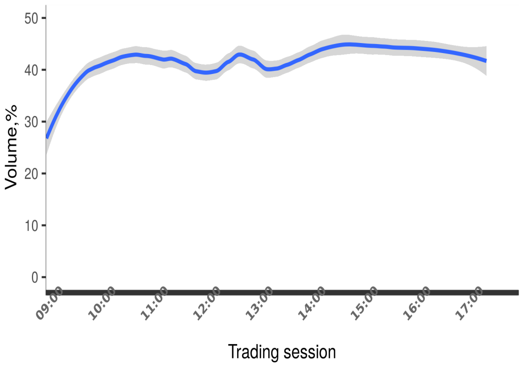
Figure 2: Liquidity provision of different categories of traders at the top 5 best limit level of the order book.



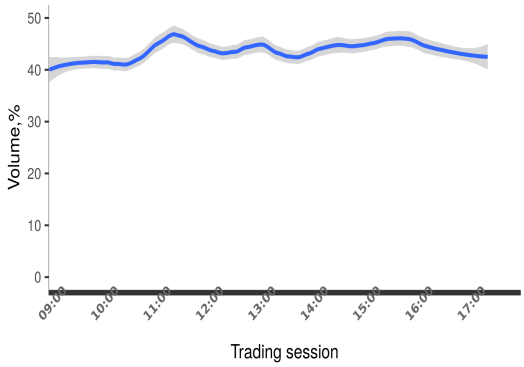
(a) Bid side, HFT, top 10 best limits



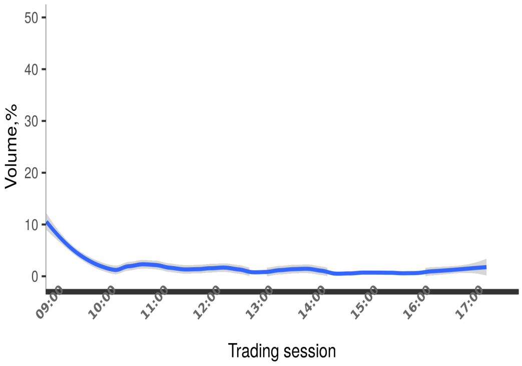
(b) Ask side, HFT, top 10 best limits



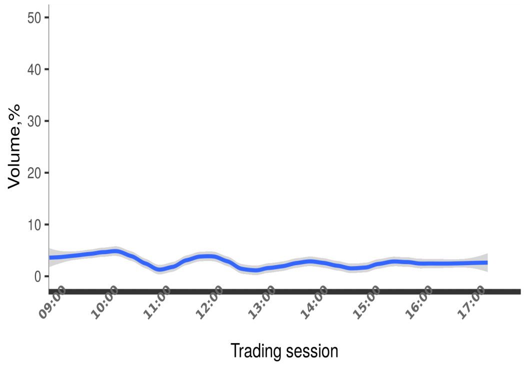
(c) Bid side, MIX, top 10 best limits



(d) Ask side, MIX, top 10 best limits

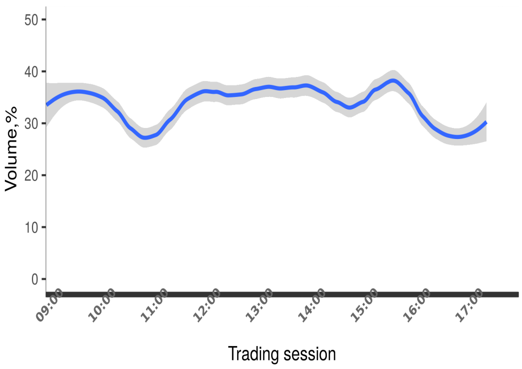


(e) Bid side, NON, top 10 best limits

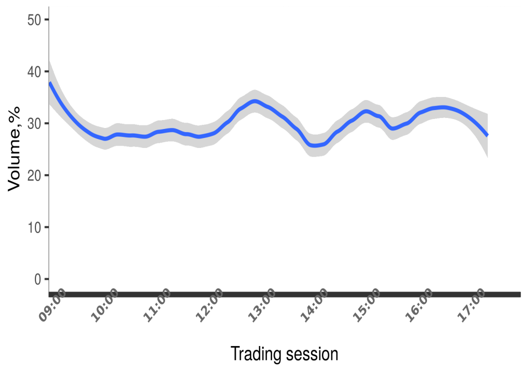


(f) Ask side, NON, top 10 best limits

