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Abstract

The technological development of the financial markets have completely changed the trading landscape. Electronic markets operate almost on a continuous basis, processing orders and trades in microseconds. The increase in trading speed allows markets to operate far beyond human capabilities, and generate an unprecedented wealth of data. The availability of high-frequency data allows researchers to analyze the trading environment through a magnifying lens, observing the real-time behavior of the market participants. The contribution of this dissertation is to analyze the intraday dynamics that drive price discovery and liquidity provision in the equity and sovereign bond market, discerning the role of High Frequency Traders during the pre-opening phase, their role as designated market makers in the equity market, and the behavior of the market makers in the secondary market of sovereign bond, during the Treasury auctions.

The first chapter examines the strategic behavior of High Frequency Traders (HFTs) during the pre-opening phase and the opening auction of the Euronext Paris exchange. Using data provided by the Base Européenne de Données Financières à Haute Fréquence (BEDOFIH), we find that HFTs actively participate in the pre-opening phase. Contrary to common wisdom, HFTs do not delay their order submission decisions until the very last moment of the pre-opening phase of the trading day. HFTs are able to successfully extract information from the pre-opening order flow, as manifested by the potential profits they can make on the positions they take in the opening auction. Furthermore, HFTs make profits on orders submitted in the last second before the opening auction; however, so do slow traders as well, suggesting that speed is not a necessarily condition to make profits in these last second orders. HFTs lead the price discovery process during the pre-opening phase, and neither harm nor improve liquidity provision in the opening auction. Our analysis highlights that HFTs who "come early to the party" make profits, however, they also improve market quality and do not have privileges, since we show that the speed advantage is not a necessary condition to make profits: also NON-HFT traders that trades on their own account come early to the party and make profits.

The second chapter analyses the role of designated liquidity providers played by high-frequency traders (HFTs) as defined by the forthcoming MiFID II regulation. Using data from the NYSE Euronext Paris with a specific identifier for electronic market-making activity, I find that HFTs do provide liquidity to the market, but strategically so to avoid being adversely selected by other fast traders when providing liquidity to them. Conversely, when they provide liquidity to slow traders, there is no evidence of adverse selection. I exploit a change in the liquidity provision agreement that introduces more competition among market makers to show that greater competition is beneficial for the market. Liquidity provision increases and the quoted bid-ask spread decreases. The adverse selection costs faced by all traders decreases, especially for slow traders.

The third chapter investigates how the bond supply influences the price and the liquidity in the secondary market during the primary auction days. The analysis focus on the intraday behavior of the primary dealers (that are also market makers) to capture their risk aversion before and after the auction. Using quote data from the Mercato Telematico dei titoli di Stato (MTS), I find evidence of an intraday pronounced inverted V-Shape on the yield difference, which goes up with a maximum at the auction time, and then recovers more than two hours after. This indicates a strong price pressure around the auction time. The analysis of liquidity shows that the bid-ask spread is usually better on the auction days, but rise sharply at the time of the auction. I also show that a proportion of the dealers is risk averse, and prefers to not expose themselves in the secondary market. They withdraw their quotes just before the auction and start quoting again from ten to twenty minutes later. The sovereign bond crisis exacerbates the dry-up of liquidity for Italy and the price pressure for Germany. However, the ECB intervention through the Public Sector Purchase Program (PSPP) appears to restore the market makers confidence, especially for Italy.

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Summary

Introduction

The global markets evolve dramatically in the last decade, and the entire market microstructure has been radically changed, due to the improvements in the speed of trading, the fragmentation of the markets, and the rise of the electronic trading. High frequency trading (HFT) introduced speed as a fundamental asset in the trading environment: Equity and Bond market operates almost on a continuous basis, and are able to process and record data at the microsecond or even at the nanosecond level.

On the one hand, this complex revolution allows electronic trading companies to enter the market and use sophisticated algorithms for their quoting and trading activity. As described in O'Hara, 2015, the technology for algorithmic trading in the exchanges has been developed over the 90's, where the US regulation (Reg ATS ans Reg NMS) introduced the Alternative Trading Systems to increase competition and liquidity.

These developments have had a dramatic impact on the behavior of market participants in financial markets, and have implications for the investors, the market makers, the exchanges and the regulators. However, it has been established that the presence of electronic trading is beneficial for the market. Angel, Harris, and Spatt, 2011 analyze many different metrics of market quality, finding that the increasing automation of the exchanges in the last twenty years increase market depth and dramatically reduced transaction and trading costs.

On the other hand, the availability of high-frequency data allows researchers to analyze the trading environment through a magnifying lens, observing the real-time behavior of the market participants. However, the opportunity to analyze very detailed data does not come without any downsides. The issues that could arise analyzing high-frequency databases were pioneered two decades ago by Goodhart and O'Hara (1997). The authors underline the strengths but also the weaknesses related to data abundance, and advice researchers "to determine from this wealth of data the underlying fundamentals that drive market and asset price behavior". Moreover, high-frequency data sets are very difficult to store, manage and analyze. To provide some orders of magnitude, the dataset analyzed in the first two chapters of this thesis can be summarized as follows:

- 9152 stock-day combinations (37 components of the CAC40 Index, for around 250 days)
- Around 1 million events (messages) per stock-day
- On average, 32 messages per seconds, with a peak of 670 messages per seconds

The following numbers translate into a stock-day limit order book (LOB) that could have more than one billion rows, with an average size of around 52 GB. O'Hara, 2015 and Hasbrouck and Saar, 2013 underline for the equity market that quotes could be the main source of uncertainty since most of them are modified or canceled within milliseconds or less. This have an impact also on the size of the data to store but most importantly on the traffic generated through the exchange.

The bond markets have not yet reached the level of activity and sophistication of the equity markets, mainly due to the different market model that relates to the participation of the dealers. In the coming years, most likely also these markets will be dominated by the electronic traders. For instance, the Mercato dei Titoli di Stato (MTS) already provides co-location facilities and and fast connections, together with a timestamp available at the microsecond level. In this new environment, both High Frequency Traders (HFTs) and Market Makers assume a central role in the functioning of financial markets, in terms of price discovery and provision of liquidity. Price discovery refers to the speed and unbiasedness of the process by which new information is incorporated into the price of an asset. Liquidity refers to the cost and speed of entering and exiting from a position in a small time interval. Both activities are carried out through posting quotes and trading.

Information can reach the market at any time, but usually, the most important news about a stock are not released during the trading day, but when the market is closed, or it has not yet opened. The overnight information, as well as the release before the opening, could potentially create high volatility, due to the lack of consensus about the price of the stock. For that reason, most of the exchanges start their trading day with an accumulation period, called pre-opening phase, followed by an auction, which allows clearing the market at one specific opening price.

Thus, one important research question is related to the role of HFTs in the pre-opening phase, and the difference in their behavior between this period and the continuous trading phase that follow. In other words, are HFTs providing price discovery and liquidity during the initial phase of the trading day? In principle, the presence of HFTs in the absence of trading appears to be counter-intuitive: if they cannot trade, what are the advantages to participate and provide price discovery? There might be some advantages to actively participate, and Chapter 1 of this dissertation attempt to address this question.

While price discovery is particularly relevant during the pre-opening period, when there is no trading, the provision of liquidity becomes fundamental, starting from the opening auction and during the entire trading day. For that reason, many exchanges introduced some players that play the role of facilitating the provision of liquidity when there are no contemporaneous orders. These players are usually referred as “market makers”. A growing part of the existing literature shows that HFTs becomes the endogenous liquidity providers. However, the forthcoming MiFID II regulation officially introduces the automatic liquidity provision by electronic market makers in all the European exchanges. Are the electronic designated market makers beneficial for the investors and the financial markets in general? Are the classical theoretical market microstructure models able to capture at least some of the features of the new trading environment? The classical Glosten and Milgrom (1985) framework assumes that the market maker is exposed to the adverse selection, which derives from different levels of information across traders. This information paradigm appears to be no longer suitable to describe the reality, as pointed out by O’Hara, 2015. The models of Budish, Cramton, and Shim (2015) and Menkveld and Zoican (2017) share the same intuition related to the adverse selection, which comes from the speed of reaction (or the latency) of traders rather than the fundamental information on the value of the stock. Being fast means that a trader can impose adverse selection cost to slower traders, but can clearly suffer the same costs when providing liquidity to other fast traders. Nevertheless, speed is probably not the only source of adverse selection, but it seems to be a proxy able to discriminate between "informed" traders, able to exploit the trading opportunities in a microsecond environment.

If the role of electronic market makers in the equity market becomes mandatory, due to the MiFID II directive, in the sovereign bond market their position is part of the market model from the beginning. In the MTS sovereign bond market, for instance, all the primary dealers have market making duties, that requires them to quote single or two side prices, and to not diverge from the average quoted spread among all market makers. In both the equity and the bond market, the most important responsibility is to provide liquidity to the market. This exposes the market maker to a risk that has to be compensated, usually granting them advantages or another kind of compensations. Needless to say, their position could lead to opportunistic behaviors, since they could exploit their informational advantage.

Regarding the bond market, primary dealers (market makers) are also required to participate in the primary auction of the sovereign debt. Prior research[1] documented that capital constraint, the limited risk-bearing capacity of the dealers and the imperfect capital mobility, could create price pressures that last days and culminates in the auction day. However, what happens exactly in the hours surrounding the auction? The use of intraday data allows to track the behavior of the dealers, that become very risk averse and withdraw a considerable part of their quotes from the market. Their influence in the liquidity of the market is clearly substantial, especially when it dries up.

To summarize, the contribution of this dissertation is to shed light on the intraday dynamics that determines the price discovery and drive the provision of liquidity. Specifically, the focus is on the role of HFTs and the market making activity on both the equity and the sovereign bond market. The following sections briefly outline the contribution of each chapter.

Chapter 1

The first chapter investigates the role of HFTs in the pre-opening phase and the opening auction of the NYSE-Euronext Paris Exchange, and aim to answer the question of whether and why they come "early to the party," rather than just start to post orders at the very beginning of the main trading phase. Specifically, the focus of the analysis is whether, and to what extent, HFTs contribute to price discovery and liquidity provision during the période d'accumulation des ordres or the phase de pré-ouverture (the pre-opening phase or order accumulation period), and the fixing d'ouverture (opening auction) versus the phase principale de négociation en continu (main trading phase), taking into account the different roles they play and the strategies they apply.

The analysis is based on data from the Base Européenne de Données Financières à Haute Fréquence (BEDOFIH) for the NYSE-Euronext Paris exchange, which defines three trader categories: HFT, MIXED, and NON-HFT. HFTs are pure-play HFT firms, e.g., Citadel, and MIXED firms are investment banks with HFT activity, e.g., Goldman Sachs. The remaining traders are classified as NON-HFT. The pure-play HFTs are referred as PURE-HFTs and MIXED traders as MIXED-HFTs, to make this distinction explicit.

The main findings are that PURE-HFTs do come early to the party, but not from the very beginning of the pre-opening phase. Contrary to the expectation, given

[1] Among others, Lou, Yan, and Zhang (2013) and Beetsma et al. (2016a). A detailed literature review is presented in Chapter 3.

the absence of immediate execution, HFTs (both PURE and MIXED) are the main participants in the pre-opening phase and the opening auction. HFT participation in the pre-opening phase and the opening auction is carried out mainly via their OWN accounts, with their activity on their market making (MM) accounts being of marginal importance. Most of the HFTs start their quoting actively just after 8.30 a.m., i.e., well before the 9.00 a.m. opening auction. This behavior might indicate the desire to observe and learn from the pre-opening order flow before making their order submission decisions.

Interestingly, HFTs post many orders in the pre-opening phase that are unlikely to be executed in the opening auction under NYSE-Euronext Paris regulations. The purpose of these orders is "fishing", i.e., gaining time priority on orders that would be triggered only under extreme market movements, such as the "Flash Crash" in the US market on May 6, 2010. Therefore, they come early to the party to (i) acquire information from the order flow, (ii) benefit from the priority option for "flash crash" orders, and (iii) benefit from the priority option in the opening auction.

HFTs generally make profits on executed orders submitted in the very last minute of the pre-opening phase, and make losses on other orders (assuming that the position is liquidated at the market price one minute after the auction). Zooming into the last second of the pre-opening phase notice that HFTs' cumulative profit increases consistently with time over in this last second. Surprisingly, we also observe similar cumulative profit patterns for NON-HFT-OWN.

Finally, to investigate whether HFTs perform any useful "social role," the analysis focus on whether HFTs contribute to price discovery during the pre-opening phase, and to liquidity provision in the opening auction. HFTs, as a group, lead price discovery consistently throughout the pre-opening phase. The main contribution to the price discovery process in the pre-opening phase stems from the proprietary trading activity of HFTs and NON-HFTs. This evidence is consistent with the profit analysis and suggests that both HFTs and NON-HFTs that submit orders in the last second are informed traders. HFTs as a group do neither harm nor improve liquidity provision in the opening auction, assuming that traders provide liquidity, if they trade against the overnight market movement. All in all, the results suggest that the presence of HFTs does not deteriorate market quality in the pre-opening phase in terms of liquidity provision, and substantially contributes to the price discovery process.

Chapter 2

The second chapter examines the activity of HFTs under a specific liquidity provision agreement, the Supplemental Liquidity Provision program (SLP), where the NYSE Euronext allow electronic high-volume members to provide additional liquidity, under a maker/taker pricing scheme. One of the contributions of this work is to analyze the dual role of HFTs, that could "wear the hat" of designated market makers, playing a beneficial function for the market, or act only opportunistically.

The analysis of the behavior of HFTs as designated market makers (HFT-MMs) is carried out exploiting two distinctive features of the dataset on the NYSE Euronext Paris exchange, namely (i) flags in the data that identify HFTs and market-making activity, and (ii) the SLP program, designed to promote passive execution from electronic and high volume members. The database includes two groups of market makers: HFT-MMs and MIXED-MMs, where the HFT identify the pure-play High Frequency Traders (e.g., Getco or Virtu) and MIXED, identify the investment banks with HFT activity. The activity under the market making flag, as confirmed by the exchange, is monitored continuously primarily because of the maker/taker pricing.

The empirical analysis follows the implications of the models by Budish, Cramton, and Shim (2015), Menkveld and Zoican (2017) and Aït-Sahalia and Sağlam (2017b). The first main finding is that HFT market makers do provide liquidity to the market, but strategically so to avoid trading with other fast traders. HFT-MMs appears to be able to discriminate between traders, selectively providing liquidity to NONHFTs and to fast liquidity motivated traders.

The second contribution is related to the adverse selection issue. The classical framework of Glosten and Milgrom (1985) assumes that the market makers, in their liquidity provision activity, could face traders with information advantages. The market makers will lose money providing liquidity to better-informed traders, and make money against (less informed) liquidity traders. However, the most recent microstructure models assume that the source of adverse selection is the speed of reaction, i.e, the latency of the trader. Budish, Cramton, and Shim (2015) and Menkveld and Zoican (2017) show theoretically that an HFT can assume both the role of market makers or liquidity takers, so that HFT-MMs run the risk of being adversely selected when facing other HFTs. The empirical analysis show that HFT-MMs are picked-off when they provide liquidity to other HFT-MMs and, to a lesser extent, to MIXED-MMs. In turn, they pass on adverse selection costs to slow traders. HFT-MMs opportunistically play the dual role of market makers and "bandits" when they capture the stale quotes, raising the adverse selection costs for all market participants, according to the theoretical implications of Budish, Cramton, and Shim (2015) and Menkveld and Zoican (2017).

The third contribution examine the competition effect, exploiting a change in the SLP agreement, which allows new market makers to enter and reshapes the basket of stocks where the market makers are required to provide liquidity. According to the theoretical model of Aït-Sahalia and Sağlam (2017a), increasing competition among liquidity providers should improve the liquidity available to all traders, especially for low-frequency traders, reduce the quoted spread, and decrease the adverse selection costs. Empirically, increasing competition changes the strategic behavior of the market makers. MIXED-MMs increase quoting, trading activity and the quantity they display at the best prices, but reduce their quoted spread by 8%. At the same time, HFT-MMs reduce their quantity displayed and their presence at the best bid and ask. Further, while HFT-MMs increase their gross provision of liquidity, leaving their gross liquidity consumption unchanged, MIXED-MMs trade more aggressively and consume more liquidity without increasing their passive executions. Overall, the provision of liquidity from HFT-MMs increases with higher competition, to the benefit of slow traders.

Chapter 3

The third chapter analyzes the influence of the bond supply on the behavior of the market-makers in the secondary market. This analysis aims to shed light on the intraday linkages between price movements, dry-up of liquidity, and market-makers' behavior in the auctions' days, specifically for the Italian and the German sovereign bonds.

The recent financial crisis, the importance of a well functioning primary and secondary market for the sovereign bond and the size of the secondary market itself, motivates a careful analysis of the behavior of the market participants, especially during the auction days. Both the Italian and German markets are characterized by the presence of a pool of financial institutions (mostly investment banks) that have specific duties: the primary dealers. Primary dealers are appointed to provide liquidity in the secondary market, acting as market-makers, and are also required to actively participate in the primary auctions submitting meaningful bids.

The empirical analysis, based on high-frequency quotes from the Mercato dei Titoli di Stato (MTS), reveal a statistically significant price pressure for the Italian bonds with a maturity of 5 and 10 years and for the German 10 years Bund around the auction dates, a pattern that is not present in non-auction days. The intraday evidence is consistent with the theoretical models of Duffie (2010), Boyarchenko, Lucca, and Veldkamp (2016) and Sigaux (2017), that predict a price reversal after an anticipated shock, like the treasury auction, which dates are known well in advance.

Consistently with the model of Bessembinder et al. (2016), the liquidity in terms of bid-ask spread is better around the auction days. However, dealers tend to be risk-averse during the auction times, since a portion of them withdraw their quotes few minutes before the auction time. A two-stage analysis shows that the uncertainty around the auction push dealers to reduce the amount quoted, reducing the total depth of the market. The first stage uses minute-by-minute time interval from five minutes before the auction, to five minutes after the auction, in order to analyze the response of the liquidity measures in the time immediately surrounding the auction. The second stage takes into account the subsequent adjustments that occur after the announcement of the auction results.

The results of the first stage indicates that, for Italy, a significant number of dealers withdraw from the market exactly at the time of the auction. In terms of total depth, the quantity available starts dropping by around 10 millions two minutes before the auction and reaches the lowest peak three minutes after. For Germany, no significant effects are present for the number of proposals and the depth: both remains comparable to the non-auction days. For the second stage, there is strong evidence, especially for the Italian market, that dealers withdraw their quotes from the market and then come back to the normal level at least ten to twenty minutes later. In general, market makers widen the bid-ask spread or withdraw from the market very close to the auction time, to protect themselves from adverse selection costs.

Finally, the crisis and the PSPP have a different impact on the two countries. For Italy, the crisis strongly affected the behavior of the dealers, that withdraw from the market and become more risk-averse. This results in a wider bid-ask spread and a lower quantity quoted in the market. The PSPP program seems to restore the confidence of the dealer, as all the measures improve substantially. The results for Germany are mixed, mainly because the sovereign bond crisis affected the peripheral countries. For the same reason, also the PSPP seems not to affect the price and the liquidity.

Chapter 1

Coming Early to the Party

1.1 Introduction

"The U.S. stock market [is] now a class system, rooted in speed, of haves and have-nots. The haves paid for nanoseconds; the have-nots [have] no idea that a nanosecond [has] value. The haves enjoyed a perfect view of the market; the have-nots never saw the market at all. What had once been the world's most public, most democratic, financial market had become, in spirit, something more like a private viewing of a stolen work of art," – Lewis (2014)

High Frequency Traders (HFTs) have become dominant players in stock markets around the world and the object of robust debate, in recent years. Some popular writers like Lewis (2014) claim that HFTs disrupt the structure of global financial markets, affecting their fairness and efficiency. Others, especially in the academic literature, take a more nuanced view. It is shown in that literature that HFTs execute a variety of strategies and perform multiple roles in their order placement/cancellation and trading actions. In performing their multifarious roles, HFTs can, on occasion, potentially use their superior trading speed to consume liquidity and gain a trading advantage over other traders using their own account while, at other times, acting as endogenous liquidity providers, or even as designated market makers. In these various roles and strategy types, HFTs may also contribute to price discovery. Contrary to the suggestion of Lewis (2014), these findings suggest that HFT activity may, in principle, be beneficial for other agents in the market, since the latter gain immediacy of execution and, also, enjoy more informative prices. In other words, HFT activity may facilitate the efficient allocation of resources – an important function of financial markets. Hence, any overall assessment of the impact of HFTs on market quality, ameliorative or deleterious, and the design of regulatory actions to modulate their behavior has, of necessity, to rely on an analysis of the relative importance of these multiple roles. These issues have been investigated in the literature, mostly for the continuous trading phase, but have been overlooked in the pre-opening phase and the opening auction setup in major stock exchanges.

In this paper, we aim to fill this gap in the context of the pre-opening phase of the NYSE-Euronext Paris Exchange, and investigate the question of whether and why HFTs come "early to the party," rather than just start to post orders at the very beginning of the main trading phase. Further, we also aim to investigate whether, and to what extent, HFTs contribute to price discovery and liquidity provision during the période d'accumulation des ordres or the phase de pré-ouverture (the pre-opening phase or order accumulation period), and the fixing d'ouverture (opening auction) versus the phase principale de négociation en continu (main trading phase), taking into account the different roles they play and the strategies they employ.

NYSE-Euronext is the fifth largest stock exchange group in the world in terms of listed market capitalization, as of April 2013, according to the World Federation of

Exchanges, and the first among the stock exchanges in continental Europe. Besides, NYSE-Euronext Paris recognizes and facilitates the active participation of HFTs acting in various capacities: for their own account, as market makers, and on behalf of clients.[1] The major exchanges around the globe, have rules for the pre-opening phase and the opening auction, similar to those of NYSE-Euronext Paris. In particular, a striking feature of the pre-opening phase in most exchanges is the absence of immediate execution during the order accumulation phase.[2]

Our analysis is based on data from the Base Européenne de Données Financières à Haute Fréquence (BEDOFIH) for the NYSE-Euronext Paris exchange, which explicitly defines three trader categories: HFT, MIXED, and NON-HFT. HFTs are pure-play HFT firms, e.g., Citadel, and MIXED firms are investment banks with HFT activity, e.g., Goldman Sachs. The remaining traders are classified as NON-HFT. From now on, we refer to pure-play HFTs as PURE-HFTs and MIXED traders as MIXED-HFTs, to make this distinction explicit.

BEDOFIH also categorizes the different types of orders and trades placed by the various types of traders according to the type of account: some orders/trades are for the traders' own (proprietary) account (OWN), while others are on behalf of their clients (CLIENT), or for the purpose of liquidity provision by the traders as market makers (MM), using only their proprietary funds. Hence, in order to analyze the impact of a quote or trade, it is necessary to define *both* dimensions of a particular quote or trade: trader type and account type. Our analysis of the data from NYSE-Euronext Paris is explicitly based on this two-dimensional characterization of quoting and trading activity.

Our paper focuses on the resultant effects of the different roles played by HFTs during the pre-opening phase and the opening auction, in conjunction with the initial part of the main trading phase. Several questions arise relating to the broad issue we study in this paper: First, do HFTs "come early to the party," and if so, in what capacity, and why? Second, do HFTs benefit from such a presence by making a profit overall on these early orders, i.e., do they "enjoy the party?" Third, do they create any positive externality that benefits others (the rest of the market) by their coming early to the party, i.e., do they help other participants enjoy the party as well? Fourth, how do HFTs behave later on, when "everyone joins the party" during the main trading session? To answer these questions, we examine three distinct trading periods: the pre-opening phase, the opening auction and the first 30 minutes of the main trading phase.

Our main conclusions are fairly robust to a variety of empirical specifications and methodologies. We find that PURE-HFTs do indeed come early to the party, but not from the very beginning of the order accumulation period. Contrary to our expectation, given the absence of immediate execution, HFTs (both PURE and MIXED) are the main participants in the pre-opening phase and the opening auction. Interestingly, HFT participation in the pre-opening phase and the opening auction is carried out mainly via their OWN accounts, with their activity on their MM accounts being of marginal importance. One potential explanation for this behavior is that NYSE-Euronext Paris encourages liquidity provision by designated market makers

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[1] HFTs account for roughly 44% of quoting activity, and about 23% of trading activity, in our sample. Our numbers are roughly in line with those in a study by the European Securities and Markets Authority (ESMA), ESMA (2014), which estimates orders and trades with a HFT flag on NYSE-Euronext Paris at 50% and 21% respectively, of overall quoting and trading activity.

