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# High-Frequency Trading and its Impact on Market Liquidity: A Review of Literature[1]

**(Araştırma Makalesi)**

*Yüksek Frekanslı İşlemler ve Piyasa Likiditesine Etkileri: Yazın Taraması*

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**ÖZET**

*Yüksek frekanslı işlemler (YFİ) son yirmi yılda gelişmiş piyasalardaki işlemleri domine etmektedir. YFİ'nin finansal piyasalar ve katılımcıları üzerindeki etkilerine dair literatür yakın dönemde oluşmasına rağmen geniştir. Diğer yandan, birçok alt konuda devam eden akademik tartışmalar ve cevaplanmamış sorular mevcuttur. Bu çalışma YFİ'nin olumlu ve olumsuz etkilerine dair bulguların beraberce yer aldığı bir alt konu olan YFİ'nin likidite üzerindeki etkilerini inceleyen yazını taramaktadır. Çalışma kapsamında, literatürde çeşitlilik gösteren bu sonuçların varlığını açıklayan iki temel faktör olduğu ortaya konulmaktadır. Bunlardan ilki YFİ'nin piyasalardaki aktivitesinde keskin farklılıklar yaratabilen gün içi şoklar gibi olumsuz piyasa koşullarıdır. İkincisi ise YFİ yoluyla likidite sağlayıcılığı yapmanın piyasa için olumsuzluklar doğurma potansiyeline sahip olmasıdır.*

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***Keywords:***

*High-frequency trading, HFT, Liquidity, Intraday shocks, Extreme price movements*

***JEL Classification Codes:*** *G10, G12, G14*

**ABSTRACT**

*High-frequency trading (HFT) has been dominating the activity in developed financial markets in the last two decades. Despite its recent formation, the literature on the impacts of HFT on financial markets and participants is broad. However, there are ongoing debates and unanswered questions within many subtopics. We survey through the research towards HFT effects on liquidity in an attempt to explain the coexistence of evidence regarding both the positive and the negative impacts of HFT. We name two main factors leading to mixed results. Former concerns the negative market conditions such as intraday shocks, through which HFT trading patterns may sharply change. Latter regards the certain characteristics of HFT liquidity provision with the potential to present externalities for the market.*

## 1. INTRODUCTION

Higher speed in reaching and processing new data and transmitting financial decisions to the market in the form of electronic messages has always been crucial in maintaining a superior position for investors. While the latency differences among market participants' actions can be as low as seconds, milliseconds, microseconds, and even nanoseconds, they are long enough to play a major role in distributing wealth in financial markets.

In the last two decades, most of the financial markets have gone through large technological transformations enabling much faster trading.[2] Besides improving the inclusion speed of every investor, the upgraded form of the markets originated a new type of trading, high-frequency trading (HFT), a game-changer both in theory and practice.[3]

HFT can be broadly defined as trading with three characteristics: i) excessive numbers of electronic message (and order) submission ii) in low latencies, and iii) with the motivation of intraday profits from this concentrated action. Given the ultra-low latencies HFT is executed, there is no human intervention, making it a subset of algorithmic trading (AT). The main difference between the two concepts is the necessary condition of low latency activity in HFT.

By the 2000s, HFT had started to constitute a significant part of the overall trading process in financial markets. 26 HFT firms' share is documented to be as high as 74% in a 2008-2009 sample of NASDAQ stocks (Brogaard, 2010). 2012 share of HFT in the U.S. is estimated as 51% (Popper, 2012). 31 HFT firms account for 46% of total volume in the Canadian stock market in 2010-2011 (Boehmer et al., 2018). HFT share in European markets as of 2009 is, by estimate, 40% (Grant, 2010; Haldane, 2010). Similarly, HFT's participation in the trading of Swedish large stocks in a 2011-2012 sample is between 25% and 50% (Hagströmer and Norden, 2013). HFT share in U.S. equities markets in 2016 is approximately 60% (see for example Bazzana and Collini, 2020). Besides equity markets, futures markets are also concentrated with HFT activity; shares in total trading volume of U.S. foreign exchange

[2] BYX exchange utilized by CBOE reduced order processing times by around sevenfold from 445 microseconds in 2009 to 64 microseconds in 2018 (Baldauf and Mollner, 2020). HFT firms are in an arms race that leads them to send data from exchanges to electronic traders in latencies as small as 4 nanoseconds (Sprothen, 2016).

[3] Throughout the text, we use 'high-frequency trading (trader)' and 'low-latency trading (trader)' interchangeably. We use 'HFT' as the acronym for high-frequency trading; 'HFTs' as the acronym for high-frequency traders; and non-HFTs as the acronym for low-frequency traders (traders other than high-frequency traders).

futures, interest rates futures, and Treasury 10-year futures being around 80%, 66%, and also 66%, respectively (Miller and Shorter, 2016).

In addition to the fact that HFT share is quite large in developed financial markets, HFT has changed the markets and affects other market participants (non-HFTs) in many ways. In line with these, the literature on HFT, despite its recent formation, is extensive. Figure 1 depicts the numbers of Google Scholar search results with the keywords “high frequency trading” and “algorithmic trading” on a yearly basis (results for 2020 are up to September). Early papers on HFT emerged in the beginning of the 2000s, while the yearly number of papers reached 500 in 2010 and 2,000 in 2015. It is noteworthy to mention that the vast majority of academic research has been conducted on developed markets. Few studies examine HFT activity on developing markets also resulting from the fact that the emergence of HFT in these countries has been much later and in limited amounts due to less sophisticated technological infrastructure and absence of market fragmentation and dark pools (e.g., Haldane, 2010; Lee, 2015; Ersan and Ekinci, 2016; Ekinci and Ersan, 2018; Zhao and Wan, 2018).

As an example of the new norms in financial markets, more than 98% of orders are canceled, leaving less than only 2% to be executed and around one-quarter of order cancellations occurring within the first 50 milliseconds of the submission (O’Hara, 2015). Patell and Wolfson (1984) observe the first reaction to corporate announcements of U.S. listed firms in 1976-1977 in the first few minutes following the announcements, while significant trading profits occur overnight or at the opening of the next trading day. Chordia et al. (2018), on the other hand, show that S&P 500 exchange-traded fund and E-mini S&P 500 futures contract prices react to macroeconomic surprise news in 2008-2014 within the first five milliseconds where trading intensity rises by more than 100-fold.

