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A literature review on extreme price movements with reversal

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ABSTRACT

Extreme price movements with reversal (EPMRs) are positive or negative price patterns that reverse in a specific time period after the initial price change. Up to now, multiple types of EPMRs have formed, ranging from event-driven to trade imbalance-driven approaches, with numerous studies trying to explain this phenomenon. Although EPMRs have been studied for decades, the rise of the high frequency world has shed light on EPMRs with durations of a few minutes or seconds. This paper summarizes the literature on EPMRs, with a special focus on (mini) flash crashes. While high frequency traders are made responsible by numerous studies, evidence remains unclear.

1. Introduction

In the last decade, there has been an increase in literature on extreme price movements with reversal (EPMRs), especially focusing on (mini) flash crashes. According to Frijns et al. (2021), they are detrimental to welfare, because they cause enormous shifts in capital. This not only has an impact on market quality, as Boulton et al. (2014) argue, but according to Born et al. (2011) also leads to a general drop in confidence in financial markets, thus affecting all market participants.

In hand with this development goes the rise of new technology and the use of high-frequency computer-based trading (HFT), which has led to fundamental shifts in market structures around the world, as the UK Government Office of Science (2012) argues. As of the December 2020, data by the *European Securities and Markets Authority* suggests that HFT represents roughly 50% of trading volume in US equity markets and between 24% and 43% percent of trading volume in European equity markets (Breckenfelder, 2020).

Literature has especially looked into the causality of high frequency traders (HFTs) for EPMRs. The UK Government Office of Science (2012)'s report on *The Future of Computer Trading in Financial Markets* addresses this new world of trading and proposes a variety of policies to not only improve market performance, but also reduce the risk of market failure. However, we argue that in order to find adequate policies to prevent e.g. flash events, which not only negatively impact investor confidence, but also have a not negligible impact on return, one has to first get a deeper understanding of how EPMRs are defined, why they happen in the first place and how they affect financial markets.

The aim of this literature review is to give an overview of the literature on EPMRs, as recently there has been an increase in literature on mini flash crashes (MFCs). To qualify as EPMR, we require either a substantial positive or negative price movement, which is reversed in a specific time period after the initial price change and not induced by any valuation relevant information. We especially focus on four questions, namely (1) What are the different types of EPMRs? (2) How can EPMRs be explained? (3) Is there empirical evidence on how EPMRs affect market quality? and finally (4) Are there ways to predict EPMRs? Answers to these questions should first of all give researchers an overview of the literature and should help to identify research areas, that have not been covered yet. Secondly, policy makers can build on this literature to tailor future policies to current research finding.

This literature includes findings from over seventy publications spanning from 1972 until March 2022, also including more recent market structure literature, showing that the topic is highly relevant. We are aware of literature reviews by Amini et al. (2013) as well as Virgilio (2019b), Laly and Petitjean (2019) and Nokerman (2015). Amini et al. (2013) give an overview of the literature regarding the short term predictability of stock prices conditional on large prior price changes. We add to this literature, as literature on flash crashes or MFCs is not included, which is what we focus on in the context of this literature review. The review by Virgilio (2019b) on HFT includes findings on HFT and flash crashes, which we extend by including MFCs. Finally, we adopt findings from the literature reviews by Laly and Petitjean

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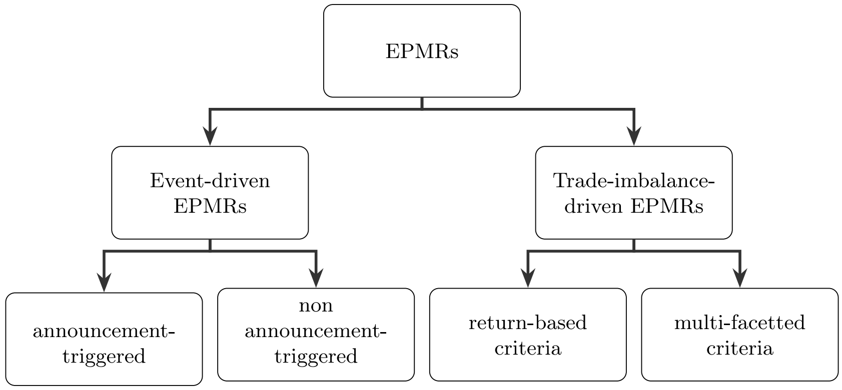

Fig. 1. This figure gives an overview of the types of EPMRs. We identify two groups in the literature, event-driven EPMRs and non-event driven EPMRs. Event-driven EPMRs can be further structured into announcement-triggered and non announcement-triggered EPMRs. Non event-based EPMRs can be identified using either return-based criteria or multi-facetted criteria.

(2019) as well as Nokerman (2015) and place them in the larger context of EPMRs.

The paper is structured as follows: We start by explaining the methodology applied to write this literature review (see Section 2). In Section 3 we give an overview of different types of EPMRs and in Section 4 we discuss possible explanations. In Section 5 we introduce empirical studies that have evaluated the effect of EPMRs on market quality. Finally, we list different methods introduced to predict EPMRs in Section 6. Section 7 contains concluding remarks.

2. Methodology

To identify relevant literature we followed the inductive research approach and used the search engines *Science Direct* and *Google Scholar*. We apply the keywords 'extreme price movement' and 'reversal', 'price reversal' and 'flash crash' in the subject area 'Economics, Econometrics and Finance' and thematically analyze the findings. Next, we used the method of *citation pearl growing*,[1] to identify further relevant papers. We also follow Thompson and Pocock (1991) and include unpublished work to avoid the impact of possible *publication bias* in this literature review.

3. Types of extreme price movements with reversal

To the best of our knowledge, extreme price movements (EPMs) were first mentioned in literature by Longin (2000), who describes them as "*market corrections during ordinary periods, and also to stock market crashes, bond market collapses or foreign exchange crises during extraordinary periods*" Longin (2000, p. 1097). However, there is no uniform definition of EPMs in literature.

As Brogaard et al. (2018) find, one can conclude from literature that EPMRs can be triggered by two types of scenarios. First of all, EPMRs can be a reaction to information arrival to the market due to an event. This is followed by rapid price adjustment to incorporate the new information in the market price. If markets are efficient, price adjustment as a reaction to news announcements are permanent and do not revert. As a result, EPMRs following an event that revert after a certain period of time seem to be a violation of market efficiency. The second scenario is a trade imbalance, which can be caused by e.g. large orders that push prices away from their fundamental value. Such pressure-induced EPMRs are not permanent and thus revert after a certain time period. An overview of this structure can be found in Fig. 1. We follow this structure proposed by Brogaard et al. (2018) and use it to introduce the different types of EPMRs.