[2] Among other exchanges, Toronto Stock Exchange, Deutsche Bourse (Xetra), Tokyo Stock Exchange and London Stock Exchange all have similar rules for the pre-opening phase, when they do not allow the execution of the orders. Thus, our results may potentially also apply to other exchanges.

only during the main trading phase, and so there is no reason for traders to mark orders with the market maker flag in the pre-opening phase.

The majority of HFTs start their quoting actively after 8.30 a.m. each trading day, i.e., well before the 9.00 a.m. opening auction We believe that this behavior indicates their desire to observe and learn from the pre-opening order flow before making their order submission decisions, with the timing being dictated by that of the “morning calls” of the large brokerage firms.[3] Interestingly, HFTs post many orders in the pre-opening phase that are unlikely to be executed in the opening auction under NYSE-Euronext Paris regulations. The purpose of these orders is “fishing”, i.e., gaining time priority on orders that would be triggered only under extreme market movements, such as the “Flash Crash” in the US market on May 6, 2010. Therefore, they come early to the party to (i) acquire information during the pre-opening phase, (ii) benefit from the priority option for “flash crash” orders in the main trading phase, and (iii) benefit from the priority option in the opening auction.

It is important to stress that the order flow and the theoretical opening price could be observed even without actively participating in the pre-opening phase by posting orders. However, submitting, modifying and cancelling orders during the pre-opening phase (beyond just observing the order flow) is crucial in order to learn about the marginal impact of an individual order on the theoretical opening price. The advantage of participating is twofold. First, traders can learn about the response of the aggregated market system to their orders, as reflected in the theoretical opening price (including “pinging” hidden quantities sitting in the limit order book). Second, traders can affect the theoretical opening price in response to new information that is constantly arriving in the market, either from news providers or from other market participants. Given the large number of order submissions and cancellations by HFTs during the pre-opening phase, it seems likely that HFTs are indeed exploiting these two advantages of participating in the pre-opening phase.

We next examine whether HFTs profit from their speed advantage in the pre-opening phase. We find that HFTs generally make profits on executed orders submitted in the very last minute of the pre-opening phase, and make losses on other orders (assuming that the position is liquidated at the market price one minute after the auction). Moreover, zooming into the last second of the pre-opening phase, we document that HFTs’ cumulative profit increases consistently with time over this last second. Surprisingly, we also observe similar cumulative profit patterns for NON-HFT-OWN.

The similar potential profit patterns of HFTs and NON-HFTs might stem from two different sources. First, the superior fundamental information possessed by at least some NON-HFTs may outweigh the speed advantage and ability to extract information from the order flow inherent to HFTs. The only way for HFTs to benefit from their speed advantage is if there is important information arriving in the market in the very last moment before the opening auction when NON-HFTs cannot take such a speedy action. However, the likelihood of such information arriving is very small, and in most cases, incremental information observed by HFTs in the very last moment before the opening auction may be of marginal importance. Second, the fixed timing of the opening auction (9.00 a.m. sharp) allows even slow traders to check the theoretical opening price a few seconds before the opening auction, even without the capacity for fast trading, and make their order submission decisions.

[3]This conjecture is based on information we received from a few (anonymous) high-frequency traders. Other explanations include the fact that several equity derivatives markets open around 8.30 a.m. Furthermore, French companies usually disclose their earnings around 8.00 a.m. and news providers, like Reuters, release their broker analysis of such corporate announcements around 8.30 a.m.

However, we acknowledge, that speed becomes important when traders liquidate positions taken in the opening auction, since during the main trading phase, only the fastest market participants can obtain the best execution terms, although this latter consideration is beyond of the scope of our analysis. We also acknowledge that some market participants might follow long-term strategies which may still be profitable over longer horizons, which we do not examine here, given our focus on short-term trading strategies.

To investigate whether HFTs perform any useful "social role," we analyze whether HFTs contribute to price discovery during the pre-opening phase, and to liquidity provision in the opening auction, as a side effect of their trading strategies. We find that HFTs, as a group, lead price discovery consistently throughout the pre-opening phase. We also document that proprietary traders, HFTs and NON-HFTs alike, are the main contributors to the price discovery process in the pre-opening phase. Moreover, a quarter of the residual price discovery in the last second is carried out by NON-HFTs. This evidence is consistent with our profit analysis and suggests that both HFTs and NON-HFTs that submit orders in the last second are informed traders. Further, we find that HFTs, as a group, do neither harm nor improve liquidity provision in the opening auction, assuming that traders provide liquidity, if they trade against the overnight market movement. All in all, our results suggest, that the presence of HFTs does not deteriorate market quality in the pre-opening phase in terms of liquidity provision, and substantially contributes to the price discovery process.

The outline of the paper is as follows. In Section 2, we review the academic literature on HFT activity, mostly in the main trading phase, and price discovery and liquidity provision during the pre-opening phase and the opening auction, mostly from the pre-HFT era. In Section 3, we present our research issues in detail and also state the specific hypotheses we test in the paper. In Section 4, we describe the institutional structure of trading on NYSE-Euronext Paris, and the order and trade data we examine. We present our research methodology and our empirical results in Section 5. We conclude in Section 6.

1.2 Literature review

The literature on HFTs is relatively new and is well summarized in the following review papers: Chordia, Goyal, Lehmann, and Saar (2013), Jones (2013), Biais and Foucault (2014), O'Hara (2015), and Menkveld (2016). In our review, we will focus, therefore, only on the aspects of this broad literature, which are closely related to our research in this paper. Our study is related to two different strands of this literature: the effect of HFTs on market quality, broadly defined, and the role of HFTs in the pre-opening phase. We discuss each of these issues in detail below.

First, our study contributes to the literature on the impact of HFTs on market quality. The accumulated evidence provided by these various studies suggests that HFTs form a very heterogeneous group of traders and, as part of their strategies, they might contribute both positively or negatively to market quality, depending on the context.[4] This is in contrast to the popular, consistently negative view presented by

[4]This literature is vast, including, among others, Hendershott, Jones, and Menkveld (2011), Easley, Prado, and O'Hara (2012), Hagströmer and Norden (2013), Hendershott and Riordan (2013), Malinova, Park, and Riordan (2013), Menkveld (2013), Brogaard, Hendershott, and Riordan (2014a), Brogaard, Hagströmer, Norden, and Riordan (2015), Baron, Brogaard, Hagströmer, and Kirilenko (2016), Biais, Declerck, and Moinas (2016), Korajczyk and Murphy (2016), and Kirilenko, Kyle, Samadi, and Tuzun (2017b).

Lewis (2014). There are two aspects to market quality: the speed and accuracy of price discovery and market liquidity. There is considerable research on both aspects of market quality in the context of HFT activity, which we review next.

The previous literature shows that HFTs aid price discovery, as they are typically better informed than other market participants. HFTs are able to collect information from multiple sources: directly from the order flow of multiple securities and multiple markets, but also from news feeds, social networks, historical data, etc., reacting fast when the market moves in a favorable way.[5] Given that these informational and speed advantages may seem unfair to other market participants, Budish, Cramton, and Shim (2015) suggest that a different market design, namely, frequent batch auctions, might attenuate these advantages. They argue that the speed advantage of the HFTs is marginal in the context of frequent batch auctions; however, it still pays off, if the new information arrives very close to the auction. Since we are looking at the behavior of HFTs, before and during the opening call auction, our paper sheds some light on this issue as well, even though it is not the main purpose of the paper, and our context is somewhat different, admittedly.

Liquidity is the other important aspect of market quality. Menkveld and Zoican (2017) provide a theoretical framework to characterize the duel between opportunistic and non-opportunistic HFTs, and conclude that the resulting effect on the liquidity provision depends on which group of HFTs dominates the market, while Hagströmer and Norden (2013) and Benos and Sagade (2016) provide empirical evidence on this issue. Besides, Brogaard, Hendershott, and Riordan (2014a) and Brogaard, Riordan, Shkilko, and Sokolov (2014) show that in the main trading phase, HFTs trade against transitory (extreme) price movements, while Van Kervel and Menkveld (2016) and Korajczyk and Murphy (2016) show that HFTs also trade in the opposite direction of the large institutional orders, at the time of their initiation. In our paper, we investigate whether HFT trading activity in the opening auction amplifies or dampens overnight price movements, and find that HFTs as a group neither exacerbate nor moderate overnight price movements.

However, it is important to underscore that the existing literature focuses almost exclusively on the role of HFTs in the main trading phase only, thus excluding the pre-opening phase and the opening auction from the analysis. In our current paper, we shed light on this missing link, contributing to the literature by focusing on the pre-opening phase and the opening auction, while contrasting the behavior of HFTs in these phases with the main trading phase. We also find that there is a considerable difference between the impact of HFTs on market quality in the pre-opening phase as opposed to the first 30 minutes of the main trading phase, conditional on the role they play.

Second, our work is also related to the earlier literature on the pre-opening phase and opening auction in the financial markets. Price discovery in the pre-opening phase has been extensively studied prior to the emergence of HFTs.[6] Cao, Ghysels, and Hatheway (2000), Ciccotello and Hatheway (2000), and Barclay and Hendershott (2003) investigate the price discovery mechanism in the pre-opening phase of NASDAQ. However, there are several important differences between the pre-opening phase in NASDAQ and NYSE-Euronext Paris. In particular, NASDAQ is a dealer

[5]For a theoretical justification, see Foucault, Hombert, and Roşu (2016), Cespa and Foucault (2011), and Gerig and Michayluk (2014); for empirical evidence, see Hendershott and Riordan (2013), Brogaard, Hendershott, and Riordan (2014a), and Hu, Pan, and Wang (2016).

[6]E.g., Amihud and Mendelson (1991), Biais, Hillion, and Spatt (1999), Cao, Ghysels, and Hatheway (2000), Ciccotello and Hatheway (2000), Madhavan and Panchapagesan (2000), Barclay and Hendershott (2003), and Davies (2003).

market (not a limit order book market) on which dealers might enter non-binding, crossed or locked quotes to signal the direction of the price movement. Equally importantly, the NASDAQ interdealer market is open for order execution, whereas there is no order execution during the pre-opening phase in the case of NYSE-Euronext Paris. Biais, Hillion, and Spatt (1999) and Davies (2003) investigate the pre-opening phase in NYSE-Euronext Paris and Toronto Stock Exchange, respectively, with both these markets sharing similar pre-opening mechanisms. These papers, thus, find that the majority of quoting activity occurs as close as possible to the opening auction, which naturally leads to the fact that prices are typically noisy in the beginning of the pre-opening phase, and gradually reflect more information towards the end of the pre-opening phase. The important difference between the two papers is that Davies (2003) focuses on the behavior of designated market makers in the pre-opening phase, while Biais, Hillion, and Spatt (1999) do not distinguish between different types of market participants. In contrast, we differentiate our paper from these prior studies because (i) we analyze the behavior of HFTs in the pre-opening phase, and (ii) we find that the majority of quoting activity of HFTs does *not* occur close to the opening auction. Besides these empirical studies, Medrano and Vives (2001) develop a theoretical model of the strategic behavior of informed traders in the pre-opening phase, which suggests that in the presence of other informed traders, strategic traders intentionally manipulate prices (in order to keep them uninformative) by entering large orders in the beginning of the pre-opening phase and cancelling them right before the auction.

It is noteworthy that there are almost no existing studies that examine the actions of HFTs in the pre-opening phase and opening auction, except Bellia, Pelizzon, Subrahmanyam, Uno, and Yuferova (2016), Anagnostidis, Fontaine, and Varsakelis (2017), and Boussetta, Lescourret, and Moinas (2017). Bellia, Pelizzon, Subrahmanyam, Uno, and Yuferova (2016) analyze the role of HFTs in the pre-opening phase of the Tokyo Stock Exchange. However, this prior study does not have either the HFT identification provided and monitored by the regulators, or the role flag relating to whether they are acting as designated market makers, proprietary traders, or traders who act on behalf of their clients. Moreover, Bellia, Pelizzon, Subrahmanyam, Uno, and Yuferova (2016) do not investigate the reasons for HFTs to come early to the party. Two other papers using data from the same source, Anagnostidis, Fontaine, and Varsakelis (2017) and Boussetta, Lescourret, and Moinas (2017), have an entirely different objective relative to this current paper, as they focus solely on the role of price discovery by HFTs in the pre-opening phase. Anagnostidis, Fontaine, and Varsakelis (2017) develop a theoretical model for HFT and NON-HFT participation in the pre-opening phase and show that order placement activity by HFTs, who possess more precise information than NON-HFTs, increase price efficiency. However, when they act strategically (in order to conceal their information advantage), price efficiency might deteriorate, and improve only close to the opening auction. Empirical evidence in their paper is in line with our results in this study, and suggests that HFTs lead price discovery. Boussetta, Lescourret, and Moinas (2017) study price discovery in the context of fragmented markets, and find that the pre-opening activity of slow brokers is strongly related to the price discovery process across trading venues. Both these papers use the same dataset (BEDOFIH) as we employ in this paper and, thus, also have access to the exogenous HFT classification and the role flag.[7] The other

[7]Our paper and the one of Boussetta, Lescourret, and Moinas (2017) are the outcomes of two of the three projects selected by EUROFIDAI, to whom EUROFIDAI provides free access to the BEDOFIH data, in addition to financial support.

more recent paper on the opening (and intraday) call auction is Theissen and Westheide (2016) who investigate the role of designated market makers during auctions on the Deutsche Bourse (Xetra), and find that they contribute to price stabilization. However, they do not investigate the strategic behavior of the traders during the pre-opening phase, and do not distinguish between PURE-HFT-MM and the other designated market makers.

We contribute to this stream of literature by focusing on the strategic behavior of HFTs wearing different "hats", and contrast their behavior with that of designated market makers (which has been examined earlier in the literature), with a focus on the pre-opening phase and the opening auction. We show that the previous results on the pre-opening phase are different from those we highlight in this paper, which is focused on HFT behavior. First, we confirm that the majority of trading activity (including HFT activity) does not occur at the end of pre-opening phase; in contrast, the most active period is around 8.30 a.m. on each trading day. Second, we show that HFTs participate in the pre-opening phase using their OWN accounts, and not with accounts used for designated market making. Third, we show that HFTs, as a group, lead the price discovery process; however, as a group, they do not moderate, nor do they exacerbate overnight market movements. Fourth, we document that executed orders entered at the end of the pre-opening phase are more profitable than those entered in the beginning of the pre-opening phase, no matter which trader/account category they belong to, i.e., these profits are not unique to HFT traders.

To summarize, our study contributes to the HFT literature by analyzing the behavior of the different types of HFTs in the pre-opening phase, the opening auction and the main trading phase, and comparing this behavior to that of other traders in these periods. We also study the impact of HFT activity during the pre-opening phase on trading profitability, as well as its consequences for price discovery and liquidity provision, and provide evidence that HFT behavior during NYSE-Euronext Paris pre-opening phase is different from what has been previously highlighted in the literature.

1.3 Research issues and hypotheses

Since the publication of "Flash Boys" by Michael Lewis (Lewis (2014)), there has been a discussion in the financial press and the popular literature about the role of HFT activity in global equity markets. Lewis suggests that HFTs use their speed advantage unfairly and profit from it with adverse consequences for other market participants, as indicated in the quote at the beginning of the paper. In addition, Lewis (2014) states, ""Liquidity" was one of those words Wall Street people threw around... A lot of people used it as a synonym for "activity" or "volume of trading," but it obviously needed to mean more than that, as activity could be manufactured in a market simply by adding more front-runners to it." Our analysis in this paper tests the veracity of these assertions with actual data and provides evidence-based conclusions on the complex issues surrounding HFTs activity during the pre-opening phase. (There are several other papers – see our review of the literature – that investigate similar issues in the main trading phase.)

The primary objective of our paper is to study whether HFTs come early to the party and actively participate in the pre-opening phase, even in the absence of immediate execution, and if so, what benefits they obtain from such participation. In particular, we aim to analyze the benefits, as measured by trading profits, which HFTs derive from their trading speed, in placing, modifying and cancelling their orders until the very last millisecond before the opening auction. In this connection, we also examine the incentives of other NON-HFT traders to participate in the pre-opening phase. Our secondary objective is to investigate how the presence of HFTs and, specifically, their superior trading speed, contributes to price discovery during the pre-opening phase, and liquidity provision in the auction that follows.[8] A related issue is price manipulation, as defined by the market regulator, Autorité des Marchés Financiers (AMF).[9] However, our data are not granular enough to allow us to track *individual* traders, and therefore, we defer the question of whether HFTs manipulate auction prices to future research.

As previously mentioned, we consider three periods of the trading day in our analysis: the pre-opening phase, the opening auction and the first 30 minutes of the main trading phase. The third period helps us to disentangle differences across the various types of traders from those arising due to the different trading phases. During the pre-opening phase, HFTs (as do all the other traders) have the flexibility to (i) exploit time priority, (ii) time their order placement, as well as (iii) enter subsequent modifications and cancellations. This flexibility can be thought of as a compound American option, with multiple optionalities – to place the order, to modify it in terms of price and quantity, as well as to cancel it. Such an option is essentially a nested option, first to place the order, and then to modify or cancel the order, given that it was placed. In other words, it is an option on an option. In our first hypothesis, we investigate whether HFTs make use of this optionality, and use their speed advantage to do so. Hence, the null hypothesis that we test is that HFTs delay their order submission/cancellation decision as close as possible to the opening auction, in line with the usual intuition about the early exercise of American options. The previous literature provides evidence that this was the typical behavior for market participants before the emergence of HFTs.[10] However, we aim to test this hypothesis again because there could be several reasons, especially for HFTs, to exercise the American option before maturity due to (i) external flows of information, which induce the execution of the option in order to gain time priority, (ii) extraction of information from the order flow, for example, by investigating the presence of hidden orders and (iii) attempts to affect the theoretical opening price.[11]

Hypothesis 1. *Independent of the account type for which they act, HFTs (PURE-HFTs and MIXED-HFTs) delay their order submission/cancellation decision during*

[8] A previous paper has investigated a similar issue using data from the Tokyo Stock Exchange (Bellia, Pelizzon, Subrahmanyam, Uno, and Yuferova (2016)). However, TSE data do not provide details of the account type of quotes and trades. Therefore, in that case, the purpose of order submission cannot be analyzed explicitly, but can only be inferred, using statistical methods. Thanks to the detailed classifications provided by the BEDOFIH dataset for NYSE-Euronext Paris, we are able to investigate, at a granular level, which subgroups of HFTs participate and contribute to liquidity provision during the opening auction.

[9] In their document on "Joint Guidance on Auction Manipulation," (AMF (2010)), the AMF, the French security market regulator, together with the regulators of Belgium, Portugal and the Netherlands, defines market manipulation as "Entering significant orders in the central order book of the trading system a few minutes before the price determination phase of the auction and cancelling these orders a few seconds before the order book is frozen for computing the auction price so that the theoretical opening price might look higher or lower than it otherwise would do."

[10] Biais, Hillion, and Spatt (1999) and Davies (2003) document that the majority of the order flow occurs as close as possible to the opening auction for NYSE-Euronext Paris and the Toronto Stock Exchange, respectively. More generally, so called "bid snipping" (submitting a bid as late as possible) is a common feature of the second-price, timed, internet auctions conducted by e.g., eBay (see Roth and Ockenfels (2002), Ockenfels and Roth (2006)), as a result of strategic bidders' behavior to conceal private information and/or to avoid bidding wars with incremental bidders.

[11] Medrano and Vives (2001) suggest that informed traders may manipulate the theoretical opening price by strategically placing, modifying, and cancelling their orders.

the pre-opening phase until the very last moment before the opening auction.

The above hypothesis describes how HFTs behave by coming early to the party, but does not draw conclusions regarding whether they "enjoy the party" by coming earlier, i.e., benefit by doing so. Coming early to the party may generate several concomitant benefits: collecting information, building up inventories, etc. However, the litmus test for their participation is whether or not they make profits. We investigate this issue in the following hypothesis.

Hypothesis 2. *Independent of the account type for which they act, HFTs (PURE-HFTs and MIXED-HFTs) do participate in the pre-opening phase and the opening auction, because they are able to use their speed advantage to make profits.*

By testing this hypothesis, we indirectly investigate whether HFTs who participate in the pre-opening phase are informed traders, and whether they monetize this advantage immediately after the market commences the main trading phase (i.e., whether they enjoy the party). We aim to verify through this hypothesis if the HFTs who participate in the opening auction are informed traders in the sense that they are systematically able to make profits on their transactions. We also aim to investigate through this hypothesis whether, because of their speed advantage they are the only ones enjoying the party, i.e., if they have special privileges relative to other market participants, or the market is a level playing field, i.e., even without the same speed capacity, others still make profits, or enjoy the party, as well.

With the next hypotheses, we aim to investigate whether HFTs allow the other participants to enjoy the party by improving market quality through price discovery and liquidity provision. In a market with continuous trading, price discovery is typically thought to occur only through *actual* trades. However, in the absence of trading, i.e., during the pre-opening phase, price discovery may occur through the posting of quotes and their modification or cancellation, which conveys information to other market participants. Similarly, even in the main trading phase, trading does not happen literally continuously, but in a discrete manner, with intermittent periods of no trading. This raises the question of whether price discovery can happen even in the absence of actual trades, merely based on the posted quotes, modifications and cancellations.[12] Here, we study price discovery in the absence of execution, and examine how different types of traders contribute to it. In this manner, we overcome the restriction of the classical definition of price discovery, which happens only through market orders, as in the classical models by Kyle (1985) and Glosten and Milgrom (1985). We address this in our third hypothesis:

Hypothesis 3. *Independent of the account type for which they act, HFTs (PURE-HFTs and MIXED-HFTs) contribute to the price discovery process, during different periods of the trading day (the pre-opening phase and the first 30-minutes of the main trading phase.)*

We next examine whether HFTs use their high-speed trading capability to provide (quasi) liquidity to the market rather than act as speculative traders and absorb liquidity. In this framework, liquidity provision is a different concept than the classical one during the main trading phase. In the main trading phase, liquidity provision

[12]This investigation is not new in the context of the main trading phase, i.e., the continuous session. Kaniel and Liu (2006), Goettler, Parlour, and Rajan (2009), and Rosu (2016) model the choice of informed traders between market orders (transactions) and limit orders (quotes) in the main trading phase. Brogaard, Hendershott, and Riordan (2016) provide empirical evidence for price discovery in the main trading phase occurring largely via quote updates coming from HFTs.

can be investigated, for example, by using metrics defined in AMF (2017): market depth (number of shares at the inside levels of the limit order book) and spread (the actual round-trip transaction cost). In our framework, there is no such liquidity provision because the inside levels of the limit order book are not well-defined (given that the supply and demand schedules are crossed in the pre-opening phase); there are no transactions during pre-opening phase, and there is no bid-ask spread in the opening auction. Therefore, we define quasi-liquidity provision during the auction as the quantity of shares that are traded against the overnight market movement.[13] Based on this definition, we test whether HFTs do have a "social role," i.e., they are not merely opportunistic as Lewis (2014) claims and, even if they are seeking to profit from their own strategies, they may incidentally provide liquidity to the market. We contrast this evidence with the HFT liquidity provision in the main trading phase. Therefore, we test the following hypothesis:

Hypothesis 4. *Independent of the account type for which they act, HFTs (PURE-HFTs and MIXED-HFTs) are the main liquidity providers during the opening auction and the first 30-minutes of the main trading phase.*

In the following sections, we describe the market architecture, the dataset and the methodology we use to investigate the above hypotheses.

1.4 Institutional structure and data description

1.4.1 Institutional structure

At the NYSE-Euronext Paris exchange, securities are traded both continuously, for most liquid stocks and, in an auction, for stocks that are not sufficiently liquid.[14] The traded securities are divided into trading groups, often with each one employing its own peculiar trading procedure. Therefore, for the purpose of this study, we ensure uniformity by considering only stocks that trade continuously, and with uniform rules in terms of opening and closing procedures.