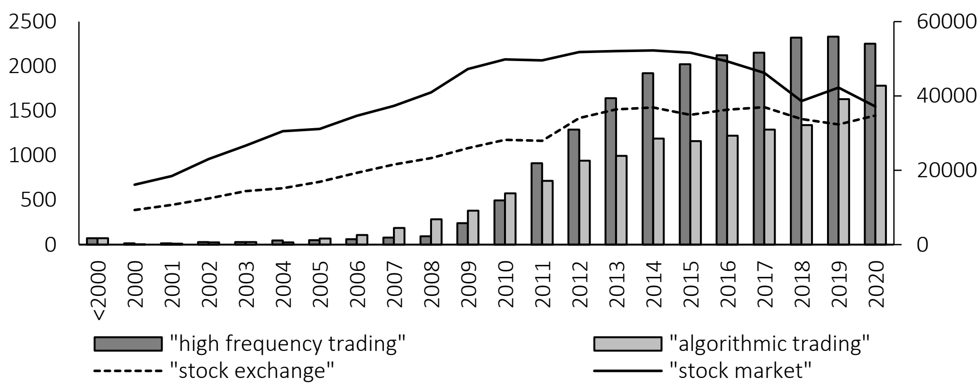


**Figure 1. Results from a basic Google Scholar search as of January 2, 2021. Notes: Left y-axis stands for the numbers on “high-frequency trading” and “algorithmic trading”; Right y-axis represents the numbers on “stock market” and “stock exchange”.**

Reaching beyond the scope of this study, HFT related topics include but not limited to its impacts on market quality, i.e., on liquidity (Hasbrouck and Saar, 2013; Brogaard et al., 2014; Brogaard et al., 2017) and on volatility (Brogaard, 2010; Zhang, 2010; Chaboud et al., 2014), HFT effects on price discovery (Carrion, 2013; Menkveld, 2013; Conrad et al., 2015), HFT through market downturns and crashes (Kirilenko et al., 2017; Brogaard et al., 2017;

Madhavan, 2012; McInish et al., 2014), HFT impacts on other participants: crowding out effect (Malinova et al., 2013; Jones, 2013; Hoffmann, 2014), adverse selection effect (Cartea and Penalva, 2012; Biais et al., 2015; Egginton et al., 2016), welfare effects (Boehmer et al., 2015; Stiglitz, 2014; Budish et al., 2015), vast HFT investments (Menkveld, 2013; Biais et al., 2015; Budish et al., 2015), HFT competition (Baron et al., 2019; Brogaard and Garriott, 2019), HFT profits (Malinova et al., 2013; Scholtus et al., 2014).

While the HFT literature is extensive, in most of the research topics, studies provide contradictory evidence to each other. In line with that, there are many open questions and ongoing debates. For example, as one of the broadest questions on HFT, is it beneficial or harmful for the markets? Or being more specific, how does HFT affect market quality components such as liquidity, efficiency, and volatility? Consequently, do we need to regulate HFT? If yes, how much and by which means? These questions and many others do not have clear answers. In an attempt to organize ideas and findings within the diverse topics regarding HFT and its impacts, several survey and discussion studies have been conducted in the last decade. These studies cover HFT strategies and profits (Goldstein et al., 2014) as well as market efficiency and welfare (Stiglitz, 2014), while the focus is mostly on HFT impacts on market quality and the regulatory actions (Prewitt, 2012; Jones, 2013; Biais and Foucault, 2014; O'Hara, 2015; Chung and Lee, 2016; Virgilio, 2019).

The main motivation of this study is to open a window in the existence of various unanswered questions on HFT with a focus on its impact on liquidity. After presenting the findings from the earlier research regarding the overall HFT impacts on liquidity, we discuss two factors that play a major role in the emergence of contradictory findings about the effects of HFT. These are i) negative market conditions and ii) the detrimental aspects that may arise due to the characteristics of HFT liquidity provision. Via this approach, we attempt to harmonize current evidence, explaining, at least up to a certain extent, the ongoing debates.

A large body of literature finds an ameliorating role of HFT in market liquidity (e.g., Brogaard, 2010; Hasbrouck and Saar, 2013; Baldauf and Mollner, 2020; Ammar et al., 2020; Malinova et al., 2013; Menkveld, 2013; Jarnecic and Snape, 2014; and Aït-Sahalia and Saglam, 2013). However, there exist a significant amount of opposing evidence against the positive HFT-liquidity relationship (e.g., Egginton et al., 2016; Breckenfelder, 2019; Van Kervel, 2015; Malceniece et al., 2019; Cespa and Foucault, 2014; Anand and Venkataraman, 2016). The first factor suggested in this study explains much of this phenomenon. A significant part of the documented liquidity related externalities of HFT as well as the controversy in findings tend to arise through negative market conditions, i.e., extreme price movements (e.g., Brogaard et al., 2018) and intraday shocks and crashes (e.g., Kang et al., 2020; Golub et al., 2012; Johnson et al., 2013; Leal et al., 2016). Similarly, the latter factor, which comprises the characteristics of the HFT liquidity provision, helps explain the controversy in findings. For example, while the HFT liquidity provision may be beneficial to the market, it may turn harmful in association with alternative forms and HFT strategies (Aït-Sahalia and Saglam, 2017; Brogaard et al., 2014). Moreover, since liquidity provision by HFTs is highly correlated, i.e., acting almost simultaneously and in the same direction, HFTs can cause or mediate liquidity shocks (Malceniece et al., 2019; Anagnostidis and Fontaine, 2020). Although many aspects of HFT and liquidity have been empirically tested and documented so far, a comprehensive summary and a broad discussion of these results are missing. We fill in this gap by exhaustively reviewing the literature from the perspectives indicated above.

The remainder of this paper is organized as follows. Section 2 surveys and discusses the current literature on the HFT role in market liquidity. It aims to illustrate the scope of the topic by touching on the main fields regarding the HFT's impact on liquidity. Section 3, by categorizing in two, i.e., the negative market conditions and the nature of HFT liquidity provision, raises the points where the HFT impacts on liquidity complicate and the evidence on its externalities becomes populated. Section 4 makes a consequent discussion addressing the availability of contradictory findings in the surveyed literature. The last section concludes.

## 2. HFT AND ITS RELATION TO LIQUIDITY

Liquidity typically refers to the ability to trade the desired quantity of a security at a low cost and as quickly as possible. Higher liquidity proves fundamental to market functioning and is often associated with lower risk since it means any desire to trade would be easily satisfied and the transaction would be quickly booked. The definition of liquidity implies a multi-layer notion that incorporates three dimensions: quantity, cost, and time. Studies that are concerned with the impact of HFT on liquidity make use of different liquidity measures. Among others, effective spread, quoted spread, realized spread, and price impact are widely utilized proxies assessing the cost dimension whereas market depth is a measure that accounts for both quantity and cost dimensions of the liquidity. Cancellation rate, complete fill rate, and partial fill rate metrics consider both quantity and time aspects. Resilience measures, on the other hand, show how the cost and quantity dimensions of liquidity change over time. Academic works in the field utilize alternative measures and proxies for liquidity and capture single or multiple dimensions of it. Thus, one reason underlying the contradictory findings may stem from the attributes of liquidity measures.