In the following subsections we first present different types of event-driven EPMRs including examples from literature (see Section 3.1). Next, we list trade-imbalance-driven EPMRs identified in literature (see Section 3.2). For each subtype we additionally note if the EPMRs that fall under this category are predominantly short-term or long-term.[2]

3.1. Event-driven EPMRs

The group of event-driven EPMRs includes all EPMRs that are caused by the arrival of some kind of news to the market. This news arrival can be either announcement-triggered or non announcement-triggered, allowing to further divide the group of event-driven EPMRs into two sub-groups. We start by listing types of event-driven EPMRs that are announcement-triggered in Section 3.1.1 and continue with non announcement-triggered EPMRs in Section 3.1.2. The duration of event-driven EPMRs is predominantly long-term.

3.1.1. Announcement-triggered EPMRs

Starting with the group of announcement-triggered event-driven EPMRs, empirical literature has identified several announcement-triggered price movements which are partly reversed. These announcements can be either made by the company itself (*internal* announcement) or by e.g. authorities, regulators or rating agencies, which we refer to as *external* announcements.

Some literature suggests that internal announcements can lead to an EPMR. As it is sheerly impossible to list all company announcements that can lead to an EPMR, we list a few examples, which have been found to sometimes be followed by an EPMR. For example, Chae et al. (2013), who study companies in the IRRC database within a time period from September 1990 to December 2005, find takeover vulnerability to lead to a large price run-up prior to takeover announcements. They find that as the demand for a quick response as well as for immediacy have the potential to trigger an overreaction, takeover vulnerability is positively related to short-term price reversals. Next, Andres et al. (2016) study open market share repurchase announcements for non-financial firms included in the German Composite DAX index (CDAX) from May 1998 to December 2008. They detect

[1] According to Rowley and Slack (2004) citation pearl growing is the process of picking up suitable terms from existing documents to retrieve other documents.

[2] We define EPMRs with a price reaction and the following reversal lasting one day or less as short-term EPMRs. EPMRs lasting more than one day are referred to as long-term EPMRs.

a negative share price performance prior to a repurchase announcement, which is then followed by a positive and significant announcement day abnormal return. Finally, looking at seasoned equity offerings (SEOs), Dasilas and Leventis (2013) study both short-term and long-term share price behavior surrounding SEOs from firms listed on the Athens Stock Exchange, which had announced a SEO between 1999 and 2006, and find share prices to rally before and reverse after the announcement of SEOs.

Literature has also found external announcements to have the possibility of leading to an EPMR. For example, Ellul et al. (2011) study insurance companies' transaction and year-end position data from the National Association of Insurance Commissioners (NAIC) from 2001 to 2005 and detect bonds that are subject to a high probability of being downgraded and thus having to be sold by regulation constrained insurance companies exhibiting price declines that subsequently reverse. Next, Breedon et al. (2018) study the role of algorithmic traders following the removal of the cap on the Swiss franc on January 15, 2015, which led to an extremely sharp appreciation against both the Euro and the US Dollar in the first 20 min, reversing in the subsequent hour.

3.1.2. Non announcement-triggered EPMRs

Event-driven EPMRs not triggered by an announcement are market reactions to news without an explicit announcement. Again, a full list of news arrival that was found to lead to an EPMR is not manageable, which is why we only list a few examples.

Literature has mainly found the occurrence of terrorist attacks. For example, Boubaker et al. (2015) study the short-term overreaction to specific events for 100 listed stocks with no price limits on the Egyptian stock exchange (EGX) between 2003 and 2010 and detect negative and significant abnormal returns for three days after a terrorist attack which is then followed by a price reversal on day four post event. Next, Burch et al. (2016) study common stocks and closed-end funds using *Center for Research in Security Prices* (CRSP) daily returns and market capitalization information after the terrorist attacks on 9/11 and find that price declines after the markets reopened are followed by price reversals in the subsequent two weeks.

3.2. Trade-imbalance-driven EPMRs

Next to event-driven EPMRs, literature has identified EPMRs which cannot be explained by news arrival to the market. This type can be identified by establishing a set of criteria on returns (as previously reviewed by Amini et al. (2013)) or adding additional criteria. We thus differentiate between a return-based (see Section 3.2.1) and a multi-facetted identification process (see Section 3.2.2). While long-term EPMRs are predominantly detected using a return-based identification process, short-term EPMRs are usually detected using a multi-facetted identification process.

3.2.1. Return-based identification process

One way to identify trade-imbalance-driven EPMRs is to apply a set of criteria on returns. There are many ways to set return-based criteria, including

- setting a return based benchmark and applying this benchmark to a chosen group of financial instruments (e.g. Bremer and Sweeney (1991) study large negative 10-day rates of return of at least 10% of Fortune 500 companies using daily CRSP stock returns covering the period 1962 to 1986, which are followed by larger than average positive rates of return lasting for about two days.),
- using residuals from market models as benchmark (e.g. Brown et al. (1988) use CRSP daily stock return data covering the period July 1962 to December 1985 and calculate mean-adjusted residuals and build their sample off of the size of the residual being at least 1% or 2.5%. They use those samples to study firm-specific events and find for unfavorable events that the average postevent returns tend to be significantly positive.),
- using returns exceeding prior standard deviation of returns as benchmark (e.g. Pritamani and Singal (2001) study the return behavior following large price change events using data consisting of all common stocks listed on the NYSE or the AMEX from 1990 to 1992 and define a large abnormal price change as the index adjusted abnormal returns being more than three times the standard deviation away from the mean.) and
- looking at a group of financial instruments and declaring the top and bottom percentile of returns as EPMRs (e.g. DeBondt and Thaler (1985) test whether the overreaction hypothesis is predictive using monthly return data for NYSE common stocks between January 1926 and December 1982. They rank the cumulative market-adjusted excess returns and take the top and bottom decile to form their winner and loser portfolio.).

3.2.2. Multi-facetted identification process

In addition to return-based criteria, studies use criteria regarding time, duration, ticks and recovery to identify trade-imbalance-driven EPMRs. The cumulation of several criteria make up the definition of special sub-groups of EPMRs, including *market quality breakdowns (breakups)*, *mini flash crashes* (MFCs) and flash crashes.

Gao and Mizrach (2016) study so-called *market quality breakdowns (breakups)* for stocks that are in both CRSP and NYSE's Daily Trade and Quote (TAQ) databases from all three major U.S. exchanges from April 6, 1993 to December 31, 2013. They can be considered as type of trade-imbalance-driven EPMR. Their identification not only requires the fulfillment of criteria regarding return, but also regarding time and ticks: The criteria they apply to identify a market quality breakdown (breakup) is a price fall (rise) to 10% below (above) the 9:35 price that rises (falls) back to at least 2.5% below (above) the 9:35 price by 15:55. Regarding ticks, the lowest (highest) tick must be repeated at least once in the subsequent second to avoid fleeting quotes or errors. They choose a price change of at least 10% because circuit breakers are placed at this level.