The schedule of the trading day at NYSE-Euronext Paris is divided into six segments: the pre-opening phase, the opening auction, the main trading phase, the pre-closing phase, the closing auction and the trading-at-last phase. The pre-opening phase lasts from 7.15 AM until 9.00 AM, when the opening auction is carried out. After the opening auction at 9.00 AM, the main trading phase, i.e. the continuous trading period, takes place from 9.00 AM to 5.30 PM. A second order accumulation period known as the période d'accumulation des ordres - phase de pré-clôture (pre-closing phase - order accumulation period) starts at 5.30 PM and lasts only five minutes, followed by the fixing de clôture (closing auction). The phase de négociation au dernier cours (trading-at-last phase) goes from 5.35 PM to 5.40 PM, and aims to execute additional orders at the closing price. The pre-closing phase, the closing auction and the trading-at-last phases are excluded from the scope of this study, since we focus our attention on the beginning of the day, when the information accumulated

[13] This definition is in line with one of Brogaard, Riordan, Shkilko, and Sokolov (2014), who measure liquidity provision in the main trading phase by the directional trade imbalances computed as the difference between trading activity in the direction of the returns and trading activity in the opposite direction. In particular, Brogaard, Riordan, Shkilko, and Sokolov (2014) look at the extreme price movements and find that, in these cases, on average, HFTs provide liquidity.

[14] There are several small, illiquid stocks that are traded exclusively via auctions. We do not include these stocks in our sample, as there is usually no HFT activity in such securities.

overnight is reflected in market prices. We focus only on the first 30 minutes of the main trading phase when this information is being reflected in market activity.[15]

1.4.2 Data

Our data are obtained from the BEDOFIH, which provides tick-by-tick order-level data from NYSE-Euronext Paris with microsecond time-stamps. The data cover the complete history of orders (new order entry, execution, revision of quantity or price, and cancellation, for both the visible and hidden segments of orders in the pre-opening and main trading phases).

The sample period we examine is the year 2013 for the 37 French stocks that belong to the CAC40 index.[16] These stocks all have the same trading rules and HFT activity is present in all of them. We exclude from our initial sample, composed of 9,435 stocks-days combinations, four trading days and 148 stock-days due to technical issues on NYSE-Euronext or half-day trading (31 January 2013, 6 June 2013, 24 December 2013 and 31 December 2013). Further, we exclude 135 stock-days because we are unable to match the opening price due to suspensions of the stock or erroneous orders submitted during the pre-opening phase. We end up with 9,152 stock-days, or 97% of the initial sample.[17] For the purpose of our analysis, we focus on the pre-opening phase, the opening auction, and the first 30-minutes of the main trading phase.

The BEDOFIH database also has an additional classification, established by the French stock market regulator, which allocates each trader to one of three groups: PURE-HFT, MIXED-HFT and NON-HFT. This classification, revised once a year, is the result of a set of quantitative requirements and knowledge of the traders' IDs. The identification algorithm is based on the median lifetime of an order (including both modifications and cancellations), plus a threshold based on the total number of cancellations. A further check is carried out taking into account the identity of the trader.[18] The three trader groups are mutually exclusive and, during the year, their group classification cannot be changed (see EUROFIDAI (2014)). Recall that, dedicated HFT players, such as Citadel, fall into the PURE-HFT category, while slow traders are NON-HFTs. The MIXED-HFT category includes large investment banks and large brokers such as Goldman Sachs, and is the most active category in our sample.[19] All these traders can have their OWN (proprietary) trading desks that trade as quickly and frequently as PURE-HFTs, but they can also execute orders on behalf of their CLIENTS and, hence, take large positions in one or more stocks on their behalf. NYSE Euronext Paris also identifies each order with a flag that allows us to distinguish the actual account used to submit a particular order. Along this dimension, it is possible to distinguish between orders emanating from a trader's

[15] Other details of the trading architecture and taxation are reported in the Internet Appendix, Section A.1.

[16] Three stocks of the CAC40 are not included in our database since their main trading venues are Amsterdam (Arcelor Mittal and Gemalto) and Brussels (Solvay).

[17] The French market is very fragmented: Euronext covers around 63% of the total daily volume traded, followed by Bats (20%) and Turquoise (9%), according to the Fidessa Fragmentation Index, as of 2014. Unfortunately, we do not have order-level data with trader/account identifiers for these other markets and we do not analyze them.

[18] Conversations we had with AMF analysts confirm that they are confident that they are able to classify all HFT entities correctly, and that their classification is rather stable; a HFT in one year is likely also a HFT the year after.

[19] We note that this classification is based on the observed performance of the trader, and does not preclude the possibility that both HFTs and NON-HFTs have similar technological capacities, with the difference that the latter category does not utilize this capacity in full at all times.

OWN account (proprietary trading) or OWN orders, those on behalf of the client or CLIENT orders, or those submitted due to their market making affiliation, MM orders. Alternatively, an order can also be flagged as a parent company order (PARENT) or related to retail market organization (RMO) and retail liquidity provision (RLP) activities.[20]

In this section, we describe HFT participation in these different roles, during the pre-opening phase and the first 30-minutes of the main trading phase. Table 2.1 presents the descriptive statistics of our sample, distinguishing between the pre-opening phase (Panel A), the first 30-minutes (Panel B) and the entire trading day including pre-opening and closing phases (Panel C). The median volume (in # of shares) at the opening auction is 1.2% (63,996 / 5,295,324) of the median total daily trading activity. The median number of messages submitted during the pre-opening phase is 3,578, out of which new orders are only 25.2% (903 / 3,578), and the rest comes from order modifications and cancellations of newly entered and "forgotten" orders, i.e., orders that are transferred from the previous days (the median number of such orders is 2,353 or 65.8% of the total # of messages).

[20] RLP orders can be executed only against RMO orders.

Table 1.1: **Orders' Characteristics**

This table presents the summary statistics across stock-days for order submission, quoting activity and trading activity in our sample. We split the data according to the period of the day when the orders were submitted, modified, canceled, or executed. In particular, Panel A presents summary statistics for the pre-opening period and opening auction, Panel B presents summary statistics for the first 30 minutes of the main trading phase, and Panel C presents summary statistics for the entire trading day including pre-opening and closing phases. The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A: Pre-opening period and Opening Auction

	Median	SD	P5	P95
Total # of messages	3'578	2'702	946	9'644
# of new orders	903	762	300	2'604
# of orders from the previous days	2'353	1'971	456	6'850
# of modified orders	94	141	19	418
# of cancelled orders	85	187	23	432
Total volume (# of shares) traded	63'996	712'192	10'556	593'696
Number of trades	324	336	132	1'000
Total value (euro) traded	2'513'097	5'558'760	436'146	13'757'064

Panel B: First 30 minutes of the main trading phase

	Median	SD	P5	P95
Total # of messages	17'969	12'275	7'215	44'249
# of new orders	8'630	5'821	3'546	21'047
# of modified orders	1'260	1'279	414	4'144
# of cancelled orders	7'963	5'418	3'132	19'297
Total volume (# of shares) traded	296'348	4'255'484	53'568	3'053'344
Number of trades	1'640	2'208	560	6'280
Total value (euro) traded	11'078'753	22'515'901	2'778'637	56'429'965

Panel C: Entire day (including Pre-Opening and Closing)

	Median	SD	P5	P95
Total # of messages	291'873	197'106	123'398	723'125
# of new orders	141'797	94'993	60'449	348'691
# of modified orders	15'077	13'882	5'025	46'272
# of cancelled orders	133'698	91'248	55'491	332'714
Total volume (# of shares) traded	5'295'324	28'012'086	1'355'736	38'461'680
Number of trades	23'816	17'908	10'780	65'148
Total value (euro) traded	200'118'166	235'785'046	69'697'864	745'175'744

To investigate the presence of the different group of traders in the pre-opening phase, and in the first 30-minutes of the main trading phase, we define the activity ratio based on the number of quotes, the Quote Activity Ratio (QAR) as:

$$QAR_{p,j,k,l} = \frac{\text{Number of quotes}_{p,j,k,l}}{\sum\limits_{l} \text{Number of quotes}_{p,j,k,l}} \tag{1.1}$$

where p is one of the two periods considered, the pre-opening phase and first 30-minutes of the main trading phase, and the QAR relates to stock j, day k, and trader group l. In the QAR computation, we include only messages related to orders entered on day k and discard orders entered on the previous days.

For the opening auction, and for the first 30-minutes of main trading phase, we calculate the Trading Activity Ratio (TAR) in an analogous manner, by considering the number of shares actually traded:

$$TAR_{p,j,k,l} = \frac{\text{Number of shares traded}_{p,j,k,l}}{\sum\limits_{l} \text{Number of shares traded}_{p,j,k,l}} \tag{1.2}$$

where p is one of the two periods considered for stock j, day k, and trader group l.

Table 1.2 shows average quoting activity (also split up by different message types), QAR, and average trading activity, TAR, for the pre-opening phase and the opening auction (Panel A) and for the first 30-minutes of the main trading phase (Panel B). PURE-HFTs are the most active market participants in terms of the QAR during the pre-opening phase (38.5% across all accounts), and the second most active group in the first 30-minutes of the main trading phase (44.3%). Notably, NON-HFTs contribute 30.4% to the message traffic in the pre-opening phase, and only 3.0% in the first 30-minutes of the main trading phase. Adding the account dimension reveals that most of the PURE-HFT activity in the pre-opening phase is carried out through their OWN accounts, while in the first 30-minutes of the main trading phase, the most active accounts for PURE-HFTs, in terms of the QAR, are those of MMs, with a similar pattern shared by MIXED-HFTs. The explanation for this differing behavior is related to the design of the SLP program, which provides benefits to liquidity providers only during the main trading phase. During the first 30-minutes of this period, the quoting activity under the MM flag represents around 55% of the total quoting activity (28.9% for the PURE-HFTs, 26.3% for the MIXED-HFTs).

Zooming into quoting activity by the types of messages, we observe that all traders use *Limit Orders* most of the time, while *Market Orders* are used mainly during the pre-opening phase. (In the interest of clarity, we group together regular limit orders, stop limit orders and pegged orders as *Limit Orders* and regular market orders, stop market orders and market-to-limit orders as *Market Orders*.) We show that most of the message traffic in the pre-opening phase is generated by new limit order submissions (71.20%), while new market orders constitute only 8.28% of the total # of messages. The majority of new limit order submission arises from PURE-HFT-OWN traders (33.62%), followed by NON-HFT-CLIENT (13.04%) and MIXED-HFT-OWN (10.68%) traders. Notably, PURE-HFT-OWN cancel only 6.07% of their limit orders during the pre-opening phase, as compared to 81.44% during the first 30 minutes of the main trading phase, with similar cancellation patterns documented for MIXED-HFT-OWN/MM. In aggregate terms, only 6.90% of the message traffic in the pre-opening phase is generated by limit order cancellations, as compared to 44.06% of the message traffic in the first 30 minutes of the main trading phase.

TABLE 1.2: **Quoting and Trading Activity**

This table shows the proportion of quoting activity stemming from new orders, revisions, and cancellations, the average quoting activity (see Equation (1.1), and the average trading activity (see Equation (1.2)) by trader/account type, for the pre-opening phase and the opening auction (Panel A) and the first 30-minutes of the main trading phase (Panel B). *Limit orders* include limit orders, stop limit orders and pegged orders. *Market orders* include market orders, stop market orders and market to limit orders. All the numbers in each panel, for limit and market orders, sum to 100%. Quoting and trading activity sum to 100% across trader/account type, for each panel. Data are presented for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT) and six account types (OWN, CLIENT, MM, parent company orders, or PARENT, related to retail market organization or RMO, and retail liquidity provision, or RLP activities). The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A: Pre-opening period and Opening Auction

		Limit orders			**Market orders**			**Average Quoting Activity**	**Average Trading Activity**
		New orders	Modification	Cancellation	New orders	Modification	Cancellation		
PURE HFT	Client	0.18%		0.00%	0.02%		0.00%	0.2%	0.3%
	Own	33.62%	2.40%	2.04%	0.14%		0.00%	38.2%	4.9%
	RLP								
	MM	0.08%		0.04%	0.00%			0.1%	0.1%
MIXED HFT	Client	3.95%	2.88%	0.42%	0.44%	0.33%	0.07%	8.1%	14.9%
	Own	10.68%	2.48%	1.84%	2.51%	0.30%	1.09%	18.9%	35.2%
	RLP								
	MM	0.61%	1.45%	0.13%				2.2%	2.8%
	Parent	0.96%	0.00%	0.12%	0.53%	0.00%	0.33%	1.9%	6.5%
NON-HFT	Client	13.04%	0.25%	2.06%	4.40%	0.44%	0.56%	20.7%	27.1%
	Own	8.06%	0.89%	0.25%	0.23%	0.09%	0.04%	9.6%	8.1%
	RMO	0.02%	0.00%	0.00%	0.01%	0.00%	0.00%		0.1%
	Parent	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.0%	0.1%

Panel B: First 30 minutes of the Main Trading Phase

		Limit orders			**Market orders**			**Average Quoting Activity**	**Average Trading Activity**
		New orders	Modification	Cancellation	New orders	Modification	Cancellation		
PURE HFT	Client	0.03%		0.02%	0.00%	0.00%	0.00%	0.1%	0.3%
	Own	2.09%	1.31%	1.70%				5.1%	1.9%
	RLP	4.31%	1.67%	4.27%				10.3%	0.0%
	MM	14.82%	0.43%	13.68%				28.9%	20.7%
MIXED HFT	Client	1.65%	0.85%	1.33%	0.00%	0.00%	0.00%	3.8%	8.8%
	Own	6.83%	0.96%	6.04%	0.01%	0.00%	0.00%	13.8%	35.0%
	RLP	2.39%		2.36%				4.7%	0.0%
	MM	13.26%	0.36%	12.67%				26.3%	7.7%
	Parent	1.69%	0.77%	1.51%	0.00%	0.00%	0.00%	4.0%	6.9%
NON-HFT	Client	0.60%	0.26%	0.23%	0.16%	0.00%	0.07%	1.3%	13.1%
	Own	0.42%	1.01%	0.25%	0.00%	0.00%	0.00%	1.7%	5.5%
	RMO	0.00%			0.00%	0.00%	0.00%	0.0%	0.0%
	Parent	0.00%						0.0%	0.0%

We now turn to the trading activity of different trader categories in the opening auction and the first 30-minutes of the main trading phase. Interestingly, PURE-HFTs as a group are responsible for only 5.3% of the trading activity during the opening auction. The majority of trading activity, therefore, stems from MIXED-HFTs (59.4%) and NON-HFTs (35.3%). However, during the first 30-minutes of the main trading phase, the trading activity of PURE-HFTs rises to 22.9%, with almost 20.7% coming from transactions for which they wear their MM "hat." All in all, 28.4% of the total trading activity comes from transactions where at least one of the two counterparties is acting as an MM during the first 30-minutes of the main trading phase. To sum up, the trading activity of PURE-HFTs is very limited during the opening auction, while during the main trading phase, PURE-HFTs act mainly as market makers: PURE-HFTs' TAR is four times higher during main trading phase than during pre-opening phase.[21]

HFTs are often referred to as the "fastest" market participants, which is by no means obvious. To establish this in our sample, we provide summary statistics on the quoting speed of different trader categories for different periods during the day. We define speed as the time elapsed between order entry/modification and modification/cancellation of the same order. Table 1.3 presents the summary statistics of the speed distribution of the different trader groups and account types. In line with our expectation, traders are faster during the main trading phase than in the pre-opening phase (due to the absence of immediate execution). During the main trading phase, both PURE-HFT-OWN and MIXED-HFT-OWN traders are very fast, with a 1st (5th) percentile of the speed distribution of 0.28 (0.50) and 0.02 (0.36) milliseconds respectively, as compared to NON-HFT-OWN traders with a speed of 0.48 (21.66) milliseconds. This finding suggests that both PURE-HFT-OWN and MIXED-HFT-OWN traders engage in strategies that require high speed. Remarkably, NON-HFT-OWN traders also might occasionally be very fast, e.g., we may observe extremely high speed if a smart router algorithm sends an order to multiple venues and, once an order is executed on one of them, the algorithm cancels the remaining orders. However, as can be seen from the 5th percentile of the speed distribution, NON-HFT traders do not have the capacity to be persistently fast. During the pre-opening phase, PURE-HFT-OWN are much faster than MIXED-HFT-OWN traders, with a 1st (5th) percentile of the speed distribution of 0.62 (0.99) and 34.96 (452.86) milliseconds, respectively. It is noteworthy that NON-HFT-OWN are more than twice as fast as MIXED-HFT-OWN traders during the pre-opening phase, as measured by the 5th percentile of the speed distribution.[22]

[21]We observe substantial variation in HFT quoting and trading activity across stock-days. Nevertheless, HFTs are present in every stock, and on every day. The Internet Appendix, Sections A.2 and A.3 present more details on the cross-sectional and time-series distribution of HFTs activity in the pre-opening phase and the opening auction.

[22]The statistical speed comparison of different trader categories is available in Internet Appendix, Section A.4.

Table 1.3: **Speed of the Traders**

This table shows the distribution of speed capacity for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT) and six account types (CLIENT, OWN, RLP, RMO, MM, PARENT) for the pre-opening phase and the first 30-minutes of main trading phase. We refer to speed as the time elapsed between order entry/modification and modification/cancellation of the same order. We report the number of observations for which the speed can be measured, the median and the 5th percentile of the speed distribution. Speed is expressed in milliseconds. The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belongs to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Distribution of speed by stock-date

		Pre-opening Phase				First 30 minutes of the Main Trading Phase			
		Obs	Median	p5	p1	Obs	Median	p5	p1
PURE-HFT	Client	509	218'572.151	411.781	286.672	38'825	6'260.222	0.025	0.015
	Own	612'926	40.757	0.998	0.619	5'979'210	557.768	0.499	0.276
	MM	2'463	3.871	1.226	0.730	27'582'237	1'401.864	0.382	0.020
	RLP					12'468'990	415.033	2.107	0.938
MIXED-HFT	Client	270'723	10'559.414	252.372	77.849	3'785'219	8'570.877	6.016	0.026
	Own	481'779	7'777.581	452.859	34.957	12'042'621	3'265.591	0.360	0.017
	MM	115'776	4'000.250	152.875	50.503	25'462'584	4'191.120	2.315	0.219
	RLP	4	73'947.496	3'113.455	3'113.455	4'561'523	4'398.939	11.962	1.638
	Parent	32'749	146'145.375	3'094.530	1'035.097	3'938'282	10'990.470	1'000.906	998.590
NON-HFT	Client	176'896	2'011.020	470.504	57.052	965'473	16'935.029	36.383	0.018
	Own	136'782	4'155.566	186.675	38.503	2'388'079	5'732.241	21.666	0.480
	RMO	29	336'525.469	26'500.360	18'046.421	85	453'160.594	16'377.998	9'126.977
	Parent	290	437.349	18.275	12.879	186	35'925.279	3'104.647	1'722.902

1.5 Empirical results

1.5.1 The order submission decision

Hypothesis 1. *Independent of the account type for which they act, HFTs (PURE-HFTs and MIXED-HFTs) delay their order submission/cancellation decision during pre-opening phase until the very last moment before the opening auction.*

When do HFTs join the party? As mentioned earlier, the decision to submit an order during the pre-opening phase may be viewed as an American option. From the intuition of option theory, we know that, in the absence of dividends or some other benefit, it is optimal to exercise an American option only at the expiry date. Hence, one would expect that traders who are able to act fast should postpone their decision until the very last moment. Biais, Hillion, and Spatt (1999) and Davies (2003) confirm this conjecture with their empirical analysis of aggregate trader behavior. However, it is not clear from these studies if *all* traders exhibit the same behavior. We investigate this issue with our sample by looking at the order submission decisions made by different trader categories. Figure 1.1 plots the daily number of new order submissions during the pre-opening phase for each stock-day. The figure shows that the behavior of the different trader types is quite different. On the one hand, NON-HFT-CLIENT traders actively submit orders at the very beginning of the pre-opening phase. On the other hand, only MIXED-HFT-MM traders delay their order submission decision until the very last moment. Other trader categories prefer to postpone their order submission decision at least until the middle of the pre-opening phase.

FIGURE 1.1: **New Order Submissions during the Pre-Opening Phase**

This figure shows the total number of new order submissions for the most relevant trader/account categories. Each dot represents the total number of new order submitted during the one-minute window interval, for each stock-day. The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

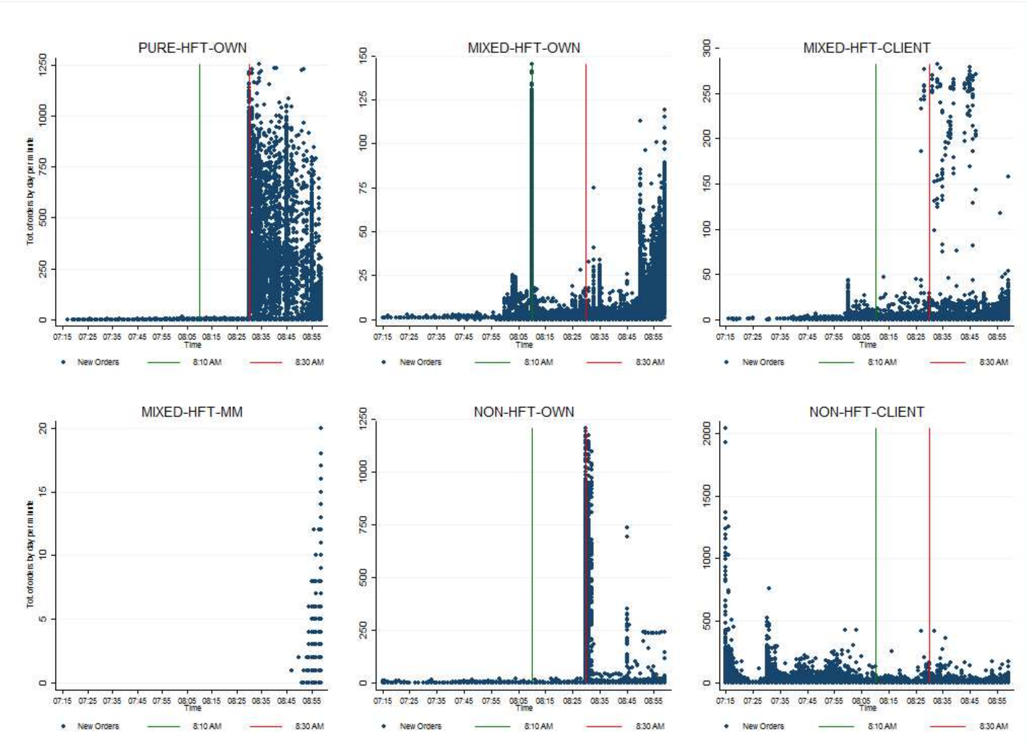
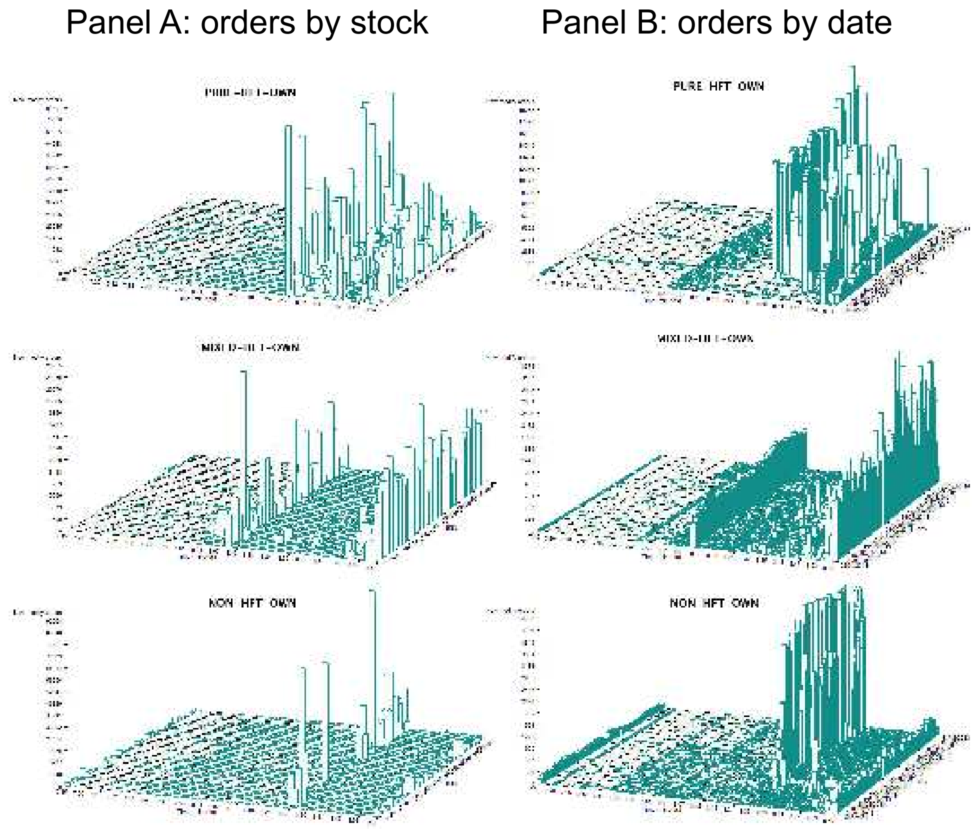


FIGURE 1.2: **New Order Submissions and Modifications across Stocks and Days during the Pre-Opening Phase**

This figure shows the total number of new order submissions for the most relevant trader/account categories. Each bar represents the total number of new order submitted during the one-minute window interval, for each stock, summed across days (Panel A) and for each day, summed across stocks (Panel B). The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belongs to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.