Additional factors that may affect the results from earlier research are the selection of the financial market(s) and time span. Specifically, findings on the developed markets differ from the ones on developing markets. Similarly, more recent datasets would differ from the earlier datasets of the mid-2000s, especially incorporating much more HFT competition and sophisticated HFT strategies.

A final practical factor in affecting the findings on HFT and liquidity relationship is the applied methodological approach. While there are various econometric approaches adapted in the surveyed literature, the majority of the studies apply one of three methodologies. The first set of studies utilize panel data regressions intending to examine the impacts of HFT on market liquidity by the use of panel datasets with dimensions such as time, HFT firm, and market. The second group of studies focuses on specific events-dates such as the introduction of a short-sale ban, colocation services, HFT taxes or extreme price movements, shocks, and crashes. These studies most commonly adapt a difference-in-differences approach. The final set of studies, concentrated on regulatory aspects and market design, are theoretical papers and highly benefit from data simulations. Appendix A briefly describes three sets of studies and their methodologies.

This section and the succeeding one do not focus on the potential differences in findings arising from one of the above-stated factors. Instead, they define and emphasize two major conceptual factors involved in the diversity of the findings regarding the HFT impacts on liquidity.

### 2.1. General Impacts of HFT on Liquidity

Considering the role and the importance of liquidity in market quality, many studies have examined HFT's impact on liquidity. On one hand, high-frequency traders (HFTs) are regarded as extremely fast traders; they are expected to increase liquidity provision, lower information production, and transaction costs, and thus, enhance market efficiency. On the other hand, HFTs' ability to react to new information and to anticipate order flow at an ultra high speed may crowd out liquidity. Accordingly, empirical findings on this issue are still inconclusive. While a large strand of previous work points out to HFT's positive influence on liquidity, e.g., through lower informational asymmetries (Brogaard, 2010; Hasbrouck and Saar, 2013; Jarnecic and Snape, 2014; Jain et al., 2016; Li et al., 2018; Baldauf and Mollner, 2020; Ammar et al., 2020), a significant number of studies focus on the adverse effects that HFT may have on liquidity, mostly due to higher competition among low latency traders or their intense quoting activities (Kirilenko et al., 2017; Malceniece et al., 2019; Breckenfelder, 2019; Ekinci and Ersan, 2020).

Brogaard (2010) examines the role of 26 HFT firms (constituting 68.5% of the dollar-volume traded) in the U.S. equity market and finds that although certain HFTs supply and others demand liquidity at times, they essentially provide the best bid and offer quotes and enhance liquidity. The author determines HFTs' impact on liquidity at a daily level and shows that HFTs tend to diminish slightly their liquidity supply and augment their liquidity demand as volatility increases. Hasbrouck and Saar (2013) are interested in whether a low-latency trading activity is beneficial or detrimental to the market during both periods of normal conditions and increased uncertainty. They find evidence of lower quoted spreads and thus, conclude that HFT improves market liquidity in both periods.[4] Jarnecic and Snape (2014) support the earlier evidence on the positive impact of HFT on liquidity while pointing out the potential challenges faced by non-HFTs. They suggest that HFTs supply liquidity to the market by submitting orders at multiple prices at or within the quote. Jain et al. (2016) utilize both traditional liquidity measures (spread and depth) and more recent ones (the cost of immediacy and limit order book slope) and reveal that the decrease in latency enhances market liquidity. The findings are intriguing since the analysis isolates the period following the launch of the Japanese low latency trading platform, Arrowhead. Li et al. (2018) find evidence that HFT improves liquidity by boosting the number of low-frequency orders and the frequency of trades. More recently, Baldauf and Mollner (2020) propose a model considering multiple trading venues, costly information acquisition, and several types of traders. They show that HFT increases liquidity through lower informational asymmetries but at the expense of price efficiency. Ammar et al. (2020) provide evidence of HFT's positive effect on intraday liquidity as well. In order to measure liquidity, the authors utilize effective spread and decompose it into transitory and adverse selection components. Thusly, they demonstrate the positive influence of HFT on liquidity results from lower adverse selection costs. Ekinci and Ersan (2020) show that HFT deteriorates market liquidity in a 2015-2017 sample of 30 blue chips from Borsa Istanbul. The finding is important in the sense that overall HFT share is considerably low (approximately 3.2% of order count and 2% of order volume) through the studied time period when the colocation services and technological improvements have been recently introduced.

[4] Authors note that these findings, however, do not imply a similar HFT impact on liquidity during extremely brief time intervals such as the "Flash Crash" of May 2010.

Breckenfelder (2019) analyzes a channel through which HFTs may reduce market liquidity, namely the competition, and detects that market liquidity deteriorates through higher competition among HFTs. Other studies, such as Bernales (2019), and Brogaard and Garriott (2019), focus also on HFT competition in the examination of HFT's role in liquidity. Brogaard and Garriott (2019) examine a sample from Alpha, a recently introduced Canadian stock market. Their dataset begins with an HFT-free period and spans through four years with the entry of 11 HFTs. Authors find that HFT competition leads to an improvement in the liquidity metrics. Bernales (2019), on the other hand, indicates that if there exist several (few) HFT firms in the market, additional HFT competition ameliorates (damages) the liquidity.

### 2.2. HFT Liquidity Provision

A trade occurs when liquidity demanders (takers) accept to buy or sell a security at the offer or bid price that liquidity suppliers (makers) provide. With respect to trading strategies, HFTs can act as liquidity demanders (speculative traders or arbitrageurs), liquidity providers, or both. The liquidity that HFTs may provide is endogenous as they usually do not bear a designated role as a market maker with special privileges or obligations. Further, they can enter and exit the market freely; there are no specific requirements to practice HFT. Therefore, HFTs' liquidity-wise function is of high interest in market microstructure analyses.

HFTs' motivation to supply liquidity mainly stems from the profitability of liquidity provision. For HFTs to sustain their liquidity supplying role that is beneficial to market quality, the cost of liquidity supply should not decline beyond an economically feasible level. This issue is partly addressed by Conrad and Wahal (2020) who conduct a study on the stock-specific and market-wide term structure of HFT liquidity provision. Their findings implicate the need for a substantial decrease in trading latency (with which information is reflected into prices) in order to make HFTs' liquidity provision economically viable.