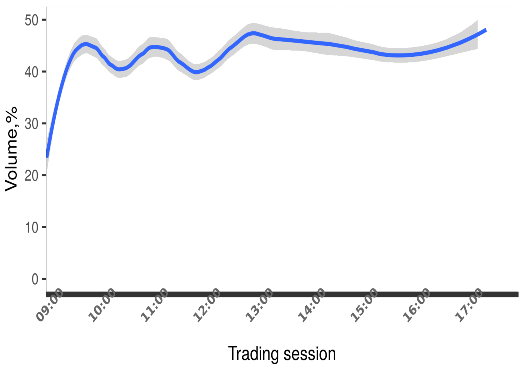
Figure 3: Liquidity provision of different categories of traders at the top 10 best limit level of the order book.



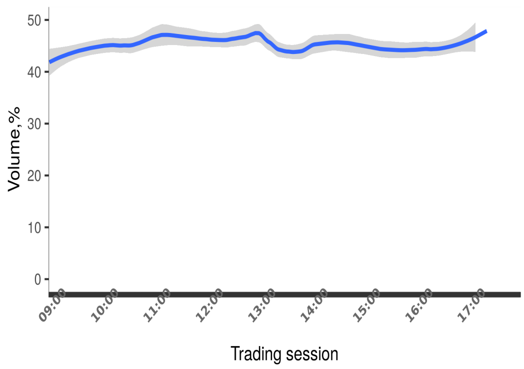
(a) Bid side, HFT, top 20 best limits



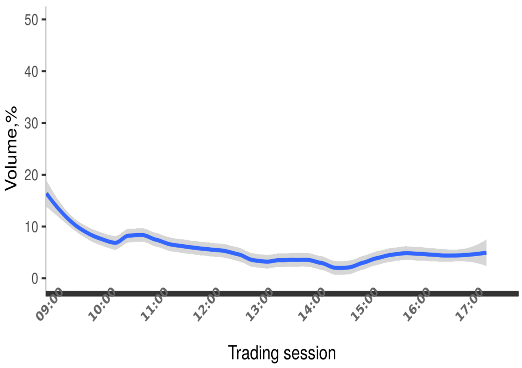
(b) Ask side, HFT, top 20 best limits



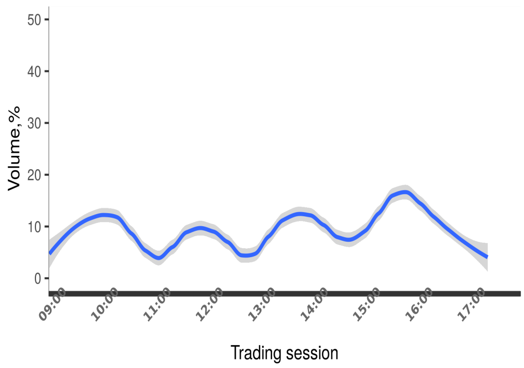
(c) Bid side, MIX, top 20 best limits



(d) Ask side, MIX, top 20 best limits



(e) Bid side, NON, top 20 best limits



(f) Ask side, NON, top 20 best limits

Figure 4: Liquidity provision of different categories of traders at the top 20 best limit level of the order book.