The party starts to become interesting in the middle of the pre-opening phase. PURE-HFT-OWN traders are almost inactive before 8.30 a.m. After 8.30 a.m., however, PURE-HFT-OWN submit a large number of orders in almost all stock-days in our sample. The exact timing of the order submission changes from one stock-day to another between 8.30 a.m. to approximately 8.55 a.m., but the number of orders submitted is similar across stock-days. We conjecture that the timing of order submission changes slightly across stock-days, in order to avoid predictable patterns in submission strategies, and thus, avoid free-riding by other market participants on the information conveyed by these order submissions (see Figure 1.2 for a breakdown of new order submissions and modifications by stock and by day). After the relevant number of new orders entered after 8.30 a.m., PURE-HFT-OWN traders remain active with a decreased intensity of order submissions, suggesting completely different behavior from the one documented in the previous literature, i.e., they do *not* exercise the American option at maturity, but instead start to exercise it well before maturity. The other main players, MIXED-HFT-OWN and NON-HFT-OWN traders, exhibit similar behavior. In particular, MIXED-HFT-OWN enter a considerable number of orders immediately after 8.10 a.m. and NON-HFT-OWN enter a considerable number of orders between 8.30 a.m. and 8.32 a.m. After that time the activity for both categories declines sharply, and rises again close to the opening auction at 9.00 a.m.

What are the factors that determine the placement of orders in the first place? Since there is no cost of placing or canceling an order, it makes sense to place an order as early as there is sufficient information about order flow from other market participants. The orders placed can always be modified or canceled, without incurring any additional cost. For both PURE-HFT-OWN and NON-HFT-OWN traders, it seems that the first flow of information arrives around 8.30 a.m., as evident in Figure 1.1. We investigate, in depth, what is driving this flow of information. Conversations with practitioners indicate to us, that the exact timing is dictated by several factors: the morning calls of the large brokerage firms, the opening time of equity derivatives markets (e.g., Eurex), order flow from the futures markets (CAC40 and STOXX50 futures contracts are open for trading from 8.00 a.m.), the information flow from news providers, (e.g. Reuters or Bloomberg). Besides, earnings announcements usually occur before 8.30 a.m. and some of the French macroeconomic news announcements are usually released around 8.00 a.m. Therefore, as soon as a large amount of information arrives in the market, both PURE-HFT-OWN and NON-HFT-OWN traders start to post orders to exploit the time priority option.

The other reason for the active participation of traders during the pre-opening phase is information extraction from the order flow. This information might come from two sources. The first is the marginal response of the aggregate system (i.e. all the other traders) to the specific strategy of the trader. The second is fundamental (private) information that comes from other market participants. Both sources of information are then reflected in the theoretical opening price, and later in the auction price. On top of the external flow of information, submitting, modifying and cancelling orders during the pre-opening phase is crucial in order to learn the marginal impact of an individual order on the theoretical opening price as well as to "ping" hidden orders.

Having documented that there are good reasons to post orders before the end of the pre-opening phase, we next consider the patterns of order cancellations. During the pre-opening phase, traders have the flexibility to time their order placement as well as subsequent modifications and cancellations, in line with exercising a compound American option to place the order, and then to modify or cancel it. What are the factors that affect cancellation decisions, and when should orders be optimally canceled? There might be several reasons to cancel an order. First, a trader might want to cancel an order in response to new information with an intent to move the theoretical opening price closer to fundamental value. Second, traders might use combinations of order submissions/cancellations to "ping" down hidden quantities. In both cases, order cancellations may occur well before the opening auction. Third, a fast trader has the option to cancel his orders at the very last moment before the opening auction, if the theoretical opening price is not in line with expectations (with or without considering the effect on the theoretical opening price).

This problem is similar to the classic case of determining the optimal stopping time of an American option. What are the costs and benefits of stopping, i.e., canceling the order? The cost is clearly the loss of the time priority, achieved from the early placement of the order, or losing one's place in the queue of all orders placed at the same price. Essentially, this amounts to the loss of the optionality or the insurance value of the option to obtain execution of the order at the initial price. There is no corresponding benefit since the agent can always place a new order at a different limit price. Hence, in the absence of a "dividend," i.e., new information, the option should be exercised in the very last moment; however, in case of a "dividend payment," i.e., information arrival, the option may be exercised earlier.

FIGURE 1.3: **Cancellations during the Pre-Opening Phase**

This figure shows the total number of order cancellations for the most relevant trader / account categories. Each dot represents the total number of cancellations during the one-minute window interval, for each stock-day. The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

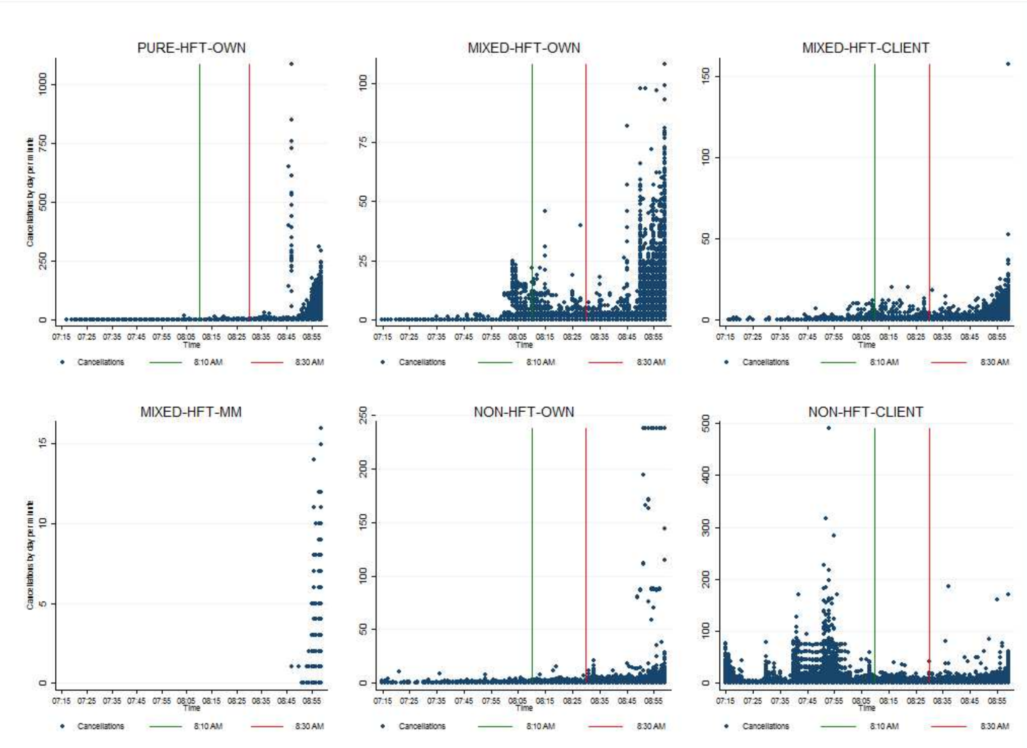


FIGURE 1.4: **Cancellations across Stocks and Days during the Pre-Opening Phase**

This figure shows the total number of cancellations for the most relevant trader/account categories. Each bar represents the total number of cancellations submitted during the one-minute window interval, for each stock, summed across days (Panel A) and for each day, summed across stocks (Panel B). The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

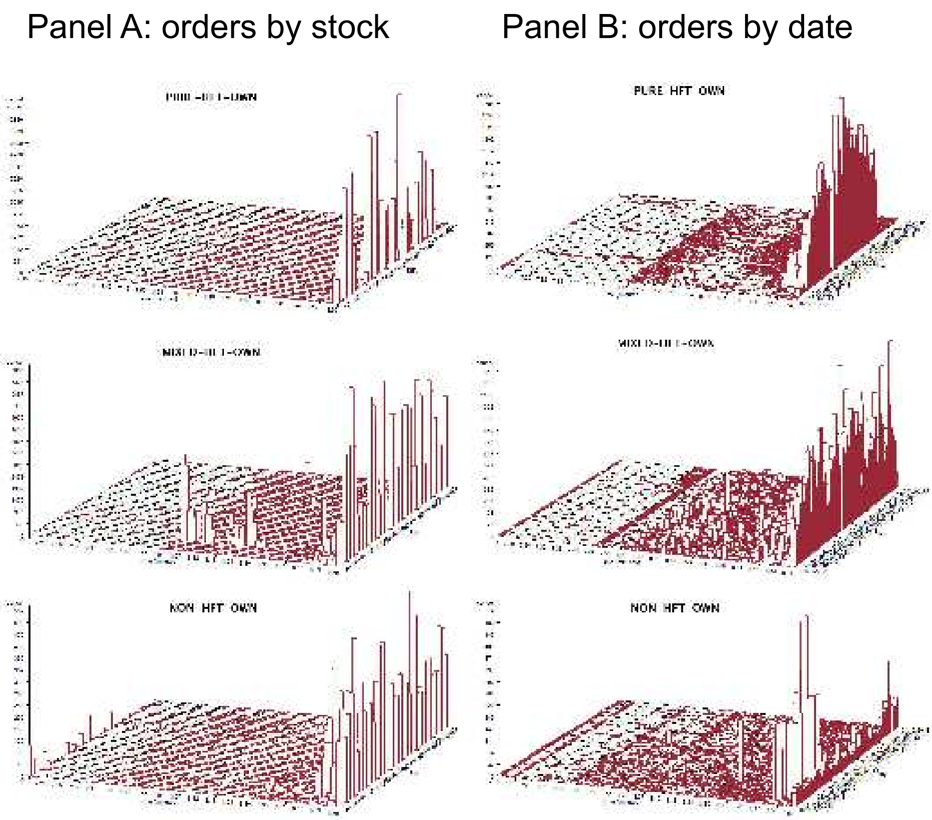


Figure 1.3 shows the pattern of cancellations for the pre-opening phase for the different trading categories, across stocks and days. With the exception of NON-HFT-CLIENT traders, whose cancellation activity starts well before 8.00 a.m., all other trader categories tend to cancel part of their orders closer to the opening auction. For PURE-HFT-OWN traders, Figure 1.3 shows that they cancel orders in a significant fashion around 8.45 a.m, as well as mostly closer to the opening auction. A reasonably large number of cancellations comes from MIXED-HFT-OWN and NON-HFT-OWN traders. However, there is a remarkable cross-sectional and time-series difference between these two categories. On the one hand, Figure 1.4 shows that the PURE-HFT-OWN traders are more selective in their cancellation activity, across stocks. On the other hand, the other two relevant traders' categories systematically cancel a consistent number of orders on all the stock in our sample. Across days, Figure 1.4 again confirms that the cancellation activity by PURE-HFT-OWN is selective,

and mostly concentrated in the very last minute of the pre-opening phase.[23][24]

New order submission and cancellation activity taken together suggests that there is no evidence that HFT activity is a result of a strategy to "ping" hidden quantities sitting in the limit order book. If the latter were true, we would observe a spike in cancellations similar to the pattern of new order submissions in Figures 1.1 – 1.2.[25] Finally, a fast trader has the option to cancel at the very last moment before the opening auction, if these orders were entered without any intention to be executed, but rather to confuse other market participants (likely, with an effect on the theoretical opening price). The latter activity is monitored by AMF, as it is considered to be price manipulation. The evidence is consistent with this view, since cancellations move the theoretical opening price in the middle of the pre-opening phase; however, cancellations have a negligible effect at the very end of the pre-opening phase. In other words, we do not find any evidence consistent with price manipulation in the spirit of the model in Medrano and Vives (2001) or the regulations in AMF (2010).[26]

We now move to a more formal test of Hypothesis 1: the order submission/cancellation hypothesis. In particular, we estimate the following probit model separately for new order entries/modifications and cancellations:

$$Pr(Y_{t,j,k,l} = 1) = \alpha_l + \sum_{t=1}^{T} \beta_{t,l} \times TD_t + \epsilon_{t,j,k,l} \tag{1.3}$$

where the $Y_{t,j,k,l}$ is equal to one, if the median number of new order submissions/modifications or cancellation per each 100 milliseconds in the time interval t is greater than the *median* of the order submissions/modifications or cancellations across day k, stock j, and time interval t, for a trader group l; TD_t is a dummy for the time interval t: 8.10-8.30, 8.30-8.59, last minute, last second, and last 100 milliseconds (all time intervals are mutually exclusive). We use the 7.15-8.10 time interval as a base case, when available; otherwise, we use the closest interval available.

We investigate first whether order submissions/modifications are different in the various intervals for the different groups of traders. The results of the probit analysis are reported in Table 1.4.

[23]There is a spike in cancellation activity by PURE-HFT-OWN traders on 25 September 2013, with the number of cancellations being almost 10 times higher than for any other day. Hence, for the sake of better visibility, the graphs exclude this day.

[24]A graphical representation of the order submissions for the last second of the pre-opening phase can be found in the Internet Appendix, Section A.5, where we show that both PURE-HFT-OWN and MIXED-HFT-OWN traders are able to submit and cancel orders even 10 milliseconds before the opening auction.

[25]Besides that, Section A.6 of the Internet Appendix shows that "iceberg orders" have only a marginal effect on the theoretical opening price. Section A.7 of Internet Appendix shows that the proportion of the hidden quantity relative to the total quantity is less than 10%, except for the last minute of the pre-opening phase.

[26]In Section 1.5.3 we apply the Weighted Price Discovery Contribution (WPDC) metric to measure which trader contributes to price discovery. A detailed breakdown of this measure, order by order, is also presented in Internet Appendix, Section A.6.

TABLE 1.4: **Order Submission**

This table shows the total number of orders submitted/modified during the particular interval of the pre-opening phase (Panel A), the total number across stock-days divided by the number of 100 millisecond intervals (Panel B), and the results of the probit regressions estimation (Panel C), where each column represents an individual probit regression for each trader/account where the dependent variable is equal to one, if the median number of orders submitted/modified in a given stock-day-interval, for each 100 milliseconds bucket, is greater than the median across stock-day-intervals of the respective trader-account group (see Equation (1.3)). ***, **, * correspond to 1%, 5%, and 10% significance levels. Standard errors are clustered at the stock level. All intervals are mutually exclusive. The base case is indicated in the table. We exclude from the regression orders submitted in the previous days that are still in the limit order book. Data and regressions are presented for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT) and two account types (OWN and MM). The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A: Total number of new and modified order submitted per account and time interval

	PURE-HFT MM	PURE-HFT OWN	MIXED-HFT MM	MIXED-HFT OWN	NONHFT OWN
Previous days		44		909	46'463
From 7:15 to 8:10		3'145		22'194	7'759
From 8:10 to 8:30	884	1'579		213'492	2'483
From 8:30 to 8:59	1'403	3'206'245	46'710	667'999	970'950
Last minute	1'397	302'359	94'332	339'933	82'905
Last second	968	16'907	7'485	24'612	13'252
Last 100 milliseconds	4	1'346	526	8'164	3'417

Panel B: Number of new and modified order submitted per account for 100ms time interval

	PURE-HFT MM	PURE-HFT OWN	MIXED-HFT MM	MIXED-HFT OWN	NONHFT OWN
From 7:15 to 8:10		0.095		0.673	0.235
From 8:10 to 8:30	0.074	0.132		17.791	0.207
From 8:30 to 8:59	0.081	184.267	2.684	38.391	55.802
Last minute	2.328	503.932	157.220	566.555	138.175
Last second	96.800	1690.700	748.500	2461.200	1325.200
Last 100 milliseconds	4.000	1346.000	526.000	8164.000	3417.000

Panel C: Probit Regression on median order submission (100 ms buckets)

	PURE-HFT MM	PURE-HFT OWN	MIXED-HFT MM	MIXED-HFT OWN	NONHFT OWN
From 7:15 to 8:10				Base	Base
From 8:10 to 8:30	Base	Base		0.473***	-0.0211
From 8:30 to 8:59	-0.0498	0.355***	Base	0.0101	0.225***
Last minute	0.721***	0.0368***	-0.0665***	0.0264***	0.0113
Last second		0.137***	0.0862***	0.351***	0.0755***
Last 100 milliseconds		0.110***	0.0961***	0.0536***	-0.0139
# obs	456	25,872	13,619	47,772	31,764
T-test on equality of coefficients					
Fstat (Pvalue)					
$\beta_{830-859}=\beta_{Lastminute}$	198.9 (0.000)	82.8 (0.000)		8.7 (0.003)	30.4 (0.000)
$\beta_{830-859}=\beta_{Lastsecond}$		23.2 (0.000)		690.9 (0.000)	13.3 (0.000)
$\beta_{Lastminute}=\beta_{Lastsecond}$		45.9 (0.000)	140.0 (0.000)	758.1 (0.000)	6.3 (0.012)

Panel A of Table 1.4 summarizes the results previously presented in Figure 1.1, and shows the total number of new orders submitted, and the number of existing orders modified, for different time intervals during the pre-opening phase. The pattern of order submission strategies across traders is very clear: PURE-HFT-OWN traders submit orders immediately after 8.30 a.m., but also during the entire last 30 minutes of the pre-opening phase. MIXED-HFT-OWN and NON-HFT-OWN orders are more concentrated around 8.10 and 8.30 a.m., but also closer to the auction.

The number of orders submitted by PURE-HFT-OWN traders (1,346) in the last 100 milliseconds prior to the opening auction is lower than those posted by NON-HFT-OWN traders (3,417), and lower than those submitted by MIXED-OWN traders (8,164). Even for the orders submitted in the last second or even in the last minute, PURE-HFT-OWN traders are not the first, but MIXED-HFT-OWN traders are. Instead, in the time bucket 8.30 – 8.59 a.m. the number of orders submitted by PURE-HFT-OWN traders is three times higher than those of the NON-HFT-OWN traders (the second group of traders for order submissions), and five times higher than the number of orders submitted by MIXED-HFT-OWN traders. Panel B of Table 1.4 reports the total number of orders submitted/modified, divided by the number of 100 milliseconds intervals for each bucket. We document that the proportion of new orders submitted for PURE-HFT-OWN traders is comparable in the last second and the last 100 ms, while for MIXED-HFT-OWN and NON-HFT-OWN traders, the number of new orders submitted in the last 100 milliseconds is two to three times higher than the orders submitted in the last second.

Panel C of Table 1.4 provides the estimation results of the probit regression for the likelihood of submitting/modifying an order per 100 milliseconds in a particular time interval, i.e., if the trader-group submits orders systematically above the median order submissions across day-stock-intervals, applying Equation (1.3). The probability of observing a number of new order submissions or modifications of existing orders greater than the median, for the PURE-HFT-OWN group between 8.30 and 8.59, is 35.5% higher than between 8.10 and 8.30. The respective probability is 13.7% higher for order submissions in the last second, and 11% higher for the last 100 milliseconds. The pattern for MIXED-HFT-OWN and NON-HFT-OWN traders is quite different compared to the one for PURE-HFTs. Compared to the base case (from 7.15 a.m. to 8.10 a.m.), the probability of observing a larger number of new orders for the former is higher in the time buckets 8.10-8.30, and also in the last second. For the latter, the higher probability buckets are those for 8.30-8.59, and again in the last second. It is noteworthy that the probability of order submissions/modifications for NON-HFT-OWN traders is not statistically significant in the last minute, and in the last 100 milliseconds, potentially indicating that their technology is reliable enough for them to wait until the last second, but not until the last 100 milliseconds.

We also conduct an F-test to compare the marginal effects of the 8.30-8.59 time interval, the last minute, and the last second intervals, and confirm that the majority of the new order submissions/existing order modifications occur between 8.30 and 8.59. Therefore, we reject our Hypothesis 1, which states that HFTs delay their order submissions decision until the very last moment of the opening auction. This behavior indicates their desire to observe and learn from the pre-opening order flow before making their order submission decisions.

We perform a similar analysis for order cancellations. In this case, the probit analysis is performed with the dependent variable $Y_{t,j,k,l}$ equal to one, if the number of cancellations in the time interval t is greater than the *median* of the cancellations across day k, time intervals t and stock j for the trader group l.

Table 1.5: **Order Cancellation**

This table shows the total number of order cancellations during the particular interval of the pre-opening phase (Panel A), the total number across stock-days divided by the number of 100 millisecond buckets (Panel B) and the results of probit regressions estimation (Panel C), for which each column represents an individual probit regression for each trader/account where the dependent variable is equal to one if the median number of orders cancelled in a given stock-day-interval, for each 100 milliseconds bucket, is greater than the median across stock-day-intervals of respective trader-account group (see Equation (1.3)). ***, **, * correspond to 1%, 5%, and 10% significance level. Standard errors are clustered at stock level. All intervals are mutually exclusive. The base case is indicated in the table. We exclude from the regression orders submitted in the previous days that are still in the limit order book. Data and regressions are presented for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT) and two account types (OWN and MM). The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A: Total number of cancelled order per account and time interval

	PURE-HFT MM	PURE-HFT OWN	MIXED-HFT MM	MIXED-HFT OWN	NON-HFT OWN
From 7:15 to 8:10		29		16'601	848
From 8:10 to 8:30	884	235		19'509	506
From 8:30 to 8:59	1'403	147'400	3'033	114'517	15'985
Last minute	203	133'554	4'906	116'507	9'787
Last second		3'977	756	7'046	1'040
Last 100 milliseconds		446		590	80

Panel B: Average number of cancelled order per account and time interval

	PURE-HFT MM	PURE-HFT OWN	MIXED-HFT MM	MIXED-HFT OWN	NON-HFT OWN
From 7:15 to 8:10		0.001		0.503	0.026
From 8:10 to 8:30	0.027	0.007		0.591	0.015
From 8:30 to 8:59	0.043	4.467	0.092	0.591	0.484
Last minute	0.006	4.047	0.149	3.531	0.297
Last second		0.121	0.023	0.214	0.032
Last 100 milliseconds		0.014		0.018	0.002

Panel C: Probit Regression on average order cancelation (100ms buckets)

	PURE-HFT MM	PURE-HFT OWN	MIXED-HFT MM	MIXED-HFT OWN	NON-HFT OWN
From 7:15 to 8:10		Base		Base	Base
From 8:10 to 8:30		0.411***		0.0823	0.0955***
From 8:30 to 8:59		0.0935	Base	0.0709***	0.0184
Last minute		0.137*	0.0876***	0.00741	-0.0472
Last second		0.322***	-0.212***	0.116***	-0.0415
Last 100 milliseconds		0.168**		0.0120	-0.0387
# obs		10,553	3,284	28,405	9,038
T-test on equality of coefficients					
Fstat (Pvalue)					
$\beta_{830-859}=\beta_{Lastminute}$		4.4 (0.037)		19.5 (0.000)	21.7 (0.000)
$\beta_{830-859}=\beta_{Lastsecond}$		82.7 (0.000)		6.0 (0.014)	16.3 (0.000)
$\beta_{Lastminute}=\beta_{Lastsecond}$		68.5 (0.000)	141.1 (0.000)	125.7 (0.000)	1.3 (0.250)

Panel A (Panel B) of Table 1.5 shows the total number (the average) of cancellations for different time intervals during the pre-opening phase. First, we observe that the number of cancellations is reasonably small as compared to the number of new order submissions/modifications. Second, the importance of speed in the pre-opening phase may be manifested through the ability to cancel the order at the very last moment to avoid an undesirable execution. Zooming into the last second/100 milliseconds, we document that PURE-HFT-OWN and MIXED-HFT-OWN traders cancel four and seven times more orders, respectively, than NON-HFT-OWN traders, in total. This finding highlights the fact that the ability to act fast permits traders to use the option to cancel more frequently.