A large body of both empirical and theoretical studies highlight the liquidity providing role of HFT. Malinova et al. (2013), Menkveld (2013), and Hagströmer and Nordén (2013), among others, show that the majority of HFTs serve as a substitute for market makers and do provide liquidity. Aït-Sahalia and Saglam (2013) propose a dynamic trading model and, likewise, document that low latency traders generate more liquidity supply when compared to non-HFTs. More recently, Aït-Sahalia and Saglam (2017) investigate the liquidity provision mechanisms of HFTs in relation to volatile periods and demonstrate that HFT liquidity provision diminishes because of the spikes in volatility and jumps which lead HFTs to trade in a less aggressive manner and reduce their participation. They also show that HFTs' decreased participation, hence their lower liquidity supply, is followed by greater volatility and jumps. Furthermore, Ke and Zhang (2019) indicate that HFT's liquidity providing (but not demanding) role exacerbates market inefficiencies. Thus, in general, HFT presence proves beneficial to investors when they act as liquidity providers.

### 2.3. News Arrival and Informational Aspects

Due to the critical value of information embodied by news releases, news and data sources are continuously monitored by all market participants. HFTs, however, can react to any newly disseminated information within a fraction of a second, if not milliseconds. Accordingly, since "a fast matching engine enables a market-making strategy to quickly update quotes on the arrival of public information and thus reduce the risk of being adversely selected" (Menkveld, 2013), HFTs' role around news arrivals brings an additional dimension to the literature in order to detect the accurate relationship between HFT activities and market liquidity.

In a theoretical model, Foucault et al. (2016) investigate the short-term price changes around news arrival by focusing on HFT activity. They show that HFT orders on “soon-to-be-released” information do not hint any price direction since they aim to exploit short-run price changes upon the information. Brogaard et al. (2014) focus on macroeconomic news announcements and the HFT order flow. They demonstrate that HFT liquidity provision is larger than its liquidity demand around the announcements. Accordingly, empirical results imply that HFTs’ liquidity supply depends on macroeconomic news arrivals under volatile market conditions.

Hautsch et al. (2017) document HFTs’ market making role around scheduled news announcements. The authors demonstrate that in the Eurex Bund Futures market, HFTs tend to provide liquidity during news arrival. Zhang (2010) focuses on analyst earnings revisions and earnings surprises. After controlling for firm-specific fundamental variables, the strength of market reaction increases by HFT. Bhattacharya et al. (2017) conduct a similar empirical study on earnings announcement data with respect to market reaction and price incorporation. They suggest that the HFT activities in announcement periods do not reduce liquidity provision. Additionally, Ke and Zhang (2019) claim that HFTs may provide liquidity and positively affect market efficiency through Post-Earnings Announcement Drift (PEAD) periods.[5] Findings also confirm that HFT activity helps to reduce the magnitude of PEAD - which is useful to market efficiency.

Though not necessarily as fast as HFT, algorithmic trading (AT) can play a part in the changes in liquidity around announcements. Studying the S&P 500 ETF, Scholtus et al. (2014) suggest that AT activities around macroeconomic news show a dynamic behavior and consequently, affect market liquidity. More specifically, lower AT activity prior to data release is followed by an immediate jump right after the release. Similar order flow and trading activity patterns are documented for the Turkish stock market by Akyıldırım et al. (2015) and Ekinci et al. (2019).

## 3. THE PERIODS WHEN HFT IMPACT ON LIQUIDITY COMPLICATES

We argue that a focus on two types of time periods would reflect the most intense debates in the recent literature regarding the impact of HFT on market liquidity. Frequently claimed view of general positive influence of HFT on liquidity as presented in Section 2, is challenged, opposed, and extended with findings obtained in these fields. The first field can be broadly defined as the HFT impacts on liquidity through negative market conditions. The second field comprises the main circumstances (periods) when HFT impacts are likely to alter due to the characteristics (nature) of HFT liquidity provision. While these fields are interrelated, we suggest that approaching the two separate angles will add value since the former places ‘market conditions’ in the leading role, and the latter highlights the related ‘HFT characteristics’.

[5] Post-Earnings Announcement Drift - PEAD is a market anomaly based on earnings announcements with a drift following the announcement (see Ball and Brown, 1968; Bernard and Thomas, 1989; 1990). The phenomenon occurs due to a market underreaction to earnings within earnings season and overreaction afterward. Overall, the drift can be observed for several months, especially on small-cap stocks - since they are not monitored and analyzed as often as large-cap stocks.

### 3.1. Negative Market Conditions

While a growing body of research analyzes HFT activity under normal market conditions, less attention has been paid to explore HFT trading patterns during periods of market stress such as market downturns, extreme price movements, and intraday shocks. Periods of high volatility and distress may not always threaten the whole market, however, if persistent for long, they can prove destabilizing. Hence, it still is an open debate whether HFTs supply liquidity when it is most needed, or they alter their strategy from market making to trade more aggressively in one direction so that they jeopardize financial stability.

#### 3.1.1. Extreme Price Movements

As a consequence of highly integrated financial markets, jumps have become much more synchronized across different assets or markets. These extreme price movements may occur due to the temporary lack of liquidity if they are endogenous in nature. Calcagnile et al. (2018) reveal that 60% of the co-jumps develop through an endogenous mechanism. Since HFTs utilize automated algorithms with extremely fast information processing capacity, their trading activities may influence the formation and amplification of or the recovery from this type of instabilities depending on their liquidity-making-taking preferences.

In line with the theoretical model of Foucault et al. (2016), Hautsch et al. (2017) show that HFTs avoid directional strategies around extreme news-implied price movements and act as liquidity suppliers. They explain this pattern by the possible unprofitability or riskiness of the aggressive trading strategies in the presence of very quick price adjustments. Nawn and Banerjee (2019) identify HFTs' role as liquidity suppliers and detect a statistically significant increase in their liquidity provision following extreme price movements.

Brogaard et al. (2018) conduct single-stock and multi-stock analyses. They observe that HFTs usually take a position in the opposite direction of extreme price movements and do not particularly lead the movements. However, the liquidity providing tendency of HFTs during extreme price movements occur only in single stocks, while their demand for liquidity prevails their supply of liquidity in cases where multiple stocks simultaneously experience extreme price movements. The coupled findings are intriguing in the sense they point out the sensitive and variable role and impact of HFT through extreme price movements. Considering the fact that the periods when multiple stocks experience extreme price movements may imply larger meaning for the well-functioning of the financial markets, HFT liquidity provision exceeded by the amount they demand from the market through these periods can be seen as an essential externality.