	5 minutes before "+" EPM at closing									5 minutes before "-" EPM at closing					
	HFT			MIX			NON			HFT			MIX		
	mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd
sentLimitOrdersBuy	238.0515	77	415.3341	186.5102	122.5	192.5546	12.4333	6	34.7925	274.6919	74	537.8627	203.800	120	245.5673
sentLimitOrdersSell	233.7423	77	418.012	188.3163	118.5	205.3356	9.45	3	27.9269	317.1564	65	775.9295	214.2047	115	279.3805
nbSentMarket/nbSentLimit	1e-04	0	0.0013	0.0024	0	0.0063	0.0575	0	0.1263	1e-04	0	0.0013	0.0031	0	0.0122
dollarVolumeNetPositions	-111.7153	-21.0405	2234.5394	-57.9604	0.5925	2615.5222	221.7326	0	930.4884	179.775	0	3343.4168	-110.5031	-0.015	5279.5319
nbCanceled	443.6392	144.5	795.1141	320.6939	191.5	347.3948	14.8583	5	60.2756	559.3318	127	1236.2368	360.5907	188	463.259
nbCanceled/nbSentLimitHFT	0.906	0.9316	0.0899	0.8251	0.8413	0.0936	0.5464	0.5322	0.2665	0.921	0.9388	0.0802	0.8252	0.8417	0.0874
nbCanceled0.5/nbSentLimitHFT	0.2689	0.24	0.1444	0.1048	0.0851	0.0849	0.0693	0	0.1486	0.2458	0.2205	0.1352	0.1034	0.0853	0.0719
	during "+" EPM at closing									during "-" EPM at closing					
	HFT			MIX			NON			HFT			MIX		
	mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd
sentLimitOrdersBuy	330.5459***	129	464.4089	286.3316***	237	218.0282	12.7676	7.5	16.2527	362.4533***	120	627.6869	294.3628***	168	319.9085
sentLimitOrdersSell	282.9592***	119.5	422.0923	246.1429***	171	219.8352	8.0634	3	14.6835	430.7617***	121	780.3758	324.7023***	203	347.6764
nbSentMarket/nbSentLimit	2e-04*	0	0.0017	0.0033***	0.001	0.0067	0.0666	0	0.1318*	1e-04	0	6e-04	0.0038***	0	0.0114
dollarVolumeNetPositions	662.5544	156.73	2239.582	1599.7535	569.0225	7229.6897	371.1142	1.05	2328.6266	-961.1122	-263.852	3380.3298	-2227.8233	-630.63	10986.7172
nbCanceled	574.89***	218.5	839.7248	449.8214***	339	378.2498	11.8028	6	20.1611	742.0561***	221	1305.8368	522.0093	311	561.5533
nbCanceled/nbSentLimitHFT	0.9094***	0.9304	0.0919	0.8284***	0.8372	0.0743	0.5682	0.5714	0.2276	0.9192***	0.9362	0.0689	0.8294***	0.8473	0.0765
nbCanceled0.5/nbSentLimitHFT	0.278***	0.2691	0.1081	0.1409***	0.1089	0.0946	0.0885***	0	0.1768	0.2671***	0.25	0.1202	0.1346***	0.1115	0.0855
	Next day, 5 min prior "+" EPM at opening									Next day, 5 min prior "-" EPM at opening					
	HFT			MIX			NON			HFT			MIX		
	mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd
sentLimitOrdersBuy	148.7063	18	345.8431	200.1802	42	445.8113	35.5447	12	88.9368	216.7956	34	478.2654	228.9669	76	410.6861
sentLimitOrdersSell	163.7562	21	403.9232	203.9419	39	468.1142	39.4065	10	132.6542	264.292	37	601.3548	240.7682	81	387.1185
nbSentMarket/nbSentLimit	0.0891	0	0.7163	0.1975	0	0.4348	0.3464	0	1.4163	0.0161	0	0.0798	0.1769	0	0.8869
dollarVolumeNetPositions	-419.0132	0	6794.327	-168.7061	0.645	3938.6397	-486.5402	0	2719.4828	425.7783	0	2456.4096	-821.8758	-51.885	8088.293
Cancel	286.4	30.5	688.5137	359.3256	31	862.4679	57.813	16	202.125	458.8686	58	1031.6376	419.7682	81	752.7641
nbCanceled/nbSentLimitHFT	0.8604	0.9382	0.5512	0.7065	0.8705	0.3333	0.8629	0.9355	1.0116	0.8569	0.9545	0.2386	0.739	0.912	0.4053
nbCanceled0.5/nbSentLimitHFT	0.1946	0.1654	0.2333	0.0739	0.0286	0.1215	0.0241	0	0.13	0.1635	0.1579	0.1541	0.0595	0.019	0.1165
	Next day, during "+" EPM at opening									Next day, during "-" EPM at opening					
	HFT			MIX			NON			HFT			MIX		
	mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd	mean	median	sd
sentLimitOrdersBuy	193.5563	35	413.1924	151.3837	58.5	240.3443	24.1261	9	60.2255	151.1871	60	276.9545	122.5364	59	168.3983
sentLimitOrdersSell	232.325	35	739.821	140.407	56	239.6554	26.5135	7	64.2991	156.7554	70	272.5866	167.5298	91	214.0341
nbSentMarket/nbSentLimit	0.089	0	0.7163	0.1978	0	0.4348	0.3891	0	1.485	0.0158	0	0.0793	0.1761	0	0.887
dollarVolumeNetPositions	79.913	0	2607.6769	397.8063	171.7325	4378.3947	-342.2127	0	2689.8366	126.6001	-103.32	2751.699	-1057.2005	-284.86	8081.2681
Cancel	396.9312	58.5	1036.4575	236.7907	62.5	414.6847	28.8829	10	80.5091	283.8633	129	485.7971	236.5563	107	332.7243
nbCanceled/nbSentLimitHFT	0.8579	0.9393	0.5514	0.6888	0.8276	0.3199	0.7932	0.7667	1.0711	0.8493	0.9355	0.2326	0.7201	0.8703	0.3926
nbCanceled0.5/nbSentLimitHFT	0.2429	0.2181	0.2315	0.1174	0.0909	0.1287	0.0265	0	0.1391	0.2127	0.216	0.1494	0.107	0.0753	0.1294