Panel C of Table 1.5 provides the estimation results of the probit regression for the likelihood of order cancellations in a particular time interval. We document that both PURE-HFT-OWN and MIXED-HFT-OWN traders cancel their orders actively in the last minute; however, they do not defer their cancellation decisions until the very last moment. In particular, PURE-HFT-OWN traders are 9.3% (13.7%) more likely to cancel their orders between 8.30 and 8.59 (the last minute) than between 7.15 and 8.10. The cancellation probability in the last 100 milliseconds (16.8%) is remarkably higher than the probability in the entire time period between 8.30 and 8.59. For MIXED-HFT-OWN traders, only the cancellation probability between 8.30 and 8.59, and during the last minute, are statistically larger than between 7.15 and 8.10; all other marginal effects are not statistically significant. Therefore, we reject the hypothesis that HFTs delay all their order cancellation decisions until the very last moment of the opening auction, but a non-trivial quantity of orders have a higher probability (16.8%) of being canceled by PURE-HFT-OWN traders in the last 100 milliseconds.

Having tested and documented that HFTs do not delay their order submissions/modifications or cancellations until the very last moment of the opening auction, we next investigate the strategic behavior of HFTs regarding whether to prevent their orders from execution or not. In Table 1.2, we observe the relatively moderate number of cancellations relative to the number of new order submissions. These low cancellation ratios may be indicative of traders' desire to execute an order at the opening auction. An alternative explanation is that certain orders are not at all meant to be executed at the opening auction. In particular, traders can exploit a particular feature of NYSE-Euronext Paris market: according to Euronext (2016), there is a collar of 6% for CAC40 stocks on a maximum opening price deviation from the previous day's close. Hence, limit buy (sell) orders with a price lower (higher) than 6% compared to the previous day closing price cannot be executed at the auction (and clearly can be hit during the main trading phase only in case of large market swings). We refer to these orders as "flash crash" orders. In Figure 1.5, we investigate whether and how many PURE-HFTs and MIXED-HFTs orders belong to this category.

FIGURE 1.5: **Flash Crash Orders during the Pre-Opening Phase**

This figure, Panels A and B, show the total number of new flash crash order submissions, where each dot represents the total number of new order submitted during the one-minute window interval, for each stock-day; Panels C and D show the order lifetime in seconds; Panels E and F display the distribution of the (log) price difference of the previous day's closing price from the limit prices of the orders submitted during the pre-opening phase by PURE-HFTs and MIXED-HFTs, respectively. The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

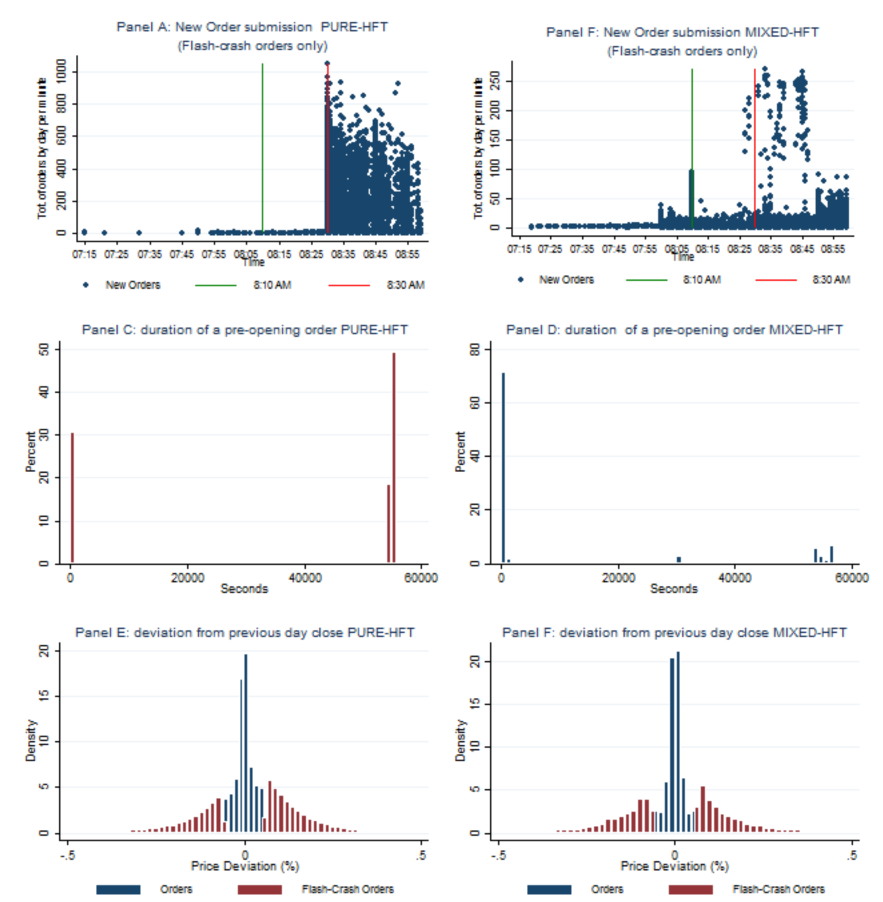


Figure 1.5, Panels A and B, show the number and timing of new flash crash orders submissions by PURE-HFT-OWN and MIXED-HFT-OWN traders, respectively. We observe that the usage of flash crash orders is mainly a feature of PURE-HFTs rather than MIXED-HFTs, and that the number and timing of flash crash order submissions is comparable to the regular orders, which is evident by comparing Figure 1.1 and Figure 1.5. A more detailed analysis reveals that the order duration (life) of an order submitted during the pre-opening phase by PURE-HFTs is strongly bimodal: an order is either cancelled or executed within one minute, or it remains until the end of the trading day (see Figure 1.5, Panel C). On the contrary, MIXED-HFTs mainly submit orders with a short lifetime (see Figure 1.5, Panel D). The orders that are cancelled or executed within one minute are perfectly in line with our expectations of HFT behavior, i.e., HFTs react fast to changes in market conditions by cancelling and resubmitting their orders. However, most PURE-HFTs post orders that can almost

never be executed at the auction, and even have very moderate chances of being executed during the main trading phase. Panels E and F of Figure 1.5 show the deviation of the limit order prices from the previous day's closing price for PURE-HFT-OWN and MIXED-HFT-OWN traders. The blue bars represent orders that can be executed at the auction, while the red bars represent orders that cannot be executed.

In summary, there is a significant number of orders that are flash crash orders, i.e., those that have prices far below or above 6% relative to the previous day's closing price. We argue that PURE-HFTs submit flash crash orders to gain time priority in case of extreme market movements, or to exploit erroneously entered orders. Given that possibility, flash crash orders should play a role only in the main trading phase, and hence, it is not surprising that other market participants do not make use of such orders, as they are not able to monitor the market continuously and react fast to changing market conditions.

Biais, Hillion, and Spatt (1999) document for the Paris Bourse that "... in fact, the last 10 minutes before the opening are the most active of the day. Further, the majority of the orders placed during the preopening period obtain execution." (Biais, Hillion, and Spatt (1999), p.1220) Contrary to these findings, we show that for PURE-HFT-OWN traders the most active period is around 8.30 am (roughly in the middle of the pre-opening phase). Moreover, most of the orders submitted by them are "flash crash" orders that cannot be executed at the opening auction, and are submitted in order to gain time priority in the main trading phase, in case of extreme market movements.

Davies (2003) focuses on the role of designated market makers in the pre-opening phase on the Toronto Stock Exchange, and documents that "high levels of pre-trade market transparency and poor incentives for early order submission cause most traders to wait until just before the TSE market opening to submit their orders." (Davies (2003), p. 492) Contrary to his findings, we document that the usage of MM accounts by HFTs (PURE and MIXED) is marginal as compared to the usage of their OWN accounts in the pre-opening phase. However, when HFTs do use their MM accounts, they indeed tend to defer their activity to the end of the pre-opening phase.

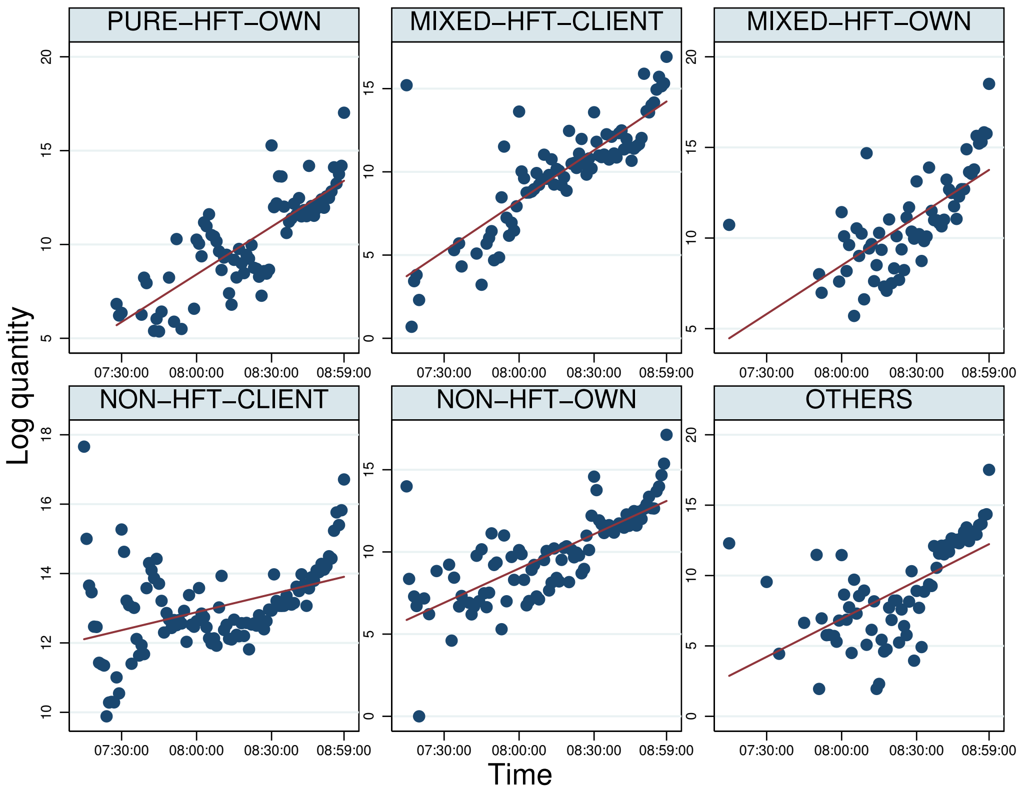
In the next section, we turn to a discussion of whether there is any pecuniary benefit for HFTs to execute their orders in the opening auction.

1.5.2 Profits

Hypothesis 2. *Independent of the account type for which they act, HFTs (PURE-HFTs and MIXED-HFTs) do participate in the pre-opening phase and the opening auction because they are able to use their speed advantage to make profits.*

FIGURE 1.6: **Time of submission and quantity executed at the auction**

The scatter plots shows, for each trader/account, the (log) of the total quantity executed at the auction and the time where the executed orders have been submitted. We exclude from the representation all market orders and the aggressive orders submitted during the pre-opening phase. The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

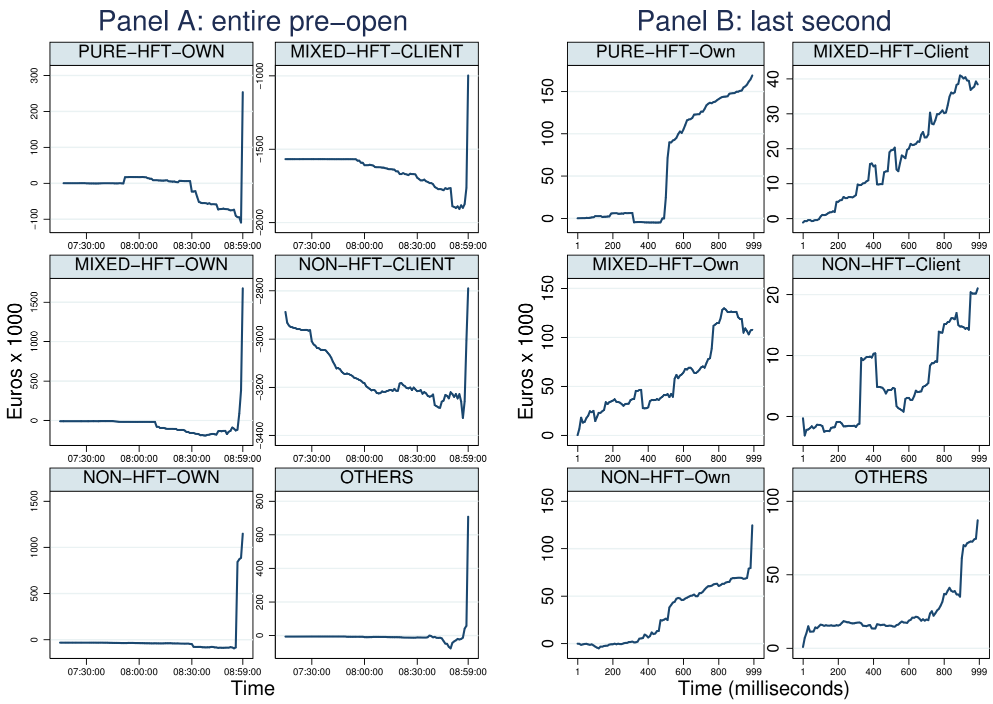


In order to test this hypothesis, we start our analysis by investigating, whether the quantity executed at the opening auction depends on the time of order entry/modification. Figure 1.6 plots the log-quantity executed in the auction aggregated by the time of order entry, excluding market and aggressive orders, for which execution is guaranteed. We show that for all categories, there is a positive relation between the time of the order entry/modification (closeness to the opening auction) and the log-quantity executed. This suggests that the ability to post an order closer to the opening auction increases the probability of being executed. However, Figure 1.6 does not allow us to answer the question of whether market participants can make larger profits on orders entered closer to the opening auction. We, therefore, investigate the ability of the different traders to potentially make profits. Figure

1.7 plots the cumulative potential profits aggregated across stock-days made on orders submitted during the pre-opening phase (Panel A), and the last second of the pre-opening phase (Panel B), assuming that the position taken in the auction is reversed one-minute after the auction at the market price, i.e., it is evaluated at the mark-to-market price one minute after the opening auction.

FIGURE 1.7: **Time of submission and cumulative profits**

The figure shows, for each trader/account, the cumulative profits (aggregated across executed order-stock-days) on the position taken at the auction and the time where the executed order has been submitted during the entire pre-opening phase (Panel A) and during last second of hte pre-opening phase (Panel B). We assume that position taken in the auction is liquidated one minute after the auction at the market price. The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.



Panel A of Figure 1.7 shows that almost all the different groups of traders lose money on orders entered at the beginning of the pre-opening phase, and potentially make money (or reduce their losses) on orders entered at the very end of the pre-opening phase. More specifically, PURE/MIXED-HFT orders show positive cumulative returns on orders executed at the opening auction, if evaluated at the mark-to-market price one minute after the auction (the only exception being the MIXED-HFT-CLIENT group). Given that the auction price evaluated one minute after is a zero-sum game, the traders that show negative cumulative returns in this case are NON-HFTs, especially the NON-HFT-CLIENT category. However, NON-HFT-OWN traders show a profit pattern similar to that of PURE/MIXED-HFT-OWN traders.

We next investigate how relevant speed is to realize these profits. In order to determine whether speed matters in generating profits, we zoom into the very last second of the pre-opening phase (see Panel B of Figure 1.7). In this manner, we are able to highlight whether fast traders can potentially make profits on late order submissions, and whether speed is a necessary condition for making profits on these orders. Surprisingly, we observe that not only is the PURE/MIXED-HFTs group able to make profits on the orders entered in the last second, but pretty much all the different groups of traders do, with the NON-HFT-OWN traders showing a capacity to generate profits similar to those of PURE-HFT-OWN traders. However, the cumulative profits of NON-HFT-OWN traders increase uniformly through the last second; in contrast, those of PURE-HFT-OWN traders are more concentrated in the last 500 milliseconds. In any case, the orders submitted by NON-HFT-OWN traders in the last few milliseconds do result in a significant increase in their cumulative profits. The explanation for this persistent pattern is twofold. First, the most likely informed traders in our groups are the NON-HFT-OWN traders, who can potentially make profits based on their informational advantage. However, the HFTs have the speed advantage to react milliseconds before the opening of the market, and potentially exercise the option to cancel. The final result is that the fundamental information available to NON-HFT traders can sometimes outweigh the speed advantage of the HFTs. Second, even slow traders often do use algorithms for order submissions and, given that the opening time is fixed, it is relatively easy to time the order submissions until the last few milliseconds before the auction.[27]

In order to formally answer the question of whether speed allows traders to engage in more profitable transactions, we estimate the following regression:

$$Profit_{t,j,k,l} = \sum_{t=1}^{T} \beta_{t,l} \times TD_t + \epsilon_{t,j,k,l} \tag{1.4}$$

where the $Profit_{t,j,k,l}$ is the profit that is made on the executed orders submitted/modified in the time interval t, for a trader group l, on day k, for stock j, assuming that the position is reversed one-minute after the auction; and TD_t is a dummy for the time interval t: 7.15-8.10, 8.10-8.30, 8.30-8.59, last minute, last second, and last 100 milliseconds (all time intervals are mutually exclusive).

[27] We also look, in detail, at the distribution of the returns across the individual orders executed. Internet Appendix, Section A.8 zooms into the picture of profits made by each order that was submitted in the last second.

Table 1.6: **Cumulative Profits**

This table shows the cumulative profits, in euros, during the particular interval of the pre-opening phase (Panel A) and linear regressions estimation separately for each trader/account (Panel B). In panel B, each column represents an individual regression for each trader/account category where dependent variable is the total return for each interval-stock-day (see Equation (1.4)). ***, **, * correspond to 1%, 5%, and 10% significance levels. All intervals are mutually exclusive. The regressions are estimated without a constant. Data and regressions are presented for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT) and two account types (OWN and MM). The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A: Total Profits for each time interval per account and time interval of order submission

	PURE-HFT MM	**PURE-HFT OWN**	**MIXED-HFT MM**	**MIXED-HFT OWN**	**NON-HFT OWN**
Previous days				-9'884.02	-33'738.52
From 7:15 to 8:10		8'488.83		-7'107.70	-5'020.14
From 8:10 to 8:30		-2'293.02		-141'723.12	-7'655.94
From 8:30 to 8:59		-115'667.13	103.98	540'266.45	933'642.52
Last minute	81.82	194'036.68	49'224.66	1'185'957.42	137'699.88
Last second	8'100.02	148'265.81	21'702.22	126'087.88	68'944.08
Last 100 milliseconds	40.64	20'717.75	50'028.00	-18'247.89	55'721.31

Panel B: Regression on cumulative returns

	PURE-HFT MM	**PURE-HFT OWN**	**MIXED-HFT MM**	**MIXED-HFT OWN**	**NON-HFT OWN**
Forgotten Orders				-898.5	-267.8*
From 7:15 to 8:10		8.258		-25.66	-13.49
From 8:10 to 8:30		-4.343		-65.64***	-18.14
From 8:30 to 8:59		-21.36*	20.80***	73.07**	171.1
Last minute	16.36***	31.51*	11.25*	160.8***	35.17
Last second	10.83***	47.87***	15.28**	26.04***	15.81***
Last 100 milliseconds	13.55*	45.14***	335.8**	-3.612	25.87***
# obs	756	16,685	5,948	27,112	16,806
Adj R^2	0.034	0.003	0.012	0.002	0.000
T-test on equality of coefficients					
Fstat (Pvalue)					
$\beta_{830-859}=\beta_{Lastminute}$		4.2 (0.048)	2.5 (0.120)	3.5 (0.071)	0.8 (0.373)
$\beta_{830-859}=\beta_{Lastsecond}$		28.7 (0.000)	0.7 (0.399)	1.6 (0.213)	0.9 (0.360)
$\beta_{Lastminute}=\beta_{Lastsecond}$	4.7 (0.036)	0.7 (0.400)	0.3 (0.620)	6.0 (0.019)	0.3 (0.617)
$\beta_{Lastsecond}=\beta_{Last100ms}$	0.1 (0.727)	0.1 (0.791)	5.1 (0.030)	9.2 (0.005)	1.7 (0.198)

Panel A of Table 1.6 shows the total profit made on the orders executed at the auction depending on the time of order entry/modification aggregated across orders, stocks, and days. We observe that virtually all traders lose money on orders entered in the beginning of pre-opening phase, and make money on orders entered at least as late as the last minute before the auction, as already highlighted in Figure 1.7.[28]

Panel B of Table 1.6 provides the results from the profit regression estimation. We observe that PURE-HFT-OWN traders as a group earn, on average, across stock-days, 45.14 euros on orders entered in the last 100 milliseconds, with the highest amount earned on last second orders: 47.87 euros. However, an F-test suggests that

[28]We also document the standard deviation of the stock-day profits for each trader/account category and show that PURE-HFT-OWN traders have the least volatile profits among proprietary traders. Besides these, profit volatility steadily decreases from one minute until 100 milliseconds before the opening auction. Results are available from the authors upon request.

we cannot reject the equality of the total profits made during these two intervals. We would like to emphasize that this is an average number and, therefore, does not exclude the possibility that some HFTs might make larger profits or larger losses. MIXED-HFT-OWN traders make the largest profits on the orders entered in the last minute before the auction (160.8 euros), while NON-HFT-OWN traders make the largest profits in the last second (15.81 euros), and the last 100 milliseconds before the auction (25.87 euros).

Panel B of Table 1.6 also provides the results of the F-test for whether cumulative profits in the last second are statistically different from those in the last minute, or in the interval 8.30 – 8.59 a.m. In most cases, the null hypothesis cannot be rejected due to the fact that profits are very volatile. The only exceptions are PURE-HFT-OWN and MIXED-HFT-OWN traders, for whom we reject the equality of profits during the last minute of the pre-opening phase and profits during the 8.30 –8.59 a.m. period. The cases where the null hypothesis that the cumulative profits of the last second are statistically equal to the cumulative profits in the last minute, are rejected: the cumulative profits in the last second are lower than those in the last minute.

Essentially, we observe that not only are HFT traders able to submit orders close to the opening auction, but they are able to earn positive profits on them. We argue that NON-HFTs traders may enjoy the same speed advantage as PURE/MIXED-HFT traders because the exact timing of the auction (9.00 a.m.) is known, and hence even slow traders may have a simple algorithm to check the theoretical opening price in a fraction of a millisecond before the opening auction, and make their order submission decisions. Our finding is in line with the theoretical predictions of Budish, Cramton, and Shim (2015), who argue that frequent batch auctions might reduce the speed advantage of HFTs and thus, make markets more "fair."

In summary, we document that speed is important for making profits on the orders executed during the opening auction; however, we fail to document that HFTs have a pronounced speed advantage relative to NON-HFTs in the pre-opening phase, perhaps due to the known fixed-timing of the auction. In the next two subsections, we discuss whether the presence of HFTs in the pre-opening phase has any positive externalities for other market participants, by looking at their effect on price discovery and liquidity provision.

1.5.3 Price discovery

Hypothesis 3. *Independent of the account type for which they act, HFTs contribute to the price discovery process, during different periods of the trading day (the pre-opening phase and the first 30-minutes of the main trading phase.*

We measure the contribution of different trader groups to price discovery, using a modified version of the weighted price discovery (WPC), a concept proposed and used by Barclay and Warner (1993), Cao, Ghysels, and Hatheway (2000), and Barclay and Hendershott (2003). Specifically, we first define the price discovery contribution, order by order (PDC), as follows:

$$PDC_{i,j,k} = Deviation_{i,j,k} - Deviation_{i-1,j,k} \tag{1.5}$$

where the $Deviation_{i,j,k}$ is a measure of the deviation of the i-th order price, for stock j, on day k, relative to the reference price, being the opening price for the call auction, or to the price observed at 9.30 a.m., 30-minutes into the main trading phase of the trading day. The deviation is calculated in two different ways for the pre-opening and main trading phases. For both versions of the calculation, a reduction in the deviation is viewed as a contribution to price discovery (the total deviation sums up to -100%).