#### 3.1.2. Intraday Shocks and Flash Crashes

Financial markets are complex systems in which multiple heterogeneous agents interact and therefore, it is difficult to attribute intraday liquidity shocks and extreme events to a specific type of agent, such as HFTs. Nonetheless, understanding the trading behavior of HFTs during and after these specific events is valuable for constructing an improved market design. One of the most well-known and studied examples of such events is the "Flash Crash" that took place on May 6th, 2010. Cespa and Foucault (2014) show that if low illiquidity and high price informativeness equilibrium is reversed, then, a liquidity crash similar to the Flash Crash is likely to occur.

Easley et al. (2012) suggest that higher-order flow toxicity may induce certain short-term high volatility periods, like the Flash Crash, and may be partly responsible for the withdrawal of large liquidity from the market.[6] Thus, HFT's liquidity provision role and trading behavior may be affected under high order flow toxicity circumstances. Easley et al. (2011) point out to CFTC-SEC report and acknowledge the tie between the Flash Crash and HFTs who liquidated positions and left the market only after the order flow toxicity increased.[7] Hautsch et al. (2017) and Kang et al. (2020) argue that HFTs take a position in the same direction with other agents in the course of extreme events. Kang et al. (2020) further distinguish between foreign and domestic HFTs and exploit the dissimilarities between two investor groups with respect to their trading activities' impact on order flow toxicity. They observe that while domestic and foreign HFTs have a difference in 'normal times', they both produce toxic orders during extreme periods.

Golub et al. (2012) analyze all Mini Flash Crashes which occurred in the U.S. between 2006 and 2011. They identify the source of Mini Flash Crashes as market fragmentation and regulatory framework, and indicate that HFTs have an adverse impact on liquidity during Mini Flash Crashes. Similarly, Johnson et al. (2013) attribute Mini Flash Crashes to the interaction between various automated algorithms. Leal et al. (2016) develop an agent-based model in which they show that HFT plays a fundamental role in generating flash crashes given their ability to increase bid-ask spreads and synchronize on the sell side of the limit order book. More recently, Leal and Napoletano (2019) construct a theoretical model where HFTs can trigger flash crashes. The authors reveal that HFT-targeted policies can impose a trade-off between a smaller number of flash crashes and a slower market recovery after a crash. Overall findings reflect the need for further research on the structure of flash crashes in specific market designs.

In financial markets, regulators are responsible to act properly and timely in order to sustain an efficient market. Therefore, abnormal prices and market activity are not allowed. Hence, to prevent an irrational market sell-off during extreme periods, exchanges implement temporary short-sale bans. A well-known short-sale ban decision is the SEC's September 2008 ban which aimed at combating market inefficiency caused by manipulation and covered 799 financial stocks. However, this has led to a series of debates in academic literature as to the decision's effects on market quality, especially as far as HFT participation is concerned. Since HFTs tend to submit orders on both sides of the limit order book (LOB), under a short-sale ban, their algorithms would be jeopardized, if not ineffective. Accordingly, short-sale ban effects on HFT activities and consequent outcomes on market quality have been studied. Among these studies, Boehmer et al. (2013) show that large-cap banned stocks suffer from liquidity more than small-cap banned stocks when various spread measures are evaluated. In addition, the study documents the negative effects of the ban on market quality due to the inability of algorithmic traders in fulfilling market-making liabilities. In the same manner, Brogaard et al. (2017) compare HFT and non-HFT activities during the ban and find that

[6] Order flow toxicity refers to the higher likelihood of a trade resulting in a loss, or simply, the adverse selection risk in the scope of high-frequency trading (Easley et al., 2012). When order flow toxicity intensifies, in the same way as other market makers, liquidity supplying HFTs bear a substantial loss risk.

[7] CFTC-SEC Report (available at https://www.sec.gov/news/studies/2010/marketevents-report.pdf ) states that HFTs initially absorbed the selling pressure and supplied liquidity to the market. After the accumulation in their long positions, however, they started to sell aggressively. Eventually, HFTs and all liquidity suppliers ceased providing liquidity to the market as fundamental buyers were unwilling to supply enough liquidity on the buy side.

short-selling HFT activity is mostly eliminated while overall HFT activity has been affected less. Moreover, during extreme market conditions, some HFT strategies negatively affect market liquidity.

### 3.2. The Nature of HFT Liquidity Provision

Under certain circumstances, the overall contribution of HFT liquidity provision becomes harder to evaluate. It may prove harmful for non-HFT participants through misleading trading activities and correlated actions of HFTs or sudden withdrawal of HFT liquidity.

#### 3.2.1. Ghost (phantom) Liquidity and Other Misleading HFT Strategies

Ghost (phantom) liquidity (GL) is one of the outcomes of those low-latency activities faced in high-speed friendly exchange structures. GL is the excess liquidity resulting from the placement of duplicate orders in multiple venues by a single trader, an HFT. It is called ghost liquidity since following the execution of an order, all the duplicates are directly canceled by the HFT. Van Kervel (2015) empirically shows that liquidity supply reduces as a result of fast trading activities across multiple venues in the U.S. Similarly, Degryse et al. (2019) document the effects of HFT-based cross-venue trading strategies on liquidity on a sample of European exchanges. Accordingly, because of conditional orders across multiple venues, consolidated liquidity becomes higher than actual, i.e., the one with true trading purposes. The authors argue that even though cross-venue cancellations create factitious liquidity, which roughly constitutes 4-7% of limit order book depth, they have no significant effect on total liquidity. Blochter et al. (2016) conduct a GL investigation in the U.S. stock market. They indicate that the cross-venue order cancellations take place as a consequence of a search for accurate price levels. Thus, the respective activities have a positive effect on the market. Korajczyk and Murphy (2019) investigate phantom liquidity with a focus on large institutional orders. They suggest that HFT has a positive effect on market liquidity by matching large institutional orders which tend to live longer due to their size.

However, counter arguments are also present on the effects of high-frequency traders engaging in GL provision. Various arguments and concerns against GL are raised by the U.S. Securities and Exchange Commission (SEC, 2010).[8] SEC (2010) describes HFT market making as a "passive market-making" strategy with the computing power advantage. Accordingly, the regulatory review presents questions on the HFT order cancellation activity such as "Does the very brief duration of many of their orders significantly detract from the quality of liquidity in the current market structure? For example, are their orders accurately characterized as phantom liquidity that disappears when most needed by long-term investors and other market participants?" (SEC, 2010). Another policy-oriented study on the GL is carried out by Aït-Sahalia and Saglam (2017) where the authors investigate the concept through a model-based analysis. The study discusses the adverse effects of GL on non-HFT market participants since HFTs' phantom liquidity may cause negative signals on non-HFTs; when cancellations occur, non-HFT orders cannot benefit from the best bid-ask quotes caused by GL. Considering its probable positive effects on the overall liquidity, the authors propose a speed bump as a possible regulatory solution. Their theoretical findings consolidate the rationale and show that a pre-cancellation resting time positively influences the overall liquidity with respect to the tighter bid-ask spread.