Regarding MFCs, there is no uniform definition in literature. Thus, we give an overview of the variations that can be found. Additionally to the return based benchmark, the identification of MFCs involves a tick and a duration criterion. They are a special form of flash crash, as they have two additional specifications. First of all, as Johnson et al. (2013) explain, MFCs differ from flash crashes as they only last a few seconds and thus the probability that humans physically intervene is low. Secondly, the rapid speed and recovery of MFCs suggests that exogenous news arrival is an unlikely cause, which is why we regard them as trade-imbalance-driven EPMRs.

Desagre et al. (2019) use a very specific definition of EPMRs[3] and argue that EPMRs are not the same as MFCs. Although this definition is just one way to define EPMRs, MFCs fulfill these criteria and can thus be regarded as a subgroup of EPMRs.

[3] Desagre et al. (2019) define EPMRs ex-post (statistically) based on the 99.9th percentile of the absolute return distribution with a duration of 10 s intervals, which exceed the duration of MFCs.

Table 1
This table gives an overview of the different names and definitions used for MFCs in literature.

Reference	Name	Max. duration (in sec)	Recovery
Nanex (2010)	Flash equity failures	1.5	
Golub et al. (2012)	Down (up) crashes		
Johnson et al. (2012)	Black swan crashes (dashes)		
Johnson et al. (2013)	Ultrafast extreme events (UEEs): crashes (spikes)		
Ozenbas and Schwartz (2018)	Mini flash crashes		
Braun et al. (2018)	Ultrafast extreme events (UEEs): flash crashes (spikes)	2	
Felez-Vinas (2017)	Mini flash crashes	2 (+300)	90%
Laly and Petitjean (2019)	Mini flash crashes	2.5	

The first set of criteria regarding the identification of MFCs was set by Nanex (2010): They consider *flash equity failures* to be crashes with an absolute price change of at least 0.8% of the initial price, which is caused by 10 or more ticks in one direction and this has to happen within a maximum of 1.5 s. Although the return and duration criterion were later adapted in literature, the tick criterion remained at 10 ticks. Golub et al. (2012) follow the criteria set up by Nanex (2010), but call MFCs *down (up) crashes*, Johnson et al. (2012) call them *black swan crashes (dashes)* and Johnson et al. (2013) refer to them as *ultrafast extreme events (UEEs): crashes (spikes)*.

Felez-Vinas (2017) follows the return criterion by Nanex (2010), extends the duration criterion to two seconds and adds a recovery criterion to identify *mini flash crashes*: The stock has to recover to at least 90% of the initial price within a time period of maximum 300 s. This criterion helps to identify those EPMRs that are due to momentary liquidity dry-ups and avoid those due to fundamental volatility. Braun et al. (2018) follow the terminology used by Johnson et al. (2013) and refer to UEEs as *flash crashes (spikes)*. They also extend the duration criterion to two seconds because of the limited time resolution of their dataset. Finally, Laly and Petitjean (2019) extend the duration to 2.5 s while keeping the other criteria by Nanex (2010) constant. They also refer to the EMPs as *mini flash crashes*, as do Ozenbas and Schwartz (2018). Table 1 gives an overview of different names used for MFCs as well as different criteria applied in literature to identify MFCs.

Brogaard et al. (2018) use a mix of the definitions above and apply three different approaches to detect EPMRs using HFT data from NASDAQ for the years 2008 and 2009, which they refer to as EPMs. First of all, they identify all intervals that belong to the 99.9th percentile of 10-s absolute midpoint returns for each stock as EPM. They give two reasons for choosing a 10-s interval: First of all, the detection of EPMs resulting from brief liquidity dislocation requires a short sampling interval. Secondly, if the interval is chosen too short, the EPMs could be split up into several price changes which are too small to be captured by the identification procedure.[4] The second approach they use accounts for predictable return correlations in time and across firms. They estimate a short-term market model using the stock i's return over the 10-s interval t as dependent variable. The independent variables are the return on the S&P 500 ETF as well as the coefficients from the previous day's regressions from $t-1$ until $t-10$. All intervals with residuals within the 99.9th percentile are identified as EPMs. The third approach they use is the jump discovery methodology by Lee and Mykland (2012).

Aquilina et al. (2018) also use a mix of the approaches when analyzing all FTSE350 stocks between January 2014 and June 2015: They refer to EPMRs as *mini flash crashes (rallies)*, that exceed three times the average realized variation of the previous 20 trading days, revert to at least 50% within less than 30 min and trigger trading volumes that are higher than the top 5%.

Coming up with a different identification approach, Tee and Ting (2019) define MFCs as significant deviation from a normal price process when analyzing all S&P 500 index constituents using daily TAQ data between 2010 and 2013 and come up with a state–space model to identify MFCs and compare it to the standard approach by Nanex (2010). They find that their model captures a broader range of MFCs. Also deviating from the standard approach, Christensen et al. (2020) develop a nonparametric identification strategy for the online detection of drift bursts[5] by embedding drift bursts into standard continuous-time models to find out if the observed price movement is generated by the drift rather than the result of volatility. They find that two thirds of the identified drift bursts are followed by price reversion and thus resemble (mini) flash crashes.

When it comes to flash crashes, they receive a lot of attention in literature because they affect the whole market. The name comes from the fact that the total duration of the crash and reversal process only lasts a few minutes. Bellia et al. (2020) define a flash crash as "*sudden and extreme price movement that occurs in a relatively short time span and retraces (partially or fully) back to its initial level*" (Bellia et al. (2020, p. 1)). The most famous flash crash happened on the US market on May 6, 2010 and thus is referred to as *the* Flash Crash in literature. Among others, Madhavan (2012), Kirilenko et al. (2017) and Menkveld and Yueshen (2019) analyze the happenings on this day, as do several reports including one by the SEC (2011). The cause is described to have been a large fundamental trader initiating a program to sell 75,000 E-mini (S&P 500 futures) contracts to hedge an existing equity position. The sell program was executed via an automated execution algorithm with an upper limit execution rate at 9% of the total volume but without any limits regarding price or time.

A similar flash crash reappeared on 24 August, 2015, which was described in an extensive report by the SEC (2015) and again in a brief literature review by Laly and Petitjean (2019). Other flash crashes mentioned by Frijns et al. (2021) involved the German DAX index on August 18, 2011 and April 17, 2013, the oil price on May 5, 2011, the Indian NSE50 equity index on October 5, 2012, the 10-year US Treasury on October 15, 2014, the UK pound on October 7, 2016, but also cryptocurrencies like Ethereum on June 21, 2017 and Bitcoin on October 10, 2017.