For the main trading phase, we focus on trades, and the deviation of the traded price is calculated as follows:

$$Deviation_{i,j,k} = \left| \frac{P_{i,j,k}}{P930_{j,k}} - 1 \right| \times 100 \tag{1.6}$$

where $P_{i,j,k}$ is the trading price at the time of the i-th transaction, for stock j, on day k, and $P930_{j,k}$ is the price at 9.30 a.m. for stock j on day k. The return in the first 30-minutes is calculated using, as the end point, the average traded price between 9.30 a.m. and 9.35 a.m., in order to minimize the effect of the bid-ask bounce. The contribution to price discovery is, therefore, the amount by which the $Deviation_{i,j,k}$ is reduced from the $Deviation_{i-1,j,k}$. A unique feature of our dataset is that the orders that initiated the trade, i.e., the "aggressive orders," are directly identified by NYSE-Euronext Paris, thus simplifying our identification, and allowing us to determine the direction of the trade.

For the pre-opening phase, $Deviation_{i,j,k}$ is defined as

$$Deviation_{i,j,k} = \left| \frac{T_{i,j,k}}{O_{j,k}} - 1 \right| \times 100 \tag{1.7}$$

where $T_{i,j,k}$ is the theoretical opening price at the time of arrival of order i, for stock j, on day k, and $O_{j,k}$ is the actual opening price for stock j on day k. A negative $PDC_{i,j,k}$ (see Equation (1.5)) reduces the deviation, and moves the price closer to the reference price. Finally, the $WPDC$ for stock j, day k, and order i, is defined as follows:

$$WPDC_{i,j,k} = \frac{PDC_{j,k}}{\sum\limits_{j} |PDC_{j,k}|} \times \frac{PDC_{i,j,k}}{PDC_{j,k}} \tag{1.8}$$

where $PDC_{i,j,k}$ is the price discovery contribution of order i, for stock j, on day k and $PDC_{j,k}$ is the accumulated price discovery contribution for stock j, on day k. The first term of WPC is the weighting factor for the stock on day k. The second term is the percentage contribution of price discovery made by order i to the total price discovery, during either the pre-opening or the main trading phase, for stock j on day k.

$$WPC_{j,k,l} = \sum \beta_l * I_l + e_{j,k,l} \tag{1.9}$$

where $WPC_{j,k,l}$ is our measure of price discovery for stock k, on day j, for trader/account l. I_l is a dummy variable that equals 1 for trader/account l.

TABLE 1.7: **Weighted Price Discovery Contribution (WPDC)**

This table shows the average $WPDC$ (Panel A) and the linear regressions estimation (Panel B). Price discovery metrics are defined in Section 1.5.3. In Panel A, each column represents $WPDC$ for different intervals in the pre-opening phase, and the first 30 minutes of the main trading phase. The last line in Panel A, represents the proportion of price discovery left for a particular interval. In Panel B, each column presents thr estimation results of the linear regression (see Equation (1.9)) for different intervals. The regressions are estimated without a constant. For the purpose of $WPDC$ computation, intervals are not mutually exclusive. ***, **, * correspond to 1%, 5%, and 10% significance levels. The $WPDC$ is presented for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT), six account types (CLIENT, OWN, RLP, RMO, MM, PARENT) during the pre-opening phase and the first 30-minutes of the main trading phase. The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A: Weighted Price Discovery Contribution (WPDC)

		Entire pre-opening	**From 8:10**	**From 8:30**	**Last minute**	**Last second**	**Last 100 milliseconds**	**First 30 min. of Main Phase**
PURE HFT	Client	0.32%	-0.09%	-0.12%	-0.14%	-0.03%		-0.31%
	MM	-0.03%	-0.02%	-0.02%	-0.06%	-0.49%		-38.31%
	OWN	-11.75%	-9.07%	-8.86%	-1.97%	-13.61%	-8.75%	-2.47%
MIXED HFT	Client	-8.75%	-7.86%	-8.90%	-2.89%	-2.30%	-1.66%	-6.88%
	MM	-6.03%	-5.07%	-5.06%	-10.54%	-2.79%	-0.75%	-6.03%
	OWN	-47.47%	-37.35%	-40.74%	-51.92%	-54.61%	-81.83%	-31.03%
	Parent	-12.71%	-10.47%	-10.03%	-14.49%	-0.91%	-0.52%	-10.00%
NON HFT	Client	3.09%	-16.48%	-13.27%	-4.31%	-0.82%	-1.42%	-1.03%
	OWN	-16.96%	-13.74%	-13.16%	-13.78%	-24.39%	-4.27%	-3.85%
	Parent	0.24%	0.24%	0.25%	0.11%	-0.04%	0.01%	0.02%
	RMO	0.05%	-0.08%	-0.07%	0.00%	0.00%		-
	WPDC left		-122.83%	-121.78%	-48.77%	-10.60%	-1.71%	

Panel B: WPDC Regression

		Entire pre-opening	**From 8:10**	**From 8:30**	**Last minute**	**Last second**	**Last 100 milliseconds**	**First 30 min. of Main Phase**
PURE HFT	Client	0.00324	-0.000950	-0.00123	-0.00142**	-0.000273		-0.00314
	MM	-0.000259	-0.000195	-0.000223	-0.000608*	-0.00493**		-0.383***
	OWN	-0.118***	-0.0907***	-0.0886***	-0.0197***	-0.136***	-0.0875***	-0.0246***
MIXED HFT	Client	-0.0875***	-0.0786***	-0.0890***	-0.0289***	-0.0230***	-0.0166**	-0.0688***
	MM	-0.0603***	-0.0507***	-0.0506***	-0.105***	-0.0279***	-0.00749**	-0.0603***
	OWN	-0.475***	-0.374***	-0.407***	-0.519***	-0.546***	-0.818***	-0.310***
	Parent	-0.127***	-0.105***	-0.100***	-0.145***	-0.00909***	-0.00520*	-0.100***
NON HFT	Client	0.0309	-0.165***	-0.133***	-0.0431***	-0.00817***	-0.0142***	-0.0103
	OWN	-0.170***	-0.137***	-0.132***	-0.138***	-0.244***	-0.0427***	-0.0384***
	Parent	0.00239**	0.00237***	0.00252***	0.00107	-0.000434	8.03e-05	0.000171
	RMO	0.000452	-0.000763	-0.000739	-3.27e-05	-1.18e-05		-0.00001
Adj R^2		0.340	0.318	0.597	0.865	0.837	0.858	0.469
# obs		3,012	3,012	3,012	2,761	2,761	1,976	4,518

Panel A of Table 1.7 reports the average $WPDC$ for each trader/account category, for the pre-opening and the main trading phases. Remarkably, orders entered in the beginning of the pre-opening phase deteriorate price discovery. Most of these orders come from the NON-HFT-CLIENT group and move the theoretical opening price away from the actual auction price. From 8.30 to 8.59, when all other trader/account types join the party, around 50% of the price discovery occurs, which translates into the fact that half of the total price discovery occurs in the last minute of the pre-opening phase. One second before the opening auction, the absolute deviation of the theoretical opening price from the actual auction price is around 10.60%. This deviation reduces to 1.71%, 100 milliseconds before the auction takes place.

The MIXED-HFT-OWN traders consistently lead to price discovery during the pre-opening phase in all sub-periods, with a $WPDC$ of 47.47% for the entire pre-opening phase. The price discovery contribution of MIXED-HFT-OWN increases, the closer the order time is to the opening auction and reaches 81.81% in the last 100 milliseconds. The contribution of PURE-HFT-OWN trades to price discovery during the entire pre-opening phase is 11.75%. In the last second (100 milliseconds), PURE-HFT-OWN trades contribute 13.61% (8.75%) to price discovery. Interestingly, NON-HFT-OWN trades contribute 24.39% (4.27%) in the last second (100 milliseconds) to $WPDC$. Most of the price discovery occurs via newly entered limit orders. Notably, in the last second and 100 milliseconds, this pattern does not change. In other words, cancellations only marginally move the price at the very last moment before the opening auction.[29]

Regression results are reported in Panel B of Table 1.7, and the F-tests for the equality of coefficients are available from the authors upon request. Regression results confirm the evidence provided by the summary statistics. Traders trading on their OWN account lead the price discovery. MIXED-HFT-OWN, NON-HFT-OWN, and PURE-HFT-OWN trades are the first, second, and third largest contributors to price discovery for the entire pre-opening phase, respectively. Notably, the same pattern is observed in the last second of the pre-opening phase. These results are consistent with our profit analysis, where we document that slow traders also profit more from the orders executed in the auction that were entered as close as possible to the auction and, therefore, these orders are likely to have greater informational content. In the first 30 minutes of the main trading phase, PURE-HFT-MM traders start actively participating in the market. They are the largest contributors to price discovery (38.31%), followed by MIXED-HFT-OWN trades with a $WPDC$ of 31.03%. The contribution of PURE-HFT-OWN trades to $WPDC$ falls to 2.47% in the main trading phase, as compared to 11.75% in the pre-opening phase.

In summary, HFTs as a group lead to price discovery during the pre-opening phase (in all sub-periods, and not only in the very last moment), and during the main trading phase, although the breakdown per trader/account shows that this contribution is provided by different HFT trader groups between the two different phases.

1.5.4 Liquidity provision

Hypothesis 4. *Independent of the account type for which they act, HFTs are the main liquidity providers during the opening auction and the first 30-minutes of the main trading phase.*

In this subsection, we investigate whether HFTs provide quasi-liquidity in the opening auction. Recall that we refer to quasi-liquidity provision because the classical definition of liquidity provision cannot be applied to the trades in the opening call auction. More specifically, in the literature, there are different definitions of liquidity provision; for example, AMF (2017) use two common metrics of the liquidity provision in the main trading phase: market depth (number of shares at the inside levels of the limit order book) and the bid-ask spread (the actual round-trip transaction cost). However, due to the absence of the immediate execution, the bid and ask schedules in

[29]The Internet Appendix Section A.6 provides a detailed breakdown of $WPDC$ for each order type: only 0.18% (2.77%) of the total price discovery is due to cancellations of limit orders, and 1.3% (0.45%) is due to cancellation of market orders in the last second (100 milliseconds).

the pre-opening phase are crossed and, hence, it is not clear how to define the inside levels of the limit order book. Besides, all orders are executed at a single price during the auction and, hence, there is no bid-ask spread in the auction, either. Therefore, we propose the concept of quasi-liquidity in the opening auction, where liquidity provision is defined as the number of shares traded against the overnight market movement, and liquidity consumption as the number of shares traded in the direction of the overnight market movement. Conceptually, this is in line with the liquidity definition of Brogaard, Riordan, Shkilko, and Sokolov (2014) who measure liquidity provision in the main trading phase as the directional trade imbalance computed as the difference between trading activity in the opposite direction of extreme price movements, and trading activity in the direction of the extreme price movement.

In order to make the measure comparable between the opening auction and the main trading phase, and in line with Brogaard, Hendershott, and Riordan (2014a), who define marketable orders as liquidity demanding orders and nonmarketable orders as liquidity supplying orders for each trade, we calculate liquidity consumption in the main trading phase as the number of shares traded, if the trader initiates the trade, and liquidity provision as the number of shares traded, if the trader does not initiate the trade.

During the main trading phase, we determine who initiates a trade by looking at the time stamp of order entry/modification of the orders culminating in transactions or looking at a particular flag, called the "aggressivity indicator," provided by NYSE-Euronext Paris on a trade-by-trade basis.[30] Based on this information, we calculate whether traders are providing or consuming liquidity in a particular transaction. Therefore, during the main trading phase, we consider the trader/account category as a liquidity provider, if it posts orders that do not initiate trades, i.e., orders that are not market orders or marketable limit orders.

For each trader/account, l, for each stock j, on each day, k, during the main trading phase, we calculate the net liquidity provision, NLP, as the difference between liquidity provision and liquidity consumption for the main trading phase:

$$\begin{aligned} NLP_{j,k,l} = & \frac{\text{Number of shares traded}_{j,k,l} \mid \text{Trader/Account}_l \text{ does not initiate trade}}{\text{Total traded volume of first 30 minutes of main trading phase}_{j,k}} \\ & - \frac{\text{Number of shares traded}_{j,k,l} \mid \text{Trader/Account}_l \text{ initiates trade}}{\text{Total traded volume of first 30 minutes of main trading phase}_{j,k}} \end{aligned} \tag{1.10}$$

However, in the case of the opening auction, we cannot distinguish between whether a particular trader/account type initiated the trade or not. Therefore, we use information about the overnight return since the close of the prior trading day to determine whether a trader/account trades in the direction of the market movement or against it. We consider a trader/account as a quasi-liquidity provider, if it trades against the market movement, i.e., if it sells (buys) when the overnight return is positive (negative). Conversely, we consider a trader/account as a liquidity consumer, if it trades in the direction of the market: it buys (sells) when the overnight return is positive (negative). We measure NLP during the opening auction as the difference between the liquidity providing volume and the liquidity consuming volume:

[30] We verify the consistency of the flag by mapping all the trades with the original submitted orders. The most recent order (the aggressive order) identifies the same trade initiator as the NYSE-Euronext "aggressivity indicator."

$$NLP_{j,k,l} = \frac{\text{Number of shares}_{j,k,l} \text{ traded against the direction of the market}}{\text{Total traded volume of the auction}_{j,k}} - \frac{\text{Number of shares}_{j,k,l} \text{ traded in the same direction as the market}}{\text{Total traded volume of the auction}_{j,k}} \tag{1.11}$$

Thereafter, we estimate the following regression to test whether a particular trader/account category provides or consumes liquidity in the net terms:

$$NLP_{j,k,l} = \sum \beta_l * I_l + e_{j,k,l} \tag{1.12}$$

where $NLP_{j,k,l}$ is our measure of price discovery for stock k, day j, trader/account l. I_l is a dummy variable that equals 1 for trader/account l.

Table 1.8: **Net Liquidity Provision**

This table shows the average net liquidity provision, i.e., liquidity provision minus liquidity consumption relative to the total trading volume (Panel A) and the linear regressions estimation (Panel B). Liquidity provision metrics are defined in Section 1.5.4. In Panel B, each column presents estimation results of the linear regression (see Equation (1.12)) for different intervals. The regressions are estimated without a constant. ***, **, * correspond to 1%, 5%, and 10% significance levels. The NLP is presented for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT), and six account types (CLIENT, OWN, RLP, RMO, MM, PARENT) during the pre-opening phase and the first 30-minutes of the main trading phase. The sample is composed of 37 stocks traded on NYSE-Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A: Average net liquidity provision

		Opening auction	First 30 minutes
PURE-HFT	Client	-0.09%	-0.03%
	OWN	1.11%	1.49%
	MM	0.01%	-10.84%
	RLP		0.01%
MIXED-HFT	Client	-3.82%	1.46%
	OWN	-2.29%	2.26%
	MM	1.68%	3.50%
	Parent	0.28%	0.01%
	RLP		-5.10%
NON-HFT	Client	0.96%	3.42%
	OWN	2.19%	3.79%
	RMO	0.04%	-0.01%
	Parent	-0.08%	0.03%

Panel B: Net liquidity provision regression by stock-date

		Opening auction	First 30 minutes
PURE-HFT	Client	-0.000902***	-0.000312*
	OWN	0.0111***	0.0149***
	MM	0.00007	-0.108***
	RLP		0.000109***
MIXED-HFT	Client	-0.0382***	0.0146***
	OWN	-0.0229***	0.0226***
	MM	0.0168***	0.0350***
	Parent	0.00283	-0.0510***
	RLP		0.000126***
NON-HFT	Client	0.00961*	0.0342***
	OWN	0.0219***	0.0379***
	RMO	0.000396***	-0.000115***
	Parent	-0.000785***	0.000288***
	# obs	100,672	118,976
	Adj R^2	0.0117	0.226
	Clustered St. Err: By Stock		

Table 1.8 Panel A reports the net liquidity provision, NLP, which we define in Equation (1.10) for the first 30-minutes of the main trading phase, and in Equation (1.11) for the opening auction. Table 1.8 Panel A shows that, in general, the HFTs are weak quasi-liquidity providers, consuming quasi-liquidity using the CLIENT account

(NLP of -0.09%) and providing quasi-liquidity with OWN accounts (NLP of 1.11%) and with their MM accounts (0.01%) at the opening auction. They are one of the largest quasi-liquidity providers in the opening auction after NON-HFT-OWN (NLP of 2.19%) and MIXED-HFT-MM (NLP of 1.68%) accounts. MIXED-HFT-CLIENT and MIXED-HFT-OWN accounts are the largest net quasi-liquidity consumers with a NLP of -3.82% and -2.29%, respectively.

We next run the regression using the specification in Equation (1.12). The results are reported in Table 1.8 Panel B, and the F-tests for the equality of coefficients are available from the authors upon request. We confirm that NON-HFT-OWN and MIXED-HFT-MM trades share first place, while PURE-HFT-OWN and NON-HFT-CLIENT trades share second place, in terms of net quasi-liquidity provision. MIXED-HFT-OWN accounts are the second largest quasi-liquidity consumers in the opening auction. In the opening auction, HFTs trading on their OWN account jointly consume quasi-liquidity, and adding activity stemming from MIXED-HFT-MM traders shows that HFTs neither provide nor consume quasi-liquidity. The latter is consistent with Davies (2003), who shows that designated market makers moderate overnight price changes.[31]

Analyzing the first 30-minutes of the main trading phase reveals that the PURE-HFT-MMs are the largest liquidity consumers with an NLP of -10.84%. The two largest liquidity providers are again the NON-HFT-OWN and MIXED-HFT-MM categories with NLP of 3.79% and 3.50% respectively, while PURE-HFT-OWN traders have a NLP of 1.49% during main trading phase. Regression analysis confirms that in the first 30 minutes of the main trading phase, NON-HFT-OWN, NON-HFT-CLIENT, and MIXED-HFT-MM traders are the main liquidity providers, while PURE-HFT-MM traders are the largest liquidity consumers. The F-test of the joint effect of the HFTs on liquidity reveals that HFTs as a group consume liquidity during the main trading phase with this effect solely driven by PURE-HFT-MM trades.

In sum, we show that HFTs, as a group, neither harm nor help quasi-liquidity in the opening auction, with those acting as designated market makers strongly moderating the overnight price movements.

1.6 Conclusion

There is an ongoing debate regarding whether HFTs use their speed advantage to help or harm the fairness and efficiency of financial markets. We examine, in detail, HFT behavior, the profitability of their trades, and the externalities of their actions, with the aim of verifying whether their quoting and trading activity during the pre-opening phase simply amplify the trading noise or lead to an improvement in price formation. The pre-opening phase, together with the opening auction, is a unique period of the trading day for many reasons: the overnight accumulation of information, the release of new information before the opening of the market, and a market setup, at least for the NYSE-Euronext Paris and some other major exchanges, which does not allow immediate execution. Therefore, this calls for a set of specific strategies that differ substantially from those during the main trading phase. The previous literature on the pre-opening phase of the trading day is focused on traditional market makers, in an earlier era when automatic high-speed trading was not predominant. In the case of NYSE-Euronext Paris, where the presence of HFTs is substantial, we find that HFTs

[31] In the Internet Appendix, Section A.9, we also perform the analysis on the presence of HFTs in the limit order book close to the theoretical opening price, which is similar to the usual analysis for liquidity provision during the main trading phase, although we note that the interpretation of such an analysis differs substantially in the pre-opening phase as compared to the main trading phase.

do not delay their order submission/cancellation decision until the very last moment before the pre-opening phase. They are neither the first nor the last to enter the market; they join the party in the middle of the pre-opening phase, after observing the initial order flow, and learn from it.

Taking a broader perspective, leveling the playing field across market participants is a common objective for both the regulators and the exchange. On the one hand, our results show that the presence of HFTs does not disrupt the market during the pre-opening phase, and the speed differences between the market players does not create substantial inequalities of market access. The comparison of the profits of the different players provides an additional indication regarding the fairness of the market: if one trader is systematically able to make profits at the expense of other trading members, then a correction mechanism has to be added by the regulators and the exchange. Our analysis of the returns shows that HFTs are able to profit from their executions in the opening auction, especially from the orders that are submitted or modified in the very last second of the pre-opening phase. However, we document similar effects for NON-HFTs as well, suggesting that speed is not a necessary condition to make profits, at least in the context of the fixed time of the opening auction. In other words, HFTs do not have special privileges by virtue of their speed advantage, relative to the other market participants. This result is in line with the theoretical prediction of Budish, Cramton, and Shim (2015), who argue that auctions lead to more "fair game" between market participants.

In terms of positive externalities, the early participation of HFTs also generates benefits for other market participants in terms of price discovery. We show that HFTs consistently lead the price discovery process through the pre-opening phase, helping the information to be incorporated promptly in prices. Nevertheless, the results for liquidity provision in the opening auction are mixed, and depend on the account type used. However, the practice of posting "flash crash" orders, with the aim of gaining time and price priority under extreme market conditions, raises the question of whether this practice could lead to instabilities, in view of the strong interconnections across venues and across markets. Even though there have been no significant episodes of market disruption in our sample period, posting an entire schedule of orders inflates the available liquidity and, in case of a "fat finger" event, may trigger trading halts, resulting in contagion effects across venues in a very short time, given the speed of trading across markets.

As a group, HFTs neither improve nor harm liquidity provision in the opening auction. The details of our findings are important for designing proper opening mechanisms in the presence of HFT participation. In particular, our results highlight the heterogeneity of the roles played by HFTs in different periods of the trading day, especially during the initial part of the day. Due to the rebate scheme provided by NYSE-Euronext only for the activity carried out using the MM flag in the main trading phase, the presence of liquidity providers in the opening auction is marginal. The rules of the exchange, in this case, strongly encourage the provision of liquidity by electronic traders only in the main part of the trading day, but not in the opening auction. This deserves further scrutiny. Our findings are also likely to be of interest to stock exchange managers, policy makers and stock market regulators to better define the market quality, and design the rules to be adopted for the pre-opening phase and the opening auction.

Chapter 2

High-Frequency Market Making: Liquidity Provision, Adverse Selection, and Competition

2.1 Introduction

Over the past decade, the evolution of the trading environment reshaped the market-making business in global equity markets, traditionally run by licensed traders such as specialists, but now firmly in the hands of High-Frequency Trading firms (HFTs), the "new players." Their prominence was acknowledged by regulators with the formal recognition of traders practising algorithmic trading strategies as official market makers and culminated in the forthcoming MiFID II Directive. This paper examines the activity of HFTs under a specific liquidity provision agreement, the Supplemental Liquidity Provision program (SLP). NYSE Euronext started the SLP to allow electronic high-volume members to provide additional liquidity, under a maker/taker pricing scheme. The novelty of my work is to directly address the HFTs' fundamental function of designated liquidity providers, and assess the risks that they face. The provision of liquidity by algorithms is pivotal to the sound functioning of the financial markets, given the forthcoming MiFID II regulation in Europe. The new regulation specifically endorses the automatic liquidity provision by electronic market makers, imposing specific binding agreements between the exchange and the trading firms.

Following the implications of the models by Budish, Cramton, and Shim (2015), Menkveld and Zoican (2017) and Aït-Sahalia and Sağlam (2017b), I show empirically that HFT market makers (HFT-MMs) do provide liquidity to the market, but strategically so, to avoid trading with other fast traders and being adversely selected when providing liquidity to them. I show that HFT-MMs discriminate between traders, selectively providing liquidity to NONHFTs. Using the realized spread as a proxy for adverse selection risk, I show that HFT-MMs are adversely selected only when they provide liquidity to other fast traders. HFT-MMs are better off when providing liquidity to slow traders, as their consistently positive realized spread shows. Finally, I exploit a change in the SLP agreement that introduces more competition among market makers, testing the theoretical prediction of Aït-Sahalia and Sağlam (2017a), and show that increasing competition among designated liquidity providers is beneficial for the market. The total provision of liquidity by market makers increases, the quoted bid-ask spread decreases, and the NONHFTs are better off in terms of a reduction in adverse selection costs.