Table 4: Significance levels are denoted by: *** $< 0.1\%$, ** $< 1\%$, * $< 5\%$. MIX-HFTs and Pure-HFTs significantly increase their order submission and in particular order canceling.

	Normal day 17h15-17h30								
	HFT			MIX			NON		
	mean	median	sd	mean	median	sd	mean	median	sd
sentLimitOrdersBuy	69.7924	38	90.9276	108.7288	77	228.193	24.0726	24	19.7569
sentLimitOrdersSell	74.4992	43	91.7748	105.4963	75	105.0307	12.8644	4	32.875
nbSentMarket/nbSentLimit	0.0011	0	0.0095	0.0494	0	0.149	0.1303	0	0.6501
dollarVolumeNetPositions	-372.0957	0	4432.233	159.4205	0	5375.7734	-885.051	0	3583.2267
nbCanceled	131.187	67	173.0099	171.0641	103	265.5117	10.0218	4	21.4248
nbCanceled/nbSentLimitHFT	0.8233	0.9463	0.2823	0.7479	0.82	0.1932	0.6081	0.5455	0.7013
nbCanceled0.5/nbSentLimitHFT	0.1722	0.1782	0.1258	0.0859	0.0629	0.1111	0.0729	0	0.192
	Normal day 9h-9h15								
	HFT			MIX			NON		
	mean	median	sd	mean	median	sd	mean	median	sd
sentLimitOrdersBuy	173.8595	47	356.4572	137.8978	59	209.9874	28.2634	9	80.2495
sentLimitOrdersSell	197.194	50	572.5984	153.0867	74	228.0901	29.7009	9	75.8733
nbSentMarket/nbSentLimit	0.055	0	0.5272	0.1876	0	0.6834	0.2678	0	1.0862
dollarVolumeNetPositions	101.617	0	2671.1695	-282.3981	0	6413.3961	-93.0965	0	3738.2185
nbCanceled	344.3679	83	828.0396	236.6811	90	378.012	25.375	11	63.9853
nbCanceled/nbSentLimitHFT	0.8539	0.9365	0.4328	0.7034	0.8553	0.3555	0.7276	0.8091	0.7935
nbCanceled0.5/nbSentLimitHFT	0.2289	0.2162	0.1979	0.1125	0.0867	0.1289	0.0196	0	0.1036

Table 5: This table reports the activity measures of different categories of traders in the normal days. This data is used to report significant changes in traders behavior during an extreme market event.

We also report the relationship between the range of EPMs and activities of different categories of traders

$$R_{i,t} = \sum_{j}^{7} \beta_j A_{i,t}^{j} + \varepsilon_{i,t}$$

where $R_{i,t}$ is the return of asset i at time interval t, $A_{i,t}^{j}$ is the value of activity of different categories of traders. In our model there are 7 explanatory variables.