To sum up, EPMRs can be divided into event-driven or trade-imbalance-driven EPMRs. When it comes to event-driven EPMRs, some are announcement-triggered, following either internal or external announcements, while others are non-announcement triggered, such as terrorist attacks. Trade-imbalance-driven EPMRs are identified by using either return-based criteria or multi-facetted criteria. These include (mini) flash crashes, which are one of the most recent developments in literature.

[4] Brogaard et al. (2018) repeat their analyses for other time intervals lasting from one second up to one minute and find their results to be qualitatively similar.

[5] Christensen et al. (2020) define drift bursts as "*short-lived locally explosive drift coefficient*" (Christensen et al. (2020, p.19)).

4. Explanations for EPMRs

When it comes to EPMRs, we identify five main explanations in literature. Although most of them can be seen as clear explanations for either event-driven EPMRs (see Section 4.1) or trade-imbalance-driven EPMRs (see Section 4.2), we dedicate a separate section to the role of HFT (see Section: 4.3), as they cannot be clearly attributed to either type of EPMR.

4.1. Explanations for event-driven EPMRs

Explanations for event-driven EPMRs are directly linked to the efficient market hypothesis (EMH), which is one of the foundations for financial asset pricing. As Mehdian et al. (2008) state, the EMH implies that "*current stock prices are unbiased estimators of their fundamental values, and they adjust instantaneously to unexpected events based on the behavior of investors who react rationally to the arrival of new information*" (Mehdian et al. (2008, p.337f)). However, as security prices not always adjust instantaneously, behavioral finance literature has come up with two extensions to the EMH, them being the overreaction hypothesis by DeBondt and Thaler (1985) and the uncertain information hypothesis by Brown et al. (1988). As the EMH and the related extensions look at price adjustments to unexpected events, they can be used as explanations for event-driven EPMRs.

In the following two sections we elaborate on how the overreaction hypothesis (see Section 4.1.1) and the uncertain information hypothesis (Section 4.1.2) can be used to explain event-driven EPMRs.

4.1.1. Overreaction hypothesis

The overreaction hypothesis states that "*investors overreact to unexpected events by setting security prices too low (high) in reaction to unfavorable (favorable) news*" (Mehdian et al. (2008, p. 338)). As soon as the market has realized these exaggerations, there is a corresponding price correction in the opposite direction. Due to these two effects, the overreaction hypothesis can be used as explanation for event-driven EPMRs. We focus on short-term overreaction, as we look at short-term price reactions. Literature on short-term overreaction has been previously reviewed by Lobe and Rieks (2011).

One of the first papers tying EPMRs to the overreaction hypothesis is by DeBondt and Thaler (1985). They test two hypotheses: (1) EPMRs will be followed by subsequent price movements in the opposite direction and (2) the more extreme the initial price movement, the greater the subsequent price movement. Brown and Harlow (1988) later refer to those hypotheses as *directional effect* and *magnitude effect*. They find support for both the directional and magnitude effect in short-term reversals as well as the *intensity effect*, studying securities of the NYSE over the previous four decades. The intensity effect suggests that the shorter the duration of the initial price change, the more extreme the subsequent response.

Atkins and Dyl (1990) study all stocks that are traded on the NYSE from January 1975 to December 1984 and link the size of the short-term overreaction to the size of the bid–ask spread of the individual stock. Cox and Peterson (1994) explain this phenomenon by the selling pressure following a large one-day price decline, which increases the probability of the closing transaction at a bid price. As a result, the reversal on the next day is due to the bid–ask bounce. Liquidity suppliers anticipate profits on the price reversals and enter the market to purchase shares. Overall, the size of the reversal depends on short-run price elasticity of the liquidity supply.

DeBondt and Thaler (1985) also analyze the *asymmetry effect* and find long-term price reversals to be more pronounced for winners than for losers, so did Atkins and Dyl (1990) and Lehmann (1990), who studies equity securities listed on the New York and American Stock Exchanges using weekly CRSP data from 1962 to 1990, for short-term price reversals.

4.1.2. Uncertain information hypothesis

The *uncertain information hypothesis* was developed by Brown et al. (1988) and gives an explanation for investor behavior in uncertain situations generated by unexpected events. They suggest that under the presence of uncertainty and imperfect information, rational risk-averse investors set prices that overreact to bad news and underreact to good news. As a result, large stock declines are followed by significant reversals. This part of the hypothesis can be used to explain EPMRs. The definition as overreaction to bad news followed by a reversal makes the uncertain information hypothesis a possible explanation for event-driven EPMRs.

For example, Mehdian et al. (2008) investigate the arrival of unexpected information in Turkey from 1997 to 2004 using daily stock returns. They find that unfavorable (and favorable) news leads to a corrective process of significantly positive cumulative abnormal returns, which can be attributed to the group of event-driven EPMRs.

4.2. Explanations for trade-imbalance-driven EPMRs

Explanations for trade-imbalance-driven EPMRs in literature are threefold. In the following section we describe how block trades (see Section 4.2.1), market fragmentation (see Section 4.2.2) and intermarket sweep orders (ISOs, see Section 4.2.3) can be used as explanations for trade-imbalance-driven EPMRs.

4.2.1. Block trades

Kraus and Stoll (1972) define block trades "*as a transaction involving a larger number of shares that*" cannot "*readily be handled in the normal course of the auction market*" (Kraus and Stoll (1972, p.569)).[6] They link the price effect caused by block trades to two different effects: First of all, the *information effect*[7] leads to a change in the underlying value of a stock. Secondly, the *distribution effect*[8] describes the temporary deviation of a price. As a result, these price effects can be classified as EPMRs and thus block trades can be used as explanation for trade-imbalance-driven EPMRs.

After analyzing NYSE block trades data between July 1968 and September 1969, their results show that within a day, the closing price significantly reverses from the block trade price. As the recovery equals the size of one commission,[9] Kraus and Stoll (1972) find a temporary discount to be necessary to bring in willing buyers. All in all, the price effect of block trades can be attributed to price pressure by institutional traders, thus this effect is subsumed under the *price pressure hypothesis*.

Regarding the post-trade behavior following block trades, Chan and Lakonishok (1993) study transactions made by 37 large

[6] We correct (Kraus and Stoll, 1972), as block trades *cannot* be readily handled in the normal course of the auction market.

[7] According to Kraus and Stoll (1972), the information effect says that the "*expected rate of return after the transaction is different from that before the transaction only if the new information concerns a change in the riskiness of the stock*" (Kraus and Stoll (1972, p. 570)).