My first contribution is to analyze the dual role of HFTs. They could "wear the hat" of designated market makers, playing a beneficial function for the market, or conversely, they could act opportunistically. Since buy and sell orders do not arrive at the same time, the classic function of the market maker is to provide liquidity when there are no contemporaneous matching orders. This activity was formerly delegated to individuals (or dealers) under specific agreements with the exchanges: NYSE introduced the so-called "specialists", while the same duties was carried out by the "animateurs" on the Paris Bourse.[1] Technological innovation, faster computers with sophisticated execution algorithms, and new trading platforms have completely changed the trading landscape. A new class of electronic liquidity providers has emerged. The "old" class of specialists has disappeared, leaving room for a "modern" version of designated market makers who make extensive use of co-location facilities, high-speed connections, and fast computers.

On this new trading environment, exchanges impose various obligations but also grant advantages to their designated liquidity providers. The "old" specialists had to always be present in the market, quote a bid-ask spread in all market condition, and maintain a fair and orderly market acting as price stabilizer in case of shocks on the demand or supply side. Their traditional advantages included fee reductions and privileges in the execution of particular orders.[2] Under the new SLP program, the "modern" electronic market makers have to be present for each assigned security of the basket only for a minimum amount of time, and without price stabilization duties. One of the benefits of this activity follows from the maker/taker fee: traders pay a reduced fee when they execute an aggressive order, and receive a rebate when they provide liquidity. Electronic market making is present all around the world, and many stock exchanges (among others, the New York Stock Exchange, Euronext, London Stock Exchange, and Deutsche Börse) have in place market-making agreements with electronic traders.

To analyze the provision of liquidity by market participants, I exploit two distinctive features of the dataset on the NYSE Euronext Paris exchange, namely (i) flags in the data that identify HFTs and market-making activity, and (ii) the SLP program, designed to promote passive execution from electronic and high volume members. Data from the Base Européenne de Données Financières à Haute Fréquence (BEDOFIH) on the NYSE Euronext Paris exchange, classify each order and trade into three categories: HFT, when submitted by a pure-play HFT (e.g., Getco or Virtu); MIXED, when submitted by an investment bank with HFT activity (e.g., Goldman Sachs, JP Morgan); or as NONHFT, if submitted by any market participants that are not recognized as an HFT. BEDOFIH also provides the account type used, flagged directly by the traders and enforced by the exchange, whereby I can distinguish between market making activity (MM) and other activity (proprietary trading, customer or retail orders). The final group of traders includes five categories, including two groups of market makers: HFT-MMs and MIXED-MMs.[3] The activity under the market making flag, as confirmed by the exchange, is monitored continuously primarily because of the maker/taker pricing.

I show that only the HFT-MMs have the characteristics of a modern version of traditional market makers (large number of quotes, high cancellation ratios, very low inventories). HFT-MMs provide a considerable amount of liquidity, around one quarter in the sample. They also take a large part of the liquidity from the market, ending up with a slightly positive net liquidity provision. The activity of MIXED-MMs is less effective compared to the activity of HFT-MMs: even if their presence in the order book is comparable to the one of the HFT-MMs, their activity in terms of trading is less than half, contributing only to 5% of the gross liquidity provision,

[1]Hasbrouck and Sofianos, 1993 describe the role of the specialist on the NYSE; Venkataraman and Waisburd (2007) illustrate the role of the designated market makers on the Paris Bourse, while also providing a historical overview of the "animateurs" in the French stock market.

[2]E.g., for the specialists at the NYSE, full knowledge of the limit order book and priority view of the incoming orders from the computerized routing system were part of the benefits accredited for their services (Hasbrouck and Sofianos, 1993)

[3]The five categories are HFT-MM, HFT-Others, MIXED-MM, MIXED-Others, and NONHFT, since there is no flagged market making activity for Non-High Frequency Traders.

and quoting a higher spread. Looking at the flow of liquidity provision, I find that HFT-MM attempt to discriminate between traders. Statistically, they are providing liquidity especially to the investment banks with HFT activities (MIXED-Others), to slow traders (NONHFTs), and to a lesser extent also to other HFT-MMs.

My second contribution is to provide an empirical estimation of the adverse selection costs paid or passed on by HFT market makers. The classical framework of Glosten and Milgrom (1985) assumes that the market makers are required to trade with anyone, and possibly facing traders with a greater information advantage. The market makers lose money providing liquidity to better-informed traders, and make money against (less informed) liquidity traders. However, the new paradigm in the most recent microstructure models assumes that the source of adverse selection is the speed of reaction, i.e, the latency of the trader. If the HFT-MM is not fast enough to update his prices after an event, another HFT will “snipe” the stale quotes, generating a potential loss for the market maker. Budish, Cramton, and Shim (2015) and Menkveld and Zoican (2017) show theoretically that an HFT can assume both the role of market makers or liquidity takers, so that HFT-MMs run the risk of being adversely selected when facing other HFTs. I show empirically that HFT-MMs are picked-off when they provide liquidity to other HFT-MMs and, to a lesser extent, to MIXED-MMs. In turn, they pass on adverse selection costs to slow traders. HFT-MMs discriminate between traders: they pay high adverse selection cost when they provide liquidity to other HFTs, and profit when providing liquidity to NON-HFTs. Confirming the theoretical implications of Budish, Cramton, and Shim (2015) and Menkveld and Zoican (2017), I verify empirically that HFT-MMs opportunistically play the dual role of market makers when they provide liquidity, and “bandits” when they capture the stale quotes, raising the adverse selection costs for all market participants.

My third contribution is to examine the competition effect, exploiting a change in the SLP agreement, which (i) allows new market makers to enter and (ii) reshapes the basket of stocks where the market makers are required to provide liquidity. On the one hand, competition in general among HFTs could lead to an arms race (Budish, Cramton, and Shim, 2015) or, when the trading speed of the exchange increases, a market maker could reduce his payoff risk and quote a lower bid-ask spread only if it is fast (Menkveld and Zoican, 2017). On the other hand, if we consider only the designated market-making activity, increasing competition among liquidity providers should improve the liquidity available to all traders, especially for low-frequency traders, reduce the quoted spread, and decrease the adverse selection costs (Aït-Sahalia and Sağlam, 2017a). I show that increasing competition changes the strategic behavior of the two groups of market makers. MIXED-MMs increase quoting, trading activity and the quantity they display at the best prices, but reduce their quoted spread by 8%. At the same time, HFT-MMs reduce their quantity displayed and their presence at the best bid and ask. Further, while HFT-MMs increase their gross provision of liquidity, leaving their gross liquidity consumption unchanged, MIXED-MMs trade more aggressively and consume more liquidity without increasing their passive executions. Overall, the provision of liquidity from HFT-MMs increases with higher competition, to the benefit of slow traders.

The outline of the paper is as follows. Section 2 provides a literature review of market makers and HFT activity, together with the specific hypotheses tested. Section 3 describes the institutional structure of trading at NYSE Euronext Paris and the details of the SLP program. Section 4 provides a detailed description of the data. The empirical evidence is presented in Section 5. Section 6 concludes.

2.2 Literature Review and Theoretical Framework

The provision of liquidity and the leading role of the market makers are key topics in the market microstructure theory. The earlier contributions in the theoretical literature, before the advent of the HFT and electronic trading systems, are well summarized by Madhavan (2000). He identifies three main strands of the literature on market-making models: the determinants of the bid-ask spread, the role of inventory, and the behavior of dealer's under asymmetric information. The earliest contribution is by Demsetz (1968). In his very stylized model, he shows that the market maker adjusts the spread in response to different market conditions, that is, the market maker plays a passive role in the price formation process, and the bid-ask spread is only the cost to provide immediacy. Garman (1976) and Amihud and Mendelson (1980) include in their models an active role of the market makers in the price discovery process, driven by the market makers' willingness to keep inventory turnover high and not accumulate large positions. These models predict that the market maker sets the prices based on the actual level of inventories subject to a preferred inventory position. The most prolific area in the literature is related to the role of information and how asymmetric information impacts the market maker's decision. The underlying idea that the market maker is facing informed trader and liquidity-motivated trader has been introduced by Bagehot (1971). A well-known formal development of this concept has been provided by Glosten and Milgrom (1985). In their model, the market maker quotes different bid-ask spreads based on the order arrival, orders that could come from a better-informed trader or liquidity traders. The model predicts that the market maker price strategy depends on the level of information asymmetry, which generates adverse selection cost, and on the volatility of the asset price.

The technological changes in the last decade and the rise of algorithmic trading and HFTs stimulate new theoretical contribution. The main difference between the classical and the new models is the introduction of the speed of trading, and its influence on the liquidity provision. Budish, Cramton, and Shim (2015) and Menkveld and Zoican (2017) introduce latency of traders as a source of adverse selection. In other words, the asymmetry between traders is not due to different sets of information, but on how fast they can act (or react) in response to a new event on the order book. In the model of Budish, Cramton, and Shim (2015) there are two types of traders: (i) investors (or liquidity-motivated traders) and (ii) trading firms (or HFTs). They assume that the investors are only liquidity takers, while HFTs could assume the role of liquidity providers, snipers, or both. Once the investors arrive to trade, the liquidity provider executes the order and immediately updates his quotes. If the liquidity provider is not fast enough to update the quotes, another HFT will snipe the stale quote. The authors derive an equilibrium where HFTs are indifferent between being a liquidity provider and a stale-quote sniper. Therefore, liquidity provision becomes costly since another player could exploit a fastliquidity provider. This outcome is similar, in spirit, to the consequences that occur when a market maker trades against a better-informed trader in Glosten and Milgrom (1985), but the source of disparity is the speed of reaction, not the information. In equilibrium, the model implies an arms race for speed, where the firms play both roles of liquidity provision (good for the investors) and stale-quote snipers (bad for investors, since the costs of liquidity increases). They conclude that a frequent set of batch auctions could address the issue of the arms race for speed. Menkveld and Zoican (2017)'s model also has three types of traders, namely the HFT-MMs, the high-frequency speculators (or bandits), and the liquidity-motivated traders. The two types of HFTs race against each other, one to provide liquidity and the other to capture the stale quote. In addition to the model itself, a remarkable difference is the introduction of the exchange latency as a critical variable. When the speed of the exchange increases, the model predicts an increase of the probability that a trade is between two HFTs rather than between an HFT and a liquidity trader. This condition could hurt liquidity because the HFT-MM is forced to raise the spread to protect against the HF-bandits.

The model of Aït-Sahalia and Sağlam (2017b) specifically describes the behavior of an HFT-MM. The authors include in the model (i) speed, (ii) informational advantage, and (iii) inventory control. The informational advantage is, as in the two models just discussed, driven by the market microstructure, that is, it depends on the speed of each member. Adverse selection still exists, but arises from the different speed of the market participants. The players are one HFT and a large number of uninformed, low-frequency traders. The central point is that HFTs act *only* as market makers. Only the HFT provides liquidity (monopolistic liquidity provider), and the bid-ask spread is determined by the optimal quoting strategy of the HFT and the orders submitted by low-frequency traders. The set of low-frequency traders is composed of patient, impatient, and arbitrageurs traders. The arbitrageurs behave like the HF-Bandits in Menkveld and Zoican (2017): they snipe stale quotes. Under a set of additional assumptions, they show some important implications for the market-making strategy of the HFT. A fast market maker provides more aggressive quotes because it can manage the inventory risk efficiently. HFT-MMs can elude the risk of being picked off by price discriminating, avoiding quoting at the best prices or reducing the displayed quantity. The models of Biais, Foucault, and Moinas (2011) and Hoffmann (2014) predict that fast trading could generate adverse selection costs to other (slow) market participants. Other theoretical contributions on speed and liquidity, among others, come from Cespa and Foucault (2011), Pagnotta and Philippon (2011), Biais, Foucault, and Moinas (2015), Jovanovic and Menkveld (2015), Foucault, Hombert, and Roşu (2016), and Foucault, Kozhan, and Tham (2017).

Most of the theoretical literature assumes that there is a representative market maker. However, what happens when multiple market makers compete against each other? Biais, Martimort, and Rochet (2000) theoretically show that an equilibrium with multiple liquidity suppliers is characterized by lower volume, higher markups, and positive profits that decrease with the number of liquidity providers. Bondarenko (2001) finds that competition leads profits to zero if there is no asymmetric information. Market makers do prefer more asymmetry than less because their expected profits are larger.

Finally, the recent paper of Aït-Sahalia and Sağlam (2017a) presents a model where two competing market makers exist: a medium-frequency trader and an HFT, and both interact with a set of low-frequency traders that could be patient, impatient, and arbitrageurs (as in the companion paper Aït-Sahalia and Sağlam (2017b)). They show that competition increases the liquidity provision, narrows the bid-ask spread, and induces the HFT to split the rent extracted from low-frequency traders. The HFT could reduce its liquidity provision compared to a monopolistic situation, but low-frequency traders are better off when the competition increases.

The empirical evidence on HFT activity is quite rich. This review focuses only on the aspects related to the market making and liquidity provision by electronic traders. Hagströmer and Norden (2013) and Menkveld (2013) introduce and describe the behavior of the so-called "modern market makers", characterized by a large volume of trading, inventories close to zero, and a considerable amount of passive executions. Malinova and Park (2016), with a detailed cross-venues dataset, study the existence of the quote-fade phenomenon on the Canadian stock exchange. The analysis of high frequency data finds some indication of quote fade and latency arbitrage, albeit not as high as in the US or European markets. The papers just discussed identify the HFTs as endogenous liquidity providers. Korajczyk and Murphy (2015) have a direct HFT-MM identifier, as I have in my database. In the context of large institutional trades, they find that both HFTs and designated market makers (DMM) provide liquidity, but only the latter keep providing liquidity during periods of stress. Other previous works show that HFTs can occasionally withdraw from the market under extreme conditions. Kirilenko et al. (2017a), studying the flash crash of May 6, 2010, show that HFTs do not entirely withdraw from the market. Up to a certain level of inventory, HFTs continue to provide liquidity up to a certain level of inventory and then they stand down from trading. Brogaard et al. (2016) find that HFTs provide liquidity to NONHFTs during extreme price movements. Addressing HFTs and competition, Breckenfelder (2013) finds that the introduction of HFTs in the Swedish market deteriorates the liquidity and increases the short-term volatility. Brogaard and Garriott (2017) argue that introducing competition among HFTs improves liquidity. Both papers deal with the introduction of additional HFTs in the market, not an increase in the competition among market makers.

Regarding the liquidity rebates, quite common on most electronic markets, Malinova and Park (2015) find that holding the total fees constant, the introduction of a maker/taker scheme does not impact the total liquidity, but conversely, the total fee matters for liquidity. This finding is consistent with the theoretical model of Colliard and Foucault (2012). Their model also predicts that changing the fee scheme has an impact on the displayed bid-ask spread, which should be lower. Cardella, Hao, and Kalcheva (2015) provide an interesting historical introduction of the maker/taker fees. They show that from the exchange perspective, a change in the liquidity-based fees affects trading volume and the revenues of the exchange. Clapham et al. (2017) analyze the Xetra Liquidity Provider Program at Deutsche Boerse and find that the program increased liquidity in the Xetra, but did not significantly affect the volume and the market liquidity of Xetra plus other venues. Finally, the work of Menkveld (2016) well summarizes all the growing theoretical and empirical literature on HFTs.

This paper is related to the work of Megarbane et al. (2017), which analyzes the behavior of HFTs under market stress conditions on the same set of stocks.[4] They find that HFTs are essential for the provision of liquidity, but that the HFTs withdrew from the market in periods of stress, especially during scheduled announcements. They also analyze the behavior of HFTs as market makers, concluding that, as a whole, HTFs do not act as market makers. I have different results that distinguish the two types of HFTs(pure HFT and MIXED) and include the account type. Another paper that uses the same data is Anagnostidis and Fontaine (2017), but only for a two-month window (from January 2, 2013 to March 28, 2013). They investigate the role of high frequency quoting in the liquidity-provision process, related to the formation of market-wide illiquidity and commonality. Their findings on liquidity provision are in line with the ones of this study. Based on the position on the order book, they infer that the NONHFT quotes are less likely to be adversely selected. Using the realized spread, I show in this paper that this conjecture is not verified.

2.2.1 Hypothesis

Episodes like the "flash crash" in the US market on May 6, 2010, raised serious doubts about the provision of liquidity by electronic traders in the modern financial markets.

[4]The the sample period is from November 2015 to July 2016 for the CAC40 stocks. I share the same classification of HFTs established by the Autorité des Marchés Financiers (AMF), the French stock market regulator. However, I do not have the identity of the traders, and they do.

However, HFT and algorithmic trading have become the new norm in most of the stock exchanges. On the NYSE, the DMM duties are, after January 2016, all managed by HFT firms.[5] Is the relative speed advantage crucial for the market-making activity? Is it beneficial for the exchanges to have agreements with high frequency firms in order to provide liquidity to the market? The recent theoretical papers presented in the literature review have a common denominator: the monopolistic provision of liquidity by the HFT. These models aim to describe the new market microstructure, where the fast traders are playing a fundamental role.

The primary objective of this paper is to empirically verify some of the implications predicted by the models of Budish, Cramton, and Shim (2015), Menkveld and Zoican (2017), and Aït-Sahalia and Sağlam (2017b) by analyzing the behavior of the HFT wearing the hat of electronic market makers, which are appointed by the exchange to provide regular liquidity to the market. This analysis is motivated by the dichotomy view that considers HFTs as liquidity providers versus liquidity takers, or bandits, and considers the fact that they can play both roles. If this dichotomy exists, and if one of the two roles prevails, it could be empirically evaluated. However, it could well be that the two roles are played by the same traders, that in some instances provide liquidity but in others react fast and consume liquidity. The referenced theoretical models allow HFTs to switch between two roles: liquidity providers and bandits.[6] In a fully electronic environment, a liquidity-motivated trader (NONHFT) posts an (aggressive) order that usually is executed immediately against liquidity-providing algorithms (HFT-MMs) standing in the book waiting for passive executions. There are many HFTs in the market, some of them are required to be present most of the time in the order book due to the liquidity-provision agreements, some others are present waiting to capture fast profit opportunities. In this environment, the HFT-MMs in principle have to monitor the order book continuously for three reasons. The first is to provide liquidity to NONHFTs, the second is to quickly update their prices to avoid being picked off by other HFTs, and the third is to close their position with profit once they provide liquidity. This behavior implies not only a considerable quoting and trading activity for the HFT-MM, but also the capability to trade selectively, and trying to avoid, when possible, other HFTs.

Empirically, I should observe two phenomena. First, since most of the quoting and trading activity is carried out via algorithms, I expect that HFT-MMs routinely provide liquidity to other algorithms. However, if HFT-MMs strategies are well-designed, they should be able to strategically reduce the provision of liquidity as much as possible to other HFTs, especially market makers. Formally I test the following hypothesis:

Hypothesis 5. *HFT-MMs provide liquidity to the market, but strategically avoid providing liquidity to other HFTs*

This hypothesis is based on the *actual* provision of liquidity represented by the shares traded. If the strategy is poorly designed, HTF-MMs provision of liquidity should be equally addressed to all the other traders, without any evidence of strategic selection of the counterparty.

[5] See Financial Times “High-frequency traders in charge at NYSE” January 26, 2016.

[6] Specifically, Budish, Cramton, and Shim (2015) assume that the HFTs are indifferent between the two roles, but in practice, some play the role of liquidity providers, some other snipers, and some perform both roles. In Menkveld and Zoican (2017) traders are also indifferent between the two roles but switch based on the market conditions. The model of Aït-Sahalia and Sağlam (2017b) instead assumes that the HFT-MM is a monopolistic liquidity provider, and there are HFT “arbitrageurs” among the liquidity-motivated traders that capture the stale quotes, as in the other two models.

The main risk of the market-making business remains the adverse selection, or the risk that the market maker is not able to close his position without losing money. In the classic microstructure theory,[7] the main source of adverse selection was due to the different levels of information on the fundamental value of the company, which motivates better-informed traders to act strategically. In the new models, the source of adverse selection is the speed. These models assume that all traders potentially have the same level of (fundamental) information, in view of the fact that the information regarding t balance sheets, earnings announcements, and macroeconomic releases are disseminated at the same time to the public, and with a very simple algorithm it is possible to incorporate the quoting decision based on these signals. The full knowledge of the order book is no longer an issue, since now one can subscribe to a contract with the exchange that allows full visibility of the order book. For an additional fee, a trader can be co-located and have the same potential speed of connection as all the other traders. The market makers, posting two-side quotes continuously, face more frequently the risk of being picked-off than other traders. The source of adverse selection is not only related to different speed, but also to the randomness of the time of arrival of the orders, or to the re-sequencing of the exchange. The marginal speed advantage could be caused by better-designed algorithms or faster connections with other exchanges. A faster reaction time after a signal implies a lower risk of being adversely selected. If the algorithm is not fast enough to update the quotes, it leaves an opportunity for another to step in, capture the stale quote, and make a profit. An additional complication arises from the fact that the same asset could be traded in different venues. Speed matters not only inside the exchange but also across venues or across instruments. The prices can potentially be influenced by the movements of the same stock traded in a different market, or by the price of other related instruments (options, futures, futures on dividends, indices, ETF). [8]

Assuming that all the HFTs (MM and others) have a comparable speed,[9] the theoretical models predict that they are picked-off most likely by other fast traders that will snipe their stale quotes. Using a proxy for the adverse selection (the realized spread), I expect that HFT-MMs will most likely be adversely selected by other fast traders, rather than by slow traders or other proprietary traders. On the other side, they will impose the adverse selection cost to other slower market participants. Empirically, I want to test the following hypothesis:

Hypothesis 6. *HFT-MMs are most likely to be adversely selected by other HFTs.*

The introduction of the new SLP agreement in 2013 allows testing of several theoretical predictions about competition among liquidity providers. The first tender of the program, dated April 2011, appointed seven firms as SLP members.[10] Megarbane et al. (2017), with the same database with the ID of the traders, identify 20 firms as SLP members. Even without a formal confirmation by the exchange, we can safely claim that the number of SLP members increased, corroborated also by the substantial rise of the MM-flagged activity in the first day of the renewal, June 3 2013.[11]. A further source of competition comes from the basket composition. Before July 2013,

[7] Among others, Bagehot (1971), Glosten and Milgrom (1985), or Kyle (1985).

[8] See, among others, Menkveld (2013), Brogaard, Hendershott, and Riordan (2014b), Malinova and Park (2016), and Gomber et al. (2017)

[9] This is a common assumption in the most recent microstructure models (see the literature review section).

[10] “Euronext launches DMM-style programme in Europe” Financial Times, April 17, 2011

[11] Comparing the average number of orders for the entire month of May with the one for June 3rd, HFT-MM experienced an increase of 23.5% of new limit orders and MIXED-MM increased by 41.8%.

each DMM was required to provide liquidity on all the stock of one basket, which each included (roughly) 10 components of the CAC40. The new regime collapses all the CAC40 stocks into a single basket, in a way that the single market maker has to provide liquidity on all 40 stocks of the CAC40. Thus, HFTs that were making the market on a restricted sample of stocks are now competing with other market makers to provide liquidity on an extended basket of 40 stocks.

In principle, increasing competition among market makers should change the behavior of the incumbent liquidity providers. The model of Aït-Sahalia and Sağlam (2017a) specifically addresses this issue, allowing competition between an HFT and an additional (medium frequency) liquidity provider. The theoretical predictions are: (i) increasing competition leads to an increase of liquidity provision faced by all traders, especially for low frequency traders. Increasing competition also reduces the quoted bid-ask spread; (ii) the HFT-MM quotes less. After a trade, the HFT-MM is less likely to be present and trade on the opposite side of the market, due to the presence of the competitor; and (iii) competition among HFTs results in splitting the rent extracted from low frequency traders, and low frequency traders tend to be better off, reducing the adverse selection.[12] These theoretical predictions provide the basis for the empirical analysis. The hypotheses tested are:

Hypothesis 7. *Increasing competition among market makers:*

3A) *Increases the liquidity provision and reduces the bid-ask spread*

3B) *Reduces the presence of HTF-MMs in the book*

3C) *Reduces the adverse selection risk for slow traders*

In the following sections, I describe the institutional structure of the NYSE Euronext Paris and the requirements for the market maker under the SLP program.