	HFT		MIX		NON	
	Estimate	$Pr(>\|t\|)$	Estimate	$Pr(>\|t\|)$	Estimate	$Pr(>\|t\|)$
sentLimitOrdersBuy	-1.355e-05	0.07914 .	1.972e-05	0.00358 **	1.619e-04	0.000994 ***
sentLimitOrdersSell	-2.112e-05	0.00925 **	-1.475e-05	0.02223 *	1.615e-05	0.709586
nbSentMarket/nbSentLimit	1.802e-01	0.41138	-5.437e-02	0.07073 .	2.225e-03	0.452848
dollarVolumeNetPositions	3.933e-07	4.97e-05 ***	9.239e-08	0.00105 **	-4.864e-08	0.733463
nbCanceled/nbSentLimitHFT	1.859e-05	0.02462 *	-3.298e-06	0.64395	-1.317e-04	0.023575 *
nbCanceled0.5/nbSentLimitHFT	-9.534e-03	0.00919 **	3.634e-03	0.47269	3.964e-03	0.040037 *

Table 6: The values in the table reports the effects of HFT activities on returns of EPMs. HFT's activities play determinant role in the EPM's formation and amplification. The only one measure of HFT's activity that does not have any significant impact on EPMs is Market-to-Limit ratio. HFTs heavenly rely on limit orders even in case of extreme market event. The number of market orders used by HFTs is really low. Signif. codes: 0.001 '***', 0.01 '**', 0.05 '*', 0.1 '.'

To analyze the significant effect market activities of different categories of traders on market returns, we run additional regression model

$$R_{i,t} = \alpha_i + \underbrace{\sum_{j}^{7} \beta_j^{HFT} A_{i,t}^{j}}_{HFT} + \underbrace{\sum_{j}^{7} \beta_j^{MIX} A_{i,t}^{j}}_{MIX} + \underbrace{\sum_{j}^{7} \beta_j^{NON} A_{i,t}^{j}}_{NON} + \varepsilon_{i,t}$$

α_i is a dummy variable controlling market conditions (the regular and abnormal periods), $A_{i,t}$ are activity measures of different categories.

	HFT		MIX		NON	
	Estimate	$Pr(>\|t\|)$	Estimate	$Pr(>\|t\|)$	Estimate	$Pr(>\|t\|)$
α	2.832e-03	0.019525**	2.832e-03	0.019525**	2.832e-03	0.019525**
sentLimitOrdersBuy	-1.010e-05	0.030214*	9.108e-06	0.00274 **	4.322e-05	0.00138 **
sentLimitOrdersSell	-1.752e-05	0.000351 ***	2.261e-06	0.33133	-2.462e-05	0.02552 *
nbSentMarket/nbSentLimit	-5.801e-03	0.723835	1.519e-04	0.88455	-1.361e-04	0.82522
dollarVolumeNetPositions	7.901e-08	0.010008 *	7.265e-08	3.95e-06 ***	3.241e-08	0.56571
nbCanceled/nbSentLimitHFT	1.437e-05	0.003960 **	-7.712e-06	0.01128 *	-1.069e-05	0.35621
nbCanceled0.5/nbSentLimitHFT	-1.863e-03	0.005958 **	1.765e-03	0.07575 .	3.819e-04	0.53250

Table 7: The values in the table reports the effects of activities measures of different categories of traders on emergenece of end-of-day EPMs. Statistics show that pure-HFTs are the main contributors to the significant changes in price variations. The only one measure of HFT's activity that does not have any significant impact on EPMs is Market-to-Limit ratio. HFTs heavenly rely on limit orders even in case of extreme market event. The number of market orders used by HFTs is really low. Signif. codes: 0.001 '***', 0.01 '**', 0.05 '*', 0.1 '.'.

5 Conclusion

This study investigated the existing of market manipulations using the rich BEDOFIH AMF - Euronext Paris High-Frequency database for 2017. We have analyzed 943,245 files to select 33,357 (ISIN x days) observations. We advance the analysis by detecting end-of-day (EOD) price dislocations to depict the identity of the main manipulators. We detect 412 EOD manipulations. We find that HFT activity is in tandem with price movements and their aggressive strategies drift the market at day-end.

Along with large investment banks, HFTs who are informed traders contribute to price reversal on the next day's opening. We contributed to extensive research work on market fairness, market supervision, and manipulative trading prevention. The study has many implications for regulators, policymakers, and financial markets. It is of particular interest to the data Intelligence department of French Authority of the Financial Markets Future studies

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