[8] According to the distribution effect, "*the expected rate of return must increase in the case of sales to convince less willing buyers to hold the security and must fall in the case of purchases to convince less willing sellers to part with the security*" (Kraus and Stoll (1972, p.570)).

[9] The mean price rise is slightly higher than one commission, which on 10.000 share of a $40 stock was at 0.62% of the total value of the transaction after the volume discount instituted on December 5, 1968, according to Kraus and Stoll (1972).

money management firms from July 1986 until the end of 1988 and find that the post-trade behavior of prices between block trade buys and sells is asymmetric. While block purchases are followed by price continuation, there is a price reversal after block sales. This reversal is consistent with the existence of short-run liquidity costs. The price continuation following block purchases is in line with information effects or imperfectly elastic demand curves, as explained by Chan and Lakonishok (1993). Aitken and Frino (1996) look at block trades on the Australian Stock Exchange between July 1991 to June 1993 and Alzahrani et al. (2013) study the price impact of block trades in the Saudi stock market from January 2005 to October 2008, they both confirm this asymmetry.

A paper by Chiyachantana et al. (2004) identifies the underlying market condition to be a major determinant of both the price impact as well as the asymmetry between the price impact of institutional buys and sells while analyzing institutional trading in international stocks from 37 countries during 1997 to 1998 and 2001. Other factors determining the price impact include order characteristics, firm-specific factors and cross-country differences. In contrast to previous studies, Chiyachantana et al. (2004) find sells to have a higher price impact in bearish markets and institutional purchases to have a higher impact in bullish markets. Another theory by Saar (2001) explains the asymmetry between buyer- and seller-initiated block trades by the history of price performance. He finds that the longer the run-up in a stock's price, the less the asymmetry. Finally, Gregoriou (2008) look at the price impact of block trades for the FTSE 100 between 1998 and 2004 and suggest that the bid–ask bias could be an explanation for this asymmetry.

4.2.2. The role of market fragmentation

The presence of market fragmentation, defined according to Lehalle and Laruelle (2017) as the state of when "*prices are no longer created in a single centralized orderbook, but in different exchanges competing with each other*" (Lehalle and Laruelle (2017, p. 102)), has been studied as possible cause of both the Flash Crash of 2010 as well as MFCs. Following Madhavan (2012), who identifies higher frequency quotation activity and high levels of fragmentation as reasons why a Flash Crash did not occur before and uses those reasons as counterpoint to the view that the Flash Crash stemmed from an unlikely confluence of events, we consider market fragmentation as possible explanation for trade-imbalance driven EPMRs. Although some papers find market fragmentation to be explanatory for the occurrence of such trade-imbalance-driven EPMRs, there is no uniform opinion in literature about the relationship between market fragmentation and their occurrence:

Starting with Madhavan (2012), he finds that the Flash Crash can be linked to the current market structure, in particular the pattern of volume and quote fragmentation. After analyzing tick data for all stocks traded in the US from 1994 to 2012, he finds fragmentation to be at its highest level in 2012 and thus high fragmentation to be part of the reason why flash crashes did not occur previously. In line with Madhavan (2012) and Golub et al. (2012) identify market fragmentation as one of the main causes of MFCs, analyzing MFCs in the US equity markets between September to November 2008, and May 2010. In contrast to these results, Gao and Mizrach (2016) study market fragmentation in the context of market quality breakdowns and do not find their measures of fragmentation to explain the frequency of market quality breakdowns.

Finally, Felez-Vinas (2017) studies the relationship between market fragmentation and market stability as of the changes in market liquidity in the presence of MFCs on the Spanish stock market. She adapts findings by Madhavan (2012) that the more fragmented market structure is partly responsible for flash crashes and argues that if markets are perfectly interrelated, their consolidated ability to absorb trades should be the same as in concentrated markets. Following from this, she hypothesizes that market fragmentation is not detrimental to market stability. As a result, Felez-Vinas (2017) identifies market fragmentation to decrease the number of MFCs. Additionally, she detects that market fragmentation allows for a faster recovery of MFCs and prevents liquidity dry-ups during MFCs, especially for large stocks.

4.2.3. The role of intermarket sweep orders (ISOs)

Next to market fragmentation, Golub et al. (2012) also find the regulation framework to be one of the main causes of MFCs, as ISOs are used aggressively. Johnson et al. (2013) analyze multiple stocks and exchanges using the NANEX NxCore software package and also suggest that ISOs could be problematic, however, they find that this is still unclear, as Golub et al. (2012) rely on particular assumptions. McInish et al. (2014) study the impact of ISOs further and detect that the use of ISOs has increased significantly on May 6th, 2010, the day of the Flash Crash. There seem to be more ISOs on the sell side of the market during the downdraft and more ISO trade throughs on the buy side of the market during the updraft. Concluding from results by McInish et al. (2014), ISOs had a disproportionate impact on market conditions during the Flash Crash and the unexpected increase in ISO use is positively related to increases in expected market volatility. Due to their responsibility for creating an impact on market conditions by first gathering on the sell side and then on the buy side, ISOs can be viewed as explanation for trade-imbalance-driven EPMRs.

4.3. The role of HFTs

When it comes to HFTs and EPMRs, literature mainly deals with three questions: First, are HFTs responsible for the cause of EPMRs? Second, how do HFT react during an EPMR? and third, what role do feedback loops play when it comes to EPMRs? As literature is still unsure about how HFTs and EPMRs are related, HFTs cannot clearly be assigned as explanation for event-driven or trade-imbalance-driven EPMRs. Due to the speed advantage of HFTs, the strand of literature dealing with HFTs mainly focuses on (mini) flash crashes. In the following we present answers to the three raised questions.

4.3.1. Causality of HFTs for EPMRs

Starting with the responsibility of HFTs for EPMRs, there is no uniform opinion in literature. Sornette and von der Becke (2011) find that HFTs have increased the likelihood of flash crashes occurring. Leal et al. (2014) attribute the emergence of flash crashes to two HFT-characteristics, namely their ability to generate high bid–ask spreads as well as their ability to synchronize on the sell side of the limit order book.[10] All in all, they find the presence of HFTs to play a fundamental role in the generation of flash crashes. Similar to ISOs, the gathering of HFTs on the sell side has an impact on market conditions, which again can be viewed as explanation for trade-imbalance-driven EPMRs. Bellia et al. (2020) analyze tick-by-tick order-level data on 37 liquid French stocks belonging to the CAC40 index and traded on NYSE-Euronext Paris for the year 2013 and argue that HFTs do play a significant role in causing flash crashes. They find that during EPMRs, the market price moves towards a new price level by initially overshooting and then declining to a price lower than the new fundamental level. They also find that informed trading by investment bank

[10] According to Leal et al. (2014), the distribution of high frequency orders significantly shifts to the sell side of the limit order book during a flash crash. In contrast, low frequency orders concentrate on the buy side.