2.3 Institutional structure and liquidity incentives

2.3.1 Institutional structure

The Euronext stock market was created on September 22, 2000, when the Amsterdam, Bruxelles, and Paris stock markets merged into a unique Pan-European exchange.[13] During 2007, Euronext merged with the New York Stock Exchange and became NYSE-Euronext. Intercontinental Exchange (ICE) acquired NYSE Euronext during 2013, and the standalone company went public during 2014. The market operates as an order-driven market model with a limit order book. The actual trading infrastructure, called Universal Trading Platform (UTP), was developed with the NYSE and introduced in all European markets during 2009. This platform connects the cash and derivative platforms of all the Euronext markets. The company has provided co-location services since 2010, when the "NYSE Euronext U.S. Liquidity Center," a data center facility located in Basildon, England, was inaugurated. The infrastructure is a part of the pioneer NYSE Euronext project that built up two twin data center facilities, one in the UK for the European markets and one in Mahwah (New Jersey) for the US markets. The EU data center provides co-location services, with capacities that range from 1 Gb to 40 Gb, allowing many software vendors to host applications and services as close as possible to the matching engine. In Europe,

[12]SeeAït-Sahalia and Sağlam (2017a), pages 3 and 15.

[13]The Lisbon Portuguese stock exchange and the London derivative exchange (LIFFE) joined the group in 2002.

market data are not consolidated. There are different levels of data feed that can be subscribed to and distributed via low latency direct feeds and through a list of data providers (including Euronext itself, ICE data services, Bloomberg, Thomson Reuters...). The most comprehensive feed is the Level 2 that provides tick-by-tick full market depth data. Level 1 provides only the best bid/offer.

Euronext Paris is the branch of the exchange that manages all the French instruments, and together with the CAC40, is the benchmark index for the French equity market. The most liquid stocks follow a fixed schedule in all Euronext equity markets, including Paris. The daily session starts at 7:15 a.m. with an accumulation period (without trading) called pre-opening phase, followed by an opening auction at 9 a.m. The main trading phase, where the continuous trading takes place and the object of this study, runs from 9:00 a.m. to 5:30 p.m. A short accumulation period of five minutes (until 5:35 p.m) is then followed by a closing auction. Finally, it is possible to trade at the closing auction price for other five minutes until 5:40 p.m. This last part of the daily schedule is called trading-at-last phase.

Since August 1, 2012, the French government has imposed a financial transaction tax (FTT) of 20 bps on the purchase of French equities, together with an HFT tax.[14] However, an HFT can easily avoid the taxation using two strategies: either not carrying on inventories or signing an agreement with the exchange to run market-making duties. Not carrying inventories is a stylized fact for HFT, while signing a liquidity provision contract with NYSE Euronext falls under the second method to avoid the taxation.

2.3.2 Liquidity Provision and the SLP Program

In the aftermath of the financial crisis of 2007-08, the NYSE proposed a six-month pilot program to enhance the provision of liquidity by electronic trading firms. The new class of NYSE market participants, under the Exchange Rule 107B, has been called " supplemental liquidity providers (SLPs)" (U.S. Securities and Exchange Commission (2008)). The orders sent by the SLP members had to be electronic, either off the floor of the exchange or directly in the exchange system, and only using the proprietary account, excluding the customer orders. The program was called "supplemental" because it was designed to complement the DMM liquidity provision in the NYSE market model. A set of requirements, related to presence in the order book and a certain amount of passive liquidity provision, was rewarded with a financial rebate fixed at 15 bps of a dollar per share for each execution. The program was extended several times and became permanent in 2015.

For the NYSE Euronext Paris market, the SLP program appears to be substantially the same. The program was introduced in 2012, with the aim of protecting the market share of NYSE Euronext against other venues (Chi-X Europe, BATS Europe, and Equiduct), rather than in response to the financial crisis. The Financial Times refers to this scheme as "similar to the DMM program in NYSE."[15] NYSE Euronext also has in place another market-making program (the liquidity-provision program, or LP). The LP members do not have any rebate scheme and are obliged to quote a minimum spread for each stock. Members of the LP scheme cannot be part of the SLP at stock level. According to Megarbane, Saliba, Lehalle, and Rosenbaum (2017), who have access to the traders' identity in the database, all SLP members are either pure

[14] Details on the introduction of the two taxes can be found in Colliard and Hoffmann (2017). The authors find no evidence of market quality improvements, and a reduction of liquidity for all market participants.

[15] "Euronext launches DMM-style programme in Europe" Financial Times, April 17, 2011.

HFTs or mixed HFTs. I can assume from this information that all market-making activity from pure HFTs is correctly captured by the HFT-MM group.

The Flash News of March 26, 2012 (NYSE-Euronext (2012b)) covers the details of the implementation of the scheme, while the Flash News of May 9, 2013 (NYSE-Euronext (2013)) introduces new requirements and also extends the possibility of joining the program to other market participants starting June 3, 2013.

The 2012 program requires that each firm[16] appointed as SLP must:

A) Commit to be present on one or more basket of stocks (CAC40 stocks are partitioned into *four* baskets).

B) Satisfy the following three rules:

   (1) Be present at least 95% of the time on both sides of the market during the continuous trading session;
   (2) Display a minimum volume of at least euro 5'000 at best limit.
   (3) Deliver the presence time committed to by the applicant during the tender process at the Euronext best limit for each assigned basket of securities, with a minimum of 10% per each security included in the basket.

In June 2013, the program was revised. The main differences were related to basket composition (rule A) and the amount of time present at the best limit (rule B3). CAC40 stocks were initially split into four different baskets, but starting June 3, 2013, all the CAC40 components are in the same basket.[17] The difference between the two contracts are:

A) Commit to be present on one or more basket of stocks (CAC40 stocks belongs to a *single* basket).

B) Amendments to rule n. (3):

   (3.1) minimum passive execution level of 0.70% in percentages of the aggregate monthly volume traded on Chi-X, BATs, Turquoise, and NYSE Euronext
   (3.2) minimum presence time of 25% at the NYSE Euronext best limit for each assigned basket, weight-averaged over the entire basket and the calendar month,
   (3.3) minimum passive execution level of 0.1% and a minimum presence time of 10% at the NYSE Euronext best limit of the continuous trading session for each security, weight-averaged over the calendar month.

In both implementations, if the SLP members fulfill the criteria, for the taker activity the minimum charge is 0.30 bps, and the maximum rebate is -0.20 bps for liquidity provision until May 2013, increased to -0.22 bps beginning June 3, 2013. There are intermediate levels that reduce the rebate amount or increase the fees up to 0.55 bps per trade, depending on the time presence and the passive executions. It is worth underlining that the time priority of the orders at the best limit price is not taken into account when determining SLP members' presence at the best prices: as soon as there is an order at the top of the book flagged as SLP, the presence is counted.

[16] According to the SLP documentation, "each legal entity may take only one role (either a regular liquidity provider or SLP role) in each security. Only one entity per member firm (or group of member firms) may apply for an SLP role per basket." (NYSE-Euronext (2012b)).

[17] Table B.1 in the Internet Appendix provides descriptive statistics of the stocks in the sample, together with which sector they belong to and the basket composition valid until the end of May 2013.

2.4 Database description

The analysis is based on data from the Base Européenne de Données Financières à Haute Fréquence (BEDOFIH) for the NYSE Euronext Paris exchange. The sample under analysis covers the entire year 2013 for 37 stocks that belong to the CAC40 Index.[18]. I exclude from the initial sample, composed of 9,435 stock-days combinations, four trading days and 148 stock-days due to either technical issues on NYSE Euronext or half-day trading (January 31, June 6, December 24, and December 31). Further, I exclude 135 stock-days because I was unable to rebuild a reliable order book. I end up with 9,152 stock-days, or 97% of the initial sample. The BEDOFIH database provides quotes and trades timestamped in microseconds, covering the complete history of each order. The data from NYSE Euronext are complemented by a flag provided by the Autorité des Marchés Financiers (AMF), the French stock market regulator, that classifies each trader into three groups: HFT, MIXED, and NONHFT. HFTs are pure-play HFT companies (e.g., Getco, Virtu), the MIXED group covers the investment banks and large brokers, which could have substantial HFT activities (e.g., BNP Paribas, Goldman Sachs). The remaining companies are NONHFTs. The classification is revised once a year, and the three trader groups are mutually exclusive (see AMF (2017) for a detailed description of the methodology). Megarbane et al. (2017), with the same database for a more recent period, with the ID of the traders, identify 20 members as HFTs in their study. According to the Financial Times, seven firms initially joined the program.[19] A reasonable proxy of the number of HFT-MMs and MIXED-MMs, albeit potentially overestimated, could be between fifteen and twenty.

NYSE Euronext also flags each order with an additional dimension: the account type used. The exchange enforced the correct flagging of each order in compliance with the Rulebook. Specifically, when submitting an order, the trading members have to flag the orders according to the following grid (NYSE-Euronext (2012a)): for own account or own account for client facilitation; for the own account of an affiliate, or when operating from a parent company of the stock; for the account of a third party, or client account; orders submitted pursuant to an liquidity provision agreement; orders submitted for retail liquidity provider (RLP) or retail matching facility (RMO). The exchange confirms that the orders flagged for liquidity provision purposes are strictly monitored and verified by the compliance department. For the analysis, the accounts not related to liquidity provision are aggregated, distinguishing only across traders (HFT, MIXED, and NONHFT).

[18]Three Components of the CAC40 are not included in the database since their main trading venues are Amsterdam (for Arcelor Mittal and Gemalto) and Bruxelles (Solvay).

[19]"Euronext launches DMM-style programme in Europe" Financial Times, April 17, 2011: *NYSE Euronext started operating a similar scheme in Europe on April 1 with about seven firms signed up, according to Rollande Bellegarde, head of European cash equities.*

2.5 Empirical Evidence

2.5.1 Traders' behavior

I define several proxies to characterize the general behavior of the traders as well as the impact of their actions on the market quality. I exclude the pre-opening period and the opening auction since, as documented by Bellia, Pelizzon, Subrahmanyam, Uno, and Yuferova (2017), there is limited flagged market-making activity during this period. For the same reason, I also exclude the closing auction and the trading-at-last phase. Thus, the sample is restricted to only the main trading phase. Table 2.1 provides a comprehensive set of descriptive statistics for the traders' groups in the sample.

TABLE 2.1: **Traders' Characteristics**

This table presents the summary statistics across stock-days for order submission, trading activity, and order book presence for three trader groups (HFT, MIXED, NONHFT) and two account types (MM and Others). The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.

Panel A: Traders' descriptive statistics

	HFT MM	**HFT Others**	**MIXED MM**	**MIXED Others**	**NON HFT**
Number of new limit orders	65'084	17'499	48'082	31'506	2'178
	(45'056)	(16'579)	(33'743)	(20'308)	(1'587)
Number of new market orders	1	1	1	122	336
	(0.5)	(0.9)	(0)	(90.9)	(359.4)
Number of cancellations	62'665	16'987	46'949	28'454	1'108
	(43'787)	(16'493)	(33'051)	(19'093)	(1'001)
Cancellation ratio (%)	96.0	92.4	97.4	89.0	43.0
	(11.3)	(22.4)	(14.3)	(5.35)	(9.11)
Quoting activity ratio (QAR %)	35.5	12.6	26.6	21.6	3.7
	(8.01)	(6.07)	(9.62)	(8.19)	(2.33)
Number of trades	3'879	249	1'567	6'247	2'661
	(2'636)	(297)	(1'236)	(3'801)	(2'048)
Value of trades (1000 euros)	26'076	1'988	11'081	73'324	25'161
	(22808)	(2515)	(10261)	(66225)	(23996)
Trading Activity Ratio (TAR %)	19.6	1.33	8.28	52.9	17.9
	(1.71)	(14.1)	(1.34)	(4.37)	(12.2)
Aggressiveness ratio (%)	44.0	39.2	67.5	48.7	54.5
	(11.3)	(22.4)	(14.3)	(5.35)	(9.11)
Inventory crossing zero (N)	18.2	4.2	6.0	7.8	5.0
	(17.2)	(4)	(5.9)	(7.4)	(4.4)
Total number of trades (Nx1000)	71'500	4'422	28'804	114'072	46'992
Total Value of trades (Millions Euro)	481'971	35'187	203'603	1'335'716	452'610
Market share of trades (%)	19	1	8	53	18
N. of Stock-Day Observations			9152		
N. of Stocks			37		

TABLE 2.1: **Traders' Characteristics (cont.)**

Panel B: Order Book Measures					
	HFT MM	**HFT Others**	**MIXED MM**	**MIXED Others**	**NON HFT**
Display order value (at best bid and ask)	27'710	11'716	16'530	13'876	17'434
	(11'445)	(10'079)	(8'529)	(6'857)	(9'873)
Time presence up to 5 price levels (%)	99.2	35.9	97.6	53.9	16
	(1.57)	(38.6)	(6.49)	(19.5)	(16)
Time presence up to 3 price levels (%)	97.6	17.0	93.3	35.2	9.0
	(3.24)	(29.3)	(10.8)	(16.4)	(10.1)
Time presence at Best Bid-Ask (%)	55.6	0.876	26.6	12.7	2.89
	(14.3)	(2.71)	(10.6)	(6.13)	(3.37)
Time presence at top of the book (%)	14.8	0.157	2.26	4.53	0.329
	(7.89)	(0.373)	(1.85)	(3.66)	(0.607)
Gross Liquidity Provision (LP %)	28.9	1.69	6.27	48	15.2
	(10.2)	(1.48)	(3.57)	(9.92)	(6.07)
Gross Liquidity Consumption (LC %)	21.70	1.17	13.20	45.30	18.60
	(6.1)	(1.39)	(5.58)	(8.31)	(7.59)
Net Liquidity Provision (NLP %)	3.60	0.26	-3.49	1.33	-1.70
	(5.63)	(0.768)	(2.93)	(4.94)	(3.25)
Quoted spread (ticks)	3.672	9.036	4.341	4.215	5.516
	(1.257)	(3.972)	(1.394)	(1.495)	(1.42)
Effective spread (ticks)	1.156	1.918	1.212	1.025	1.124
	(1.25)	(1.676)	(1.361)	(1.206)	(1.302)
Realized spread (bps) - 5 minutes	0.238	0.642	-0.0377	-0.185	-0.224
	(0.92)	(6.471)	(1.721)	(1.11)	(2.684)
N. of Stock-Day Observations			9152		
N. of Stocks			37		

Table 2.1 Panel A show that all the traders mainly use limit orders during the main trading phase: only the slower traders (NONHFTs) display a higher average number of market orders per stock-day. A peculiar characteristic of the HFTs is related to the number of order updates during the trading day, that involves submitting and canceling continuously. The number of cancellations in the sample is very high for both HFTs and MIXED traders, The *cancellation ratio*, that measures the total amount of orders canceled over the total amount of orders submitted for each stock-day, shows a remarkably high value for HFT-MMs (96.0%) and MIXED-MMs (97.4%). NONHFTs display a lower cancellation ratio, deleting less than half of the orders submitted.

A measure of the share of the total traffic generated by each trader during the main trading phase is the *quoting activity ratio (QAR)*, defined as the total number of messages for each trader (a new order submission, modification, cancellation, or trade) divided by the total number of messages for each stock-date. Panel A of Table 2.1 shows that more than a third of the traffic is generated by the HFT-MMs (35.5% of the total messages). The combined market-making activity by HFT-MMs and MIXED-MMs is responsible for 62.1% of the average total traffic during the main trading phase. HFT-Others accounts for 12.6% of the traffic, and NONHFTs for only 3.7%.

Similarly to the QAR, the *trading activity ratio* or TAR is calculated as the total number of shares traded divided by the total amount traded (buy and sell). The average values for each stock-day's trading activity show that the MIXED-Others are dominating the market in terms of total value of shares traded. HFT-MMs are the most prominent traders among the liquidity providers, with figures almost twice as big as the MIXED-MMs. Taken together, the HFT-MM, MIXED-Others, and NONHFT categories account for 90% of the shares traded. HFT proprietary trading (not under MM flags) accounts for only 1% of the shares traded.

An interesting feature of the database is that it indicates the initiator of the trade,[20], which allows definition of the *aggressiveness ratio*, or the ratio between the number of shares where the trader is initiating the trade and the total number of shares traded. A value equal to 50% indicates the typical behavior of a market maker, i.e., provide liquidity (passive trade) and then revert the trade (aggressive trade). A number greater than 50% indicates aggressive behavior. The most aggressive traders in the sample are the MIXED-MMs, followed by the NONHFTs. HFTs as a group appear to be the least aggressive in the sample, with a ratio of 44.01% for the HFT-MMs and 39.2% for the HFT-Others.

A well-known metric of HFT activity, especially when they are applying market making strategies and inventory management, is how many times the *inventories cross zero*: HFT-MMs cross on average 18 times per stock-day, more than three times the average of the MIXED-MMs. In terms of total values of the trades,

I rebuilt the entire order book, and I extract an end-of-second snapshot of up to five price levels. I also keep track of the time priority and the traders' accounts that submit the orders. The snapshots allow us to calculate a complete set of order book measures, presented in Table 2.1 Panel B. The first order book measure is the *display order value*, calculated multiplying the price by the quantity available at the best bid and best ask for each trader and then averaged across bid and ask. It represents the amount, in euro, available for trading on both sides of the book. The highest average quantity belongs to the HFT-MMs (27'710 euros across stocks and days), followed by the NONHFTs (17'344 euros). Almost all the traders post on average a quantity higher than 10'000 euros at best prices.

The constant presence on both sides of the book is not only the main characteristic but also the main duty of a market maker. I proxy the supply of immediateness of the traders measuring their *average time presence* at different price levels. This measure captures how likely a liquidity-motivated trader is to find a quote from one of the representative groups. The presence, expressed in percentage, is calculated measuring the number of seconds where there are quotes available for trading, divided by the total number of seconds in the main trading phase. I select four representative price levels: 5, 3, *best bid-ask*, and *top of the book*. If there is at least one quote in the first five (three) price levels, then the presence is counted for the bucket 5 (3). Once the quotes are at the best prices, then the presence is counted for the *best bid-ask* proxy.

However, most of the time there are many orders at the best prices coming from different traders. The only way to identify the traders that are posting at the top of the book and will have their orders executed first is to rank the orders based on the time priority. Being at the top of the book is important to get the order executed, but exposes the trader to adverse selection. On the other side, not having the time priority protects against adverse selection because the market maker could adjust their quote right before being picked-off. It is important to underline that, for the rebates under the SLP agreement, the time priority at the best limit price is not taken into account: the presence is counted as soon as there is an order at the best prices. The difference between market makers and others is remarkable: up to five price levels, HFT-MMs and MIXED-MMs are present for 99.2% and 97.6% of the time, respectively. Even if

[20] I verify the "aggressiveness indicator" provided by NYSE Euronext by looking at the timestamp of the original orders and obtaining the same results.

MIXED-Others are dominating the market in terms of executed trades, they are in the first five levels around 54% of the time. HFT-Others act more strategically, while NONHFTs, according to the statistics, are liquidity-motivated traders and are not interested in standing in the order book waiting for execution. At the best prices, for more than half of the time, it is possible to find a quote from an HFT-MMs (55.6%), which reduces to one fourth of the time (26.6%) for MIXED-MMs. HFT-MMs are at the very top of the book, with time priority, for around 15% of the time on average.

The aggressiveness indicator also indicates whether a trader is providing or consuming liquidity in a particular transaction. Therefore, during the continuous period, a trader/account is considered as a liquidity provider if she posts orders that do not initiate trades, i.e., orders that are not market orders or marketable limit orders. I then define several variables to proxy the liquidity provided by the market participants. The *liquidity provision* of trader k is defined as follows:

$$\textit{liquidity provision}_k = \frac{\text{Number of shares traded}_k \mid \text{Trader } k \text{ provides liquidity}}{\text{Total traded volume}} \tag{2.1}$$

Conversely, if the trader is aggressive, then the opposite measure is defined as *liquidity consumption*. Display order value, time presence, and liquidity provision represent the three main requirements for the SLP program, discussed in detail in Section 2.5.2. To summarize the provision of liquidity by the market participants, I choose the *net liquidity provision*, NLP, calculated as the difference between the liquidity provision (LP) and the liquidity consumption (LC) for the main trading phase:

$$NLP_k = \textit{liquidity provision}_k - \textit{liquidity comsumption}_k \tag{2.2}$$

If a trader, in a given stock-day, is providing liquidity, then the value of NLP will be positive. The statistics on the gross and net provision of liquidity are presented in Table 2.1 Panel B. In gross terms, most of the liquidity is provided and consumed by the MIXED-Others (48% provision, 45.30% consumption).[21]

The two groups of market makers in the sample display very different behavior in terms of provision of liquidity. HFT-MMs provide, on average, for each stock-day 28.9% of the liquidity, while MIXED-MMs only 6.27% in gross terms. The statistics on the NLP shows that HFT-MMs display the highest average value of the group of traders, 3.60%. Surprisingly, MIXED-MMs are almost exactly on the opposite side, with a net position of -3.49%, the lowest value of the panel. The behavior of MIXED-MMs is not entirely what one could expect from a market maker. If I consider their quoting activity and time presence in the order book, I can conclude that they are employing a market-making strategy. However, the amount of liquidity consumed compared to the amount supplied reveals a more aggressive behavior. Given the

[21] The MIXED-Others include activity carried out by investment banks that are using HFT technologies. I aggregate in this category the proprietary trading flag and the customer flag. Around 75% of the activity stems from proprietary trading, while the remaining comes from customers' orders. The proprietary trading activity by the MIXED could potentially be recognized as endogenous liquidity provision. However, their time presence in the first five price levels (53% of the time) is considerably lower than the presence of the two market makers (99.2% for HFT-MMs and 97.6% of the time for MIXED-MMs). Thus, it seems not straightforward to associate this behavior with the one of a market-making strategy. The customers' flagged activity cannot be part of market-making strategies, due to the Chinese wall in place between proprietary trading and customers' orders routing.

loose requirements for the SLP program, discussed in Section 2.5.2, MIXED-MMs could potentially be eligible for the rebates even if they are trading very aggressively.

In view of the statistics presented so far, I can safely claim that the HFT-MMs have all the characteristics of a modern electronic market makers: high quoting and trading activity, positive and sizable liquidity provision, high cancellation ratio, effective inventory management (highest number of times of inventories crossing zero), and constant presence in the order book.

To evaluate the general market quality and the strategic behavior of the traders, I also calculate a set of indicators at the stock-date-trader level, following Huang and Stoll (1996) and Colliard and Hoffmann (2017). A measure that represents the compensation required by the liquidity providers is the *quoted spread*, defined as the difference between the ask price and the bid price quoted for each trader. The measure reported is a time-weighted average quoted spread, and it is calculated as the quoted spread weighted by the number of seconds where the spread applies. Table 2.1 Panel B shows that the lowest quoted spread belongs to the HFT-MMs and the highest to HFT-Others. It is worth noting that the spread quoted by the HFT-Others is roughly three times higher than the one quoted by HFT-MMs, indicating that the former category is not intended to provide liquidity, but rather to exploit trading opportunities when the spread becomes wider. All MIXED traders have similar quoted spread (around four ticks), while NONHFTs displays a quoted spread higher than five ticks, on average.

The variable *effective spread* represents a measure of the execution costs for a liquidity provider, and is calculated as:

$$\textit{effective half spread}_{t,k} = \left| P_t - \left(\frac{Ask_t + Bid_t}{2} \right) \right| \tag{2.3}$$

where P_t is the traded price at time t by trader k that provides liquidity, and $(Ask_t + Bid_t)/2$ is the midquote existing at the time of the trade. The measure is equally weighted across all trades in a given stock-day, and it is normalized by the tick size of the stocks. Given the consistent presence of market makers, as expected the effective spread is quite similar across the traders. The average value across traders is comparable with the bid-ask spread provided by AMF (2017) (2.5 ticks on average).

The metric that better represents the profits (or losses) of the liquidity providers and is widely applied to measure the adverse selection is the *realized spread*. In the spirit of the realized spread proposed by Huang and Stoll (1996), for each transaction the measure is calculated as:

$$\textit{realized spread}_{k,t} = \begin{cases} ln(P_t) - ln(