[8] See Goldstein et al. (2014) for a detailed presentation.

Another misleading order submission strategy is 'quote stuffing' which consists of submitting and withdrawing a large number of orders that 'flood' the market. Egginton et al. (2016) indicate that 74% of US exchange-listed securities experienced at least one episode of quote stuffing during 2010 and that this activity deteriorates market quality. During periods of quote stuffing spikes, stocks face lower liquidity, higher bid-ask spread, and higher short-term volatility.

One can argue that in a market where HFTs can act as liquidity demanding arbitrageurs or speculative traders, they tend to snipe stale quotes of high-frequency market makers. That is, their trading strategy raises the cost of liquidity supply and consequently, is harmful to other investors.[9] The results in Brogaard et al. (2014) are consistent with HFTs' employment of an integrated strategy that includes both an informed liquidity demand and a profit-taking liquidity supply. Bernales (2019) underlines the association between HFTs' trading behavior as liquidity takers and competition. The author suggests that HFTs are inclined to trade more aggressively if there are few HFTs in the market. More specifically, HFTs exhibit a "predatory" trading behavior, compete more through market orders, and reduce market depth if their market participation is low. The overall findings on the HFT's liquidity offering and liquidity consuming dynamics reveal the importance of their predominant role in the market structure and design.

### 3.2.2. Commonality

The commonality in liquidity arises when a security-specific liquidity level moves analogous to that of the market. This kind of liquidity co-movement can lead to a significant increase in the systematic liquidity risk and result in sudden liquidity dry-ups. Cespa and Foucault (2014) emphasize the self-reinforcing relationship between liquidity and price informativeness as a cause of market contagion. More specifically, they point out a probable feedback loop that leads to liquidity contagion from one security to the market. Liquidity demanding HFTs, frequently, implement similar strategies simultaneously based on correlated signals and thus, may withdraw liquidity at the same time. Liquidity supplying HFTs, who may serve beneficial to the market functioning, can also turn out as detrimental due to liquidity commonality.

Anand and Venkataraman (2016) suggest that since liquidity providing HFTs are likely to leave the market under unfavorable conditions, they may cause vulnerabilities in the market. The findings in Malceniece et al. (2019) support the latter rationale and indicate that about one-fifth of the increase in liquidity co-movement occurs because of the tendency of HFTs to exit the market under adverse market conditions. The authors notice that this effect becomes even more intense during highly volatile periods. They also detect the common drivers of increased liquidity co-movement as correlated liquidity demand of opportunistic HFTs and elevated monitoring abilities of liquidity supplying HFTs. Another noteworthy outcome of their analysis is the relatively large liquidity co-movement among medium and small-cap stocks. This result supports HFTs' incremental monitoring capacity and, to a smaller extent, a habitat effect. Correspondingly, Anagnostidis and Fontaine (2020) demonstrate that, due to the speed of information diffusion and common trading strategies, HFTs' liquidity supply co-variation proves higher in comparison to that of non-HFTs'. Moreover, the authors call attention to the dynamic nature of liquidity commonality and highlight the elevated

[9] See Budish et al. (2015) and Menkveld and Zoican (2017) for latency arbitrage.

systematic risk in the securities that are massively traded by HFTs during market-wide high distress periods.

### 3.2.3. Liquidity Shocks

If HFTs believe that their potential trading losses due to asymmetric information (i.e., their adverse selection costs) are too high, they will liquidate their positions and exit the market (Easley et al., 2011). Considering HFTs' highly correlated trading strategies in comparison to non-HFTs,[10] HFT's detrimental impact on the market by creating sudden illiquidity shocks is of high concern. Kirilenko et al. (2017) determine that while HFTs did not initiate the Flash Crash that took place on May 6th, 2010, they contributed to it by their reaction to the extremely large selling pressure. This, ultimately, led to a significant reduction in the overall liquidity supply. Malceniece et al. (2019) signal a stronger possibility for liquidity shocks to spread across securities and for consequent flash crashes to occur through higher levels of liquidity co-movement (and hence greater systemic liquidity risk) caused by HFTs' trading activities. On the other hand, in case of liquidity shocks or such instabilities in the market, HFTs can respond more accurately and quickly to new information revealed by the order book than non-HFTs.[11] As a result, HFTs may support a faster market recovery from these shocks as well. To this end, Clapham et al. (2019) investigate the contribution of HFT in the recovery following liquidity shocks and conclude that low latency matters for the recovery of relative spreads. Nevertheless, HFTs' rapid liquidity provision remains limited with respect to overall order book resiliency.

## 4. DISCUSSION

Previous work examining HFT's impact on liquidity deliver mixed results (see for example Brogaard, 2010; Hasbrouck and Saar, 2013; Jain et al., 2016; Li et al., 2018; Baldauf and Mollner, 2020; Ammar et al., 2020 for the positive effects; and Egginton et al., 2016; Kirilenko et al., 2017; Breckenfelder, 2019 for the negative effects). It is widely suggested that HFT improves market quality by providing liquidity (e.g., Malinova et al., 2013; Menkveld, 2013; Brogaard and Garriott, 2019; Jarnecic and Snape, 2014; and Aït-Sahalia and Saglam, 2013). On the contrary, many studies show large amounts of correlated liquidity withdrawal HFTs are engaged in (e.g., Van Kervel, 2015; Cespa and Foucault, 2014; Anand and Venkataraman, 2016; Malceniece et al., 2019).

We suggest that this controversy is mostly due to two main factors, i.e., negative market conditions and the nature of HFT liquidity provision. These factors intersect with each other since externalities from the trading characteristics of HFT usually appear through negative market conditions. For example, while the commonality in the liquidity provision of HFT is by itself a downside, the negative outcome of this characteristic becomes much more apparent through negative market conditions.

Findings show that HFTs, to a large extent, act as liquidity suppliers and sustain their liquidity supplying role during normal times. This is, probably, because market making

[10] See, for instance, Benos et al. (2017) and Boehmer et al. (2018).

[11] Nawn and Banerjee (2019) detect a scenario supporting this logic. Authors divide the short-term volatility into two components: volatility arising from noise trading and volatility arising from information trading (driven by efficient prices). They show that the decrease in HFTs' liquidity supply is mostly associated with the rise in informational short-term volatility rather than the transitory one.

strategies generate more profit for low latency traders under normal market conditions. They occasionally act as liquidity demanders through these periods, which is also a function of the competition among themselves (Breckenfelder, 2019). In the presence of market distress such as extreme price movements and intraday shocks, however, HFTs may change their trading patterns and mostly prefer to utilize liquidity demanding strategies (Brogaard et al., 2018). This, in return, raises concerns about HFTs' overall contribution to liquidity, to well-functioning financial markets, and to the welfare of market participants.