HFTs conveys new information into a permanent price impact, which makes HFTs also a possible explanation for event-driven EPMRs. Breedon et al. (2018) also identify algorithmic traders as contributors to the decline of the EUR/CHF and USD/CHF market quality on the event day.

Regarding MFCs, Brogaard et al. (2018) find little evidence that HFTs cause MFCs. When it comes to market quality breakdowns, Gao and Mizrach (2016) find HFTs to raise the probability of market breaks, however, they do not find the effect of HFTs to be large enough to cause an event like the Flash Crash. Similarly, Desagre et al. (2019) study MFCs on 74 large, medium and small NASDAQ stocks over the period 2008 to 2010 and do not find any evidence that HFTs trigger MFCs or EPMRs. Lee et al. (2010) did not find HFTs to be the cause of the Flash Crash 2010, but rather identify the domination of market activities resulting from trading strategies responding to the same set of market variables in similar ways as well as pre-existing market micro-structural safety mechanisms with unintended consequences when triggered simultaneously to be responsible.

Braun et al. (2018) take a different approach when it comes to evaluating the role of HFT regarding MFCs. Building on findings by Johnson et al. (2013),[11] they argue that a MFC caused by many small market orders can only be linked to HFTs. This is due to the time frame in which the small market orders are placed. In contrast, MFCs involving a large price change caused by a large single market order must not necessarily involve a HFT, but could have also been caused by a human trader, as speed is not necessary in this context. Braun et al. (2018) look at order flow data for all stocks of the S&P 500 which were continuously traded during 2007 and 2008 to identify how often single market orders dominate a MFC. They come to the conclusion that about 60% of MFCs contain one market order already generating a return of 0.5%. As a result, all types of traders could be the root cause of this large single market order and HFTs are not necessarily the cause of MFCs. Finally, Golub et al. (2012) conclude that due to the speed and magnitude of the MFCs, they could only be caused by HFTs as ISOs[12] are used aggressively.[13]

Finally, Easley et al. (2011) find that the Flash Crash of 2010 was a liquidity event that can be attributed to structural features of the HFT world. As liquidity provision is dominated by computerized market makers programmed to place buy and sell orders, they avoid taking significant inventory positions. Resulting in an increase of order flow toxicity, market makers face significant losses and minimize their risk by reducing or liquidating their positions. Instead of banning HFTs, Easley et al. (2011) suggest to deal with the risks of this new market structure.[14] Supporting this argument,Dugast and Foucault (2014) find that cheaper fast trading technologies raise both information efficiency and frequency of MFCs.

4.3.2. Reaction of HFTs during EPMRs

Focusing on the reaction of HFTs during EPMRs, literature mainly focuses on trading behavior and liquidity provision of HFTs. Starting with Brogaard et al. (2018), they find HFTs to be endogenous liquidity providers without being obligated to provide liquidity during stressful times. During EPMRs, HFTs are net liquidity suppliers to non-HFTs. However, in the case of multiple EPMRs,[15] HFTs switch to demanding liquidity. This is because during multiple EPMRs, position risk accumulated by HFTs is significantly higher than normal, which likely reduces activity, especially on the supply side.[16]

Desagre et al. (2019) conduct a parallel analysis on MFCs and EPMRs and compare them regarding different stock sizes.[17] While they do not find any statistically significant results regarding MFCs, they find HFTs to exacerbate the crash during 1.5-s EPMRs, thus contradicting results by Brogaard et al. (2018).[18] Regarding the recovery of EPMRs, they find that HFTs continue to demand liquidity in the direction of the crash and only non-HFTs contribute to the recovery of stock prices after the crash. Looking at stock size, Desagre et al. (2019) find HFTs to reduce their liquidity demand during EPMRs occurring on large stocks, but increase their liquidity demand during EPMRs occurring on small stocks and trade in the direction of the crash. Additionally, Ozenbas and Schwartz (2018) study 40 large cap, 40 mid cap, and 40 small cap NASDAQ stocks for the years 2008 and 2009 and find HFTs to significantly drop liquidity provision, especially for large-cap stocks. They also find HFTs to be among the first to react to EPMRs by withdrawing. Finally, Desagre et al. (2019) detect the liquidity demand of HFTs to be higher during extreme hours of trading, such as the first five and the last five minutes of the trading day. They also suspect the liquidity demand of HFTs to be more pronounced during periods of anticipated market stress.

Continuing with MFCs, Aquilina et al. (2018) identify 40 MFCs in the UK equity market and examine the trading behavior and liquidity provision of different market participants. While hybrid firms[19] such as large investment banks trade in the direction of the price change, thus making the MFC worse, HFTs first try to lean against the price change but eventually join in making the MFC worse. All in all, HFTs are only responsible for a small amount of aggressive trading. The fact that they make small profits out of MFCs is mostly due to their superiority regarding speed. When it comes to liquidity, HFTs continue to provide liquidity, but it is consumed more quickly. Additionally, the liquidity provided moves away from the best available prices, which contributes to the MFCs. During recovery, HFTs take longer than hybrid firms to restore liquidity provided.

Concerning the behavior of HFTs, Bellia et al. (2020) find HFTs to not be beneficial to either liquidity nor efficiency of the stock market during flash crashes. They differentiate between IB-HFTs and PURE-HFTs. IB-HFTs include investment bankers and large brokers. While IB-HFTs use HFT, they are not constrained to have

[11] Johnson et al. (2013) observe that agents tend to converge on the same strategy and simultaneously flood the market with the same type of order, which generates frequent extreme price-change events.

[12] Intermarket Sweep Orders are an exemption to the Order Protection Rule in the National Market Regulation: "*An intermarket sweep order is defined in Rule 600(b)(30) as a limit order that meets the following requirements: (1) The limit order is identified as an intermarket sweep order when routed to a trading center; and (2) simultaneously with the routing of the limit order, one or more additional limit orders are routed to execute against all better-priced protected quotations displayed by other trading centers up to their displayed size.* (SEC (2005, p. 37523)).

[13] See Section 4.2.3 for more information on the role of ISOs.

[14] Easley et al. (2011) propose a solution by introducing the so-called *Volume-Synchronized Probability of Informed Trading*(VPIN) metric of order flow toxicity by Easley et al. (2012), see also Section 6.

[15] Brogaard et al. (2018) define co-EPMRs as EPMRs that occur in two or more stocks during the same 10-s time interval. They find the average co-EPMR to include 3.5 stocks.