HFTs are extremely fast traders who build their algorithms in parallel with their experience and skills. Although very few studies distinguish between individual and institutional high-frequency traders, an exceptionally large portion of low latency traders are within HFT firms (Jarnecic and Snape, 2014; Brogaard and Garriott, 2019; Kang et al., 2020). Thus, the change in their trading behavior from liquidity suppliers to liquidity demanders may be associated with their extremely fast information processing capabilities and well-established, risk-averse and profit maximizing strategies. Furthermore, HFTs do not have a designated role to supply liquidity. The lack of an obligation to supply liquidity and recent technological developments (i.e., the introduction of colocation services and faster order submission and processing systems) accentuate the significance of their speed advantage. These factors also help explain why HFTs are 'accused' of being a driver of temporary liquidity shocks in financial markets. Yet, certain empirical studies point out to the contrary; HFTs are not really found to be the cause of extreme price movements or sudden liquidity dry ups such as flash crashes (Kirilenko et al., 2017; Brogaard et al., 2018).

They, on the other hand, may contribute to the amplification of negative events such as flash crashes (Hautsch et al., 2017; Kirilenko et al., 2017). One should treat this possibility with caution and keep in mind that the price formation, and systemic instabilities for that matter, occur as a result of the interaction of all market participants. HFT share in the electronic message and order traffic as well as in trade numbers and turnover is substantially high especially in developed markets (Brogaard, 2010; Boehmer et al., 2018; Bazzana and Collini, 2020). Besides, few traders with large activity constitute the aforementioned HFT share. For example, 26 HFT firms account for 74% of the overall trading in NASDAQ (Brogaard, 2010). Similarly, 46% of all trading volume in the Canadian market is performed through 572 user IDs in 31 HFT firms (Boehmer et al., 2018). Largely correlated trading among this dominant but unpopulated trader type could aggravate high volatility periods and cause a substantial increase in the systemic liquidity risk (Malceniece et al., 2019; Anagnostidis and Fontaine, 2020).

Another critical point is the HFT's role in sudden liquidity dry ups. Liquidity shocks may destabilize the markets if they persist. HFTs, due to the commonality in their liquidity provision, may withdraw large amounts of liquidity simultaneously (Malceniece et al., 2019; Anagnostidis and Fontaine, 2020) engaging in the formation of liquidity shocks in the market. On the other hand, few studies identify that HFTs also help the recovery from liquidity shocks (see, for instance, Nawn and Banerjee, 2019; Clapham et al., 2019). Further research on this issue covering more extended periods and under different market designs is needed.

Liquidity shocks as investigated in previous work embody short-term distress periods. However, HFTs' trading behavior under longer-term bull and bear market conditions is still an open question for further research. Do their liquidity supply, along with their participation, increases during bull markets? Do they differ from non-HFTs in terms of their liquidity supply under bear market conditions? To what extent do HFTs contribute to market efficiency through liquidity supply during longer-term market downturns?

While both positive and negative impacts of HFT on liquidity are evident, a critical question is that which outperforms the other in aggregate? Therefore, further research with a broader perspective to analyze different time periods and market conditions; alternative HFT strategies and trading characteristics together will most probably contribute much to the existing literature. This will enable reaching more thorough conclusions on HFT activity and its impacts on the market and participants. Adapting the same wide approach, a related branch of studies could focus more on the welfare issues and existence and magnitude of the economic losses of non-HFTs. While there exist studies in this line, further research is needed especially in relation to HFT liquidity provision.

As a consequence of shedding more light on the positive and negative effects of HFT on liquidity, another field of research, i.e., HFT regulations, would deserve much more attention. Regulations towards liquidity supply and market efficiency have long been the concern of policy makers. Most of the previous work regarding HFT-targeting regulations remains theoretical (i.e., Aït-Sahalia and Saglam, 2017; Leal and Napoletano, 2019). However, any assumptions that do not reflect the actual financial market functioning may lead to unrealistic results in theoretical models. Furthermore, if the findings from these studies are implemented in real-life systems, it may generate unexpected outcomes in financial markets. Empirical works, on the other hand, are mostly based on single-event studies (i.e., Brogaard et al., 2017) and do not cover multiple regulatory scenarios. Thus, a higher number of comparative empirical research is necessary about regulations targeting HFTs' trading activities in order to determine required conditions for improving their liquidity provision.

A final suggestion for future research is to progress more in organizing and discussing the extensive literature on various aspects of HFT activity. Thus, the literature and further research would benefit from a larger number of discussion papers and surveys with alternative concentration points such as the impacts of HFT on price discovery and market efficiency, HFT welfare effects, and future of financial markets in the new trading era.

## 5. CONCLUSION

Though relatively recent in the research agenda, the literature on HFT and its impacts on financial markets and other agents are broad. Under many subtopics, there are studies demonstrating the positive influence of HFT in the markets, while there is also ample evidence on its externalities. Liquidity is a major component in market quality and a topic where the HFT literature has turned its attention most. Earlier findings point out the overall liquidity providing role of HFT and a consequent ameliorating effect of HFT in the markets. On the other hand, HFT activity and its consequences through negative market conditions (extreme price movements as well as intraday shocks and crashes) are debated much in association with issues such as deteriorating HFT strategies in HFT liquidity provision, HFT liquidity commonality, and HFT role in the rise and the recovery of liquidity shocks. This study organizes findings and ideas on the topic in an attempt to harmonize contradictory findings and to maintain a higher level of understanding for the interested reader.

To the best of our knowledge, this is the first study to survey the large body of literature on HFT impacts on liquidity in order to explain the coexistence of positive and negative impacts of HFT. Moreover, we emphasize two main factors that lead to controversy in the literature.

Thus, we adopt a novel approach by presenting two alternative but interrelated points of view for explaining the controversy in the literature. These are the variations as a result of different market conditions and variations due to specific trading characteristics of HFT. Given its key role, the research on HFT and its impacts on markets will certainly continue to occupy a large portion of the literature.

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## APPENDIX A

The appendix provides information on the commonly applied methodologies in the literature on the HFT impacts on market liquidity.