[16] Brogaard et al. (2020) study intra-EPMR liquidity dynamics without focusing on a specific type of trading. They find that liquidity provision intensifies towards the end of a typical EPMR. This results in improved liquidity, especially when EPMRs coincide with high idiosyncratic volatility. Their reasoning is that liquidity providers strategically allow for price pressures and are compensated from correcting pricing errors.

[17] Remember that we define a MFC as special case of EPMRs, whereas Desagre et al. (2019) argues that they are different from each other.

[18] Desagre et al. (2019) note that the differing results could be due to the application of a filter to remove consecutive crashes that pollute different crash windows.

[19] Aquilina et al. (2018) define hybrid firms as firms that mainly provide agency trading services but may use a similar technology to HFTs.

Table 2
This table gives an overview of the findings in literature regarding the role of HFTs when it comes to EPMRs. Cells noted with '–' mean that the topic is not discussed in this paper.

Reference	Causality	Trading behavior	Liquidity provision
Aquilina et al. (2018)	–	HFTs try to lean against price change but then make MFCs worse	Liquidity providers
Bellia et al. (2020)	Yes	IB-HFTs (investment bankers and large brokers) start flash crash with informed selling	–
Braun et al. (2018)	Neutral	–	–
Breedon et al. (2018)	Yes	HFTs amplify price movements by following trends	Liquidity withdrawers
Brogaard et al. (2018)	No	–	Endogenous liquidity providers, liquidity suppliers during EPMRs, liquidity demanders in case of multiple EPMRs
Desagre et al. (2019)	No	HFTs exacerbate 1.5-s EPMRs	Liquidity demanders (especially regarding small stocks, during extreme hours of trading and anticipated market stress)
Easley et al. (2011)	Yes	–	–
Gao and Mizrach (2016)	Neutral	–	–
Golub et al. (2012)	Yes	–	–
Leal et al. (2014)	Yes	Activation of HFTs is event-driven and dependent on price fluctuations, directional strategies used to exploit market information by low-frequency traders	–
Lee et al. (2010)	No	–	–
Ozenbas and Schwartz (2018)	–	HFTs withdraw among the first	Liquidity provision dropped (especially for large-cap stocks)
Sornette and von der Becke (2011)	Yes	–	–

zero inventory at the end of the day, as PURE-HFTs do. According to findings by Bellia et al. (2020), IB-HFTs seem to start the flash crash with informed selling, trading for their own and their client's account. IB-HFT market makers also start selling, even though they are contractually obliged to provide liquidity. All in all, the behavior of different IB-HFTs leads to a flash crash. Studying the interplay between low- and high-frequency trading, Leal et al. (2014) find the activation of HFTs to be event-driven and dependent on price fluctuations. Additionally, they detect that HFTs use directional strategies to exploit market information produced by low-frequency traders.

In conclusion, six of the eleven papers analyzed regarding the causality of HFTs for EPMRs find that HFTs are causal for EPMRs. During EPMRs, literature agrees on the fact that HFTs make EPMRs worse. Regarding liquidity provision, three out of five papers find HFTs to withdraw liquidity during EPMRs. These findings are summarized in Table 2.[20]

4.3.3. *Feedback loops*

Finally, we elaborate on HFTs and feedback loops: Danielsson et al. (2012) focus on shocks that are amplified by economic agents, which they call endogenous extreme events. They find that during such disruptions arising in algorithmic trading environments, there are two ways positive feedback can be generated: First of all, there might be feedback-inducing actions hard-coded into the programs of algo traders. Secondly, if the first case does not apply, interventions by the controlling or supervising entity could overrule the algorithm and thus still create feedback. The UK Government Office of Science (2012) review self-reinforcing feedback loops, which they describe as "*the effect of a small change looping back on itself and triggering a bigger change, which again loops back and so on*". They report that even if well-intentioned management and control processes are in place, these loops can amplify internal risks and lead to undesired outcomes.

Feedback loops are also discussed in empirical literature: Looking at the Flash Crash of May 2010, Danielsson et al. (2012) find evidence for the so-called *hot-potato effect*[21]: If an execution algorithm is set to sell a large number of securities, it looks at market volume to get an idea of market impact. If market volume is high, it is instructed to sell even more. Due to the speed advantage of HFTs, there is a high chance that the buyers of the large number of securities again are HFTs. As they wait for real money investors to come in, HFT sell on the securities like passing on a hot potato, which leads to increased volume. This again triggers the algorithm to sell even more, creating a feedback loop. As a result, the interaction between two algorithms leads to a destabilizing feedback loop, which is only terminated if either algorithm targets are met or circuit breakers and trading halts are set into place.

In conclusion, EPMRs can be explained depending on their type. The root cause of event-driven EPMRs can be explained by the overreaction hypothesis or the uncertain information hypothesis. When it comes to trade imbalance-driven EPMRs, they can be caused by block trades, market fragmentation or ISOs. Concerning HFTs, one has to differentiate between their causality for EPMRs, their trading behavior and liquidity provision during EPMRs and the role of feedback loops. However, there is no uniform opinion on the causality of HFTs for EPMRs.

5. Empirical evidence on the relationship between EPMRs and market quality

Some studies of the last decade focus on how MFCs affect market quality and look at different market parameters surrounding them, including liquidity, market depth, trading volume and volatility.

Concerning liquidity, Golub et al. (2012) conduct an event study and analyze market liquidity 60 s before and after the occurrence of a MFC. They find that MFCs lead to a wider spread, an increased number of locked and crossed NBBO quotes and a decrease in quoted volume, indicating that MFCs have an adverse impact on market liquidity. Additionally, they find MFCs to be associated with fleeting liquidity. In line with these results,

[20] The style of this table was inspired by Virgilio (2019a).

[21] This effect was also discovered by SEC (2011)

Aquilina et al. (2018) study 30 s before and 60 s after a MFC and find quoted spreads and the number of submitted orders to sharply increase as prices trough/peak. Bellia et al. (2020) analyze 60 s following a flash crash and confirm results by Aquilina et al. (2018) that the bid–ask spread steadily increases during a flash crash.

When it comes to market depth, the report by the SEC (2015) found market depth to be 70% below average market depth during the market crash on Monday, August 24, 2015.[22] Aquilina et al. (2018) also look at market depth and find that the ability of the market to absorb orders pulverizes during a crash.

Regarding trading volume, results by Aquilina et al. (2018) and Bellia et al. (2020) confirm that there is an increase in volume traded at the beginning of a crash. After a MFC, Golub et al. (2012) find that quoted volume at the NBBO decreases. Finally, Aquilina et al. (2018) find that there is a significant spike in volatility during a MFC.

In conclusion, empirical studies find MFCs to have a negative impact on market liquidity, as spreads increase during an EPMR. Regarding market depth, findings show that market depth goes down during EPMRs. Additionally, empirical studies show that trading volume increases at the beginning of the crash and volatility significantly spikes during an EPMR.

6. Prediction of EPMRs

Literature came up with numerous ways to predict EPMRs, including the *Volume-Synchronized Probability of Informed Trading* (VPIN) by Easley et al. (2012) (see Section 6.1), the quantitative estimate of the degree of reflexivity by Filimonov and Sornette (2012) (see Section 6.2), stability indicators by Paddrik et al. (2015) (see Section 6.3), the frequency of breakdowns (breakups) by Gao and Mizrach (2016) (see Section 6.4) and finally a model of the probability of a share to undergo an EPMR by Desagre et al. (2019) (see Section 6.5).

6.1. The Volume-Synchronized Probability of Informed Trading

Starting with the *Volume-Synchronized Probability of Informed Trading* (VPIN) metric by Easley et al. (2012), the VPIN is based on the *Probability of information-based trading* (PIN) estimation approach by Easley et al. (1996). It is suggested to be used by market makers to anticipate a rise in volatility and estimate the risk of a liquidity-induced crash.[23] The reasoning behind the VPIN is that the order arrival process is informative for subsequent price moves, especially for flow's toxicity. The VPIN deals with the difficulty of estimating PIN models in highly active markets and does not require the intermediate numerical estimation of non-observable parameters.

Regarding EPMRs, Easley et al. (2012) find the VPIN to rise to an extreme level at least two hours before the Flash Crash and to continue to increase both 1-min and 10-s time bars during the Flash Crash, remaining high for the rest of the day. They thus argue that the order flow was highly toxic during the Flash Crash, as the VPIN indicates toxicity-induced volatility. As a result, the VPIN can be used by market makers, regulators and exchanges as well as traders. First, market makers can use the VPIN as a real-time risk management tool to remain active in the market. Second, regulators and exchanges can use the VPIN to monitor liquidity provision and proactively take early action if liquidity provision is threatened, which is especially important in a HFT environment. Third, traders can develop measures based on the VPIN to control execution risk when designing algorithms.

In contrast, Andersen and Bondarenko (2014a) argue that the VPIN metric is a poor predictor of short run volatility and its predictive content is due to a mechanical relation with the underlying trading intensity. They also find that the VPIN did not reach an all-time high prior, but after the Flash Crash. Andersen and Bondarenko (2014b) later add that when controlling for current volume and volatility, the VPIN loses its predictive power for future volatility and it cannot predict crashes or volatility better than regular market indicators.

6.2. The quantitative estimate of the degree of reflexivity

The quantitative estimate of the degree of reflexivity was developed by Filimonov and Sornette (2012). By providing a direct measure of the level of endogeneity of financial markets using a self-excited conditional Poisson Hawkes model, they are able to quantify how much of price changes is due to endogenous feedback processes, as opposed to exogenous news. They call this proportion n. This gives the distance of the financial market from a critical state, which is defined as the limit of diverging trading activity in the absence of any external driving.

Filimonov and Sornette (2012) suggest this measure to be a starting point for the prediction of flash crashes, as they document an early rise of n nearing the critical value of $n = 1$ as the Flash Crash unravels, which is a sign for a strong endogenous component.

6.3. Stability indicators

Paddrik et al. (2015) use data produced in the controlled environment of an agent-based model's limit order book and examine different resiliency indicators to find out about their predictivity. Their results suggest that the combination of high-fidelity microstructure data and price data can be used to define stability indicators that can signal a high likelihood for an imminent flash crash event about one minute before it occurs. This also demonstrates that even high level data can be used by regulators to assess financial markets.

6.4. Breakdown frequency

Gao and Mizrach (2016) look into the predictability of market quality breakdowns (breakups). They use a logit model on all breakdowns (breakups) they detect analyzing the NBBOs for all stocks in CRSP and TAQ data. Gao and Mizrach (2016) find the frequency of breakdowns (breakups) to be positively autocorrelated, as two lagged probabilities are statistically significant for both breakdowns and breakups. Together with volatility at the market open, this makes them predictable by more than 32% for breakdowns and 43% for breakups, as Gao and Mizrach (2016) argue.

6.5. Probability of a share to undergo an EPMR

Desagre et al. (2019) model the probability of a share to undergo a MFC by using a logit model with lagged values,[24] of HFT^{NET},[25] absolute log return, share volume, relative spread as

[22] According to the SEC (2015), the US equity markets and equity-related futures markets experienced unusual price volatility on August 24, 2015, where both the SPDR S&P 500 ETF Trust and the E-Mini S&P 500 experienced a price decline of at least 5% below their closing price on the previous trading day.

[23] This metric has successfully been applied in literature by e.g. McInish et al. (2014) and Kitamura (2016) or Prodromou and Westerholm (2022).

[24] Values are lagged at *t–1* where *t* is an interval of 1.5 s.

[25] HFT net imbalance gives information on the direction of net trading activity by HFT opposite the MFC direction.

well as HFT participation based on trades as explanatory variables. The dependent variable is a binary variable equal to one if the 1.5-s interval t contains a MFC on stock i and zero otherwise. They repeat their model for EPMRs, which they consider to be different from MFCs.

Running their model on all, standalone, simultaneous and extreme hour MFCs (EPMRs) separately, they find HFT participation to be the main determinant of MFCs. However, results are more ambiguous when it comes to EPMRs, as results vary depending on the model specification. Moreover, they find absolute log return and relative spread to have a strong impact on the probability of a stock to undergo a MFC (EPMR) in the next interval.

7. Conclusion

The detection of (mini) flash crashes as well as the increase in the use of HFT technology in the last two decades has made it increasingly difficult for regulators to fully understand their effect on financial markets. This lack of understanding can lead to the fact that regulators fail to recognize a potential need of new regulatory policies to address these developments.

The main findings of this literature review are first of all, that there is no uniform understanding of EPMRs in literature, as most papers come up with their own definition or built on previous definitions by others. As a result, many types of EPMRs can be differentiated. Second, there is no uniform name for EPMRs, which makes it harder to compare results. Third, there is still no clear understanding of (a) if HFTs are causal for EPMRs or (b) how HFTs react during EPMRs regarding trading behavior or liquidity provision. Finally, empirical evidence on the relationship between EPMRs and market quality is still scarce. Concluding from this, future research should focus on gaining further empirical evidence, providing further insights for predictive models to help market makers, regulators, exchanges and traders to adapt their behavior.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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