### 1. Regression Analysis

Regression analysis is vividly the most commonly used methodology in academic studies investigating the influence of HFTs on liquidity. Various types of regression methodologies, e.g., ordinary least squares (OLS) regression, two-stage least squares instrumental variable (2SLS IV) regression, general method of moments (GMM) regression, logistic regression, principal component regression, and support vector regression are employed. In addition to the simple OLS approach, the 2SLS IV method is frequently applied in the literature (see Hasbrouck and Saar, 2013; Malinova et al., 2013; Brogaard et al., 2017; Jiang et al., 2014; Foucault et al., 2017).

The selection of appropriate econometric methodology depends heavily on the assumptions of the econometric model. More specifically, a researcher should consider the possibility of reverse causality if interested in the causal effect of HFT on liquidity. In the presence of endogenous regressors, the OLS estimation technique may lead to biased results. To address this issue, most empirical work adopts the instrumental variable approach. For instance, Hasbrouck and Saar (2013) apply the 2SLS IV regression to control for a potential endogeneity problem, that is the HFT activity at a stock can also be affected by an exogenous factor, represented by a correlation between the HFT variable and the error term in the OLS regression. Thus, the authors utilize an instrumental variable which proxies HFT activity at a stock by the HFT activity in stocks of companies from different industries. Similarly, Ammar et al. (2020) highlight the problematic nature of analyzing the HFT influence on liquidity due to endogeneity. Authors point out the fact that while HFTs may increase or decrease liquidity, this relationship may be bi-directional because the liquidity level of stocks may also affect HFTs' trading behavior. Thus, they make use of the system GMM methodology when estimating their dynamic model.

### 2. Difference-in-Differences Setting

Difference-in-differences regression analysis is a tool for determining the effect of a treatment T on an outcome Y and can be utilized in the case of the following generic model:

$$Y_{i,t} = \alpha_i + \gamma_t + \beta T_{i,t} + \delta X_{i,t} + \varepsilon_{i,t}$$

In Eq. (1), $\alpha_i$ refers to individual fixed effects whereas $\gamma_t$ represents time fixed effects. $X_{i,t}$ illustrate a time-variant covariate (which can be more than one i number if needed), and $\varepsilon_{i,t}$ is the error term. The estimation of the Eq. (1) with OLS may lead to biased results because of multicollinearity issues. Thus, assuming that the trends of the treatment and control groups would not change in the absence of treatment, one can adopt the difference-in-differences methodology.

The ambient trends assumption is one of the most critical features of the difference-in-differences methodology (Bertrand et al., 2004). One should treat with caution if there is no evidence of ambient trends in the outcomes of pre-treatment for the treatment and control groups. If the assumption of ambient trends holds and one can eliminate any other time-variant factors that may affect the treatment, then the difference-in-differences methodology can be utilized. A second concern with this methodology is the handling of standard errors in terms of autocorrelation. Several remedies exist for dealing with this issue. A common suggestion consists of clustering on individual panel cross-section identifier series which allows for arbitrary correlation of residuals among individual time series. This procedure aims to correct for both autocorrelation and heteroscedasticity.

A large number of studies focus on certain impactful events in determining the role of HFT on liquidity. These events include the ones with a potentially enhancing function in HFT activity (introduction of technological upgrades, colocation services, and dark pools) as well as the ones with restrictive effect on HFT participation (introduction of short-sale bans, HFT taxes, and fees). Utilizing a control group such as a financial market or group of stocks that have not experienced the change, these studies attempt to explain the effect of the change on the treatment group, e.g., a group of stocks on an outcome, e.g., liquidity (see Ye et al., 2013; Yao and Ye, 2014; Friederich and Payne, 2015; Jain et al., 2016; Jovanovic and Menkveld, 2016; Jørgensen et al., 2018; Baron et al., 2019; O'Hara et al., 2019; Oriol and Veryzhenko, 2019).

Jain et al. (2016), for instance, conduct a difference-in-differences analysis in order to determine whether their findings on the systemic risk are related to high-frequency quoting or not. They define the difference using the Tokyo Stock Exchange (TSE) Arrowhead trading platform introduction date as the pseudo-event. They construct a group of control stocks (from Osaka Stock Exchange) that did not experience any decline in trading latency over their sample period and find significant difference-in-differences effects between their sample and control stocks with respect to several liquidity measures. O'Hara et al. (2019), examine the impact of relative tick size on investors' trading strategies and their liquidity provision in two environments: tick-constrained (e.g., the spread is equal to one tick) and tick-unconstrained (e.g., when the spread is equal to several ticks). They suggest that a larger relative tick size enables HFT market makers to trade more aggressively with higher profit margins. Authors follow the difference-in-differences approach since they are also interested in differences between various sets of stocks in the matter of liquidity. More precisely, they form two groups of stocks (both sample stocks) with regard to price range and match each stock in these groups to a control stock with a small relative tick size. Control stocks have a higher price range in comparison to sample stocks, but they belong to the same industry and are similar in terms of market capitalization. They also run similar regressions considering other fundamental attributes (other than industry and size) of stocks such as volatility or the trading environment of investors who hold these stocks.

## 3. Agent-Based Model

Theoretical models are also widely adopted when investigating the HFT-liquidity relationship. Especially, for hypothetical modeling purposes, studies tend to apply an Agent-Based Model (ABM). The ABM enables authors to build and simulate their own market structure via theoretical agents, rules, and environments. (see Paddrik et al., 2012; Leal et al., 2016; Oriol and Veryzhenko, 2019). The flexibility advantage of theoretical studies to consider many constraints simultaneously may easily become a disadvantage if the assumptions deviate greatly from viable financial market conditions. For instance, since financial markets are complex systems whose properties emerge from the interaction of multiple heterogeneous agents, proper identification of the latter is of high importance. In the HFT framework, theoretical studies may isolate the properties of HFTs however, negligence of other relevant agents may lead to unrealistic results.

Paddrik et al., (2012) propose an ABM which accounts for various classes of agents and analyzes the Flash Crash phenomena. They classify market participants into six categories namely, fundamental buyers, fundamental sellers, market makers, opportunistic traders, HFTs, and small traders. They evaluate stylized facts such as the trade order and execution rates, order book construction, distribution of price returns, volatility clustering, absence of autocorrelation of returns, and aggregation of returns in order to perform a simulation that mimics real market data. More recently, Oriol and Veryzhenko (2019) construct an ABM to examine the market reaction to a flash crash. They aim to identify and compare the impact of HFT versus non-HFT activities on extreme price events such as flash crashes. Hence, the authors consider two scenarios: the first, assuming a market populated solely with non-HFTs, and the second, considering a market with both HFTs and non-HFTs. In both scenarios, they start a flash crash-like event with the introduction of a large market order. Subsequently, they perform certain experiments in order to exploit the effectiveness of specific regulations. Their model accounts for an asynchronous and order-driven market structure however, it remains relatively simplistic in comparison to a realistic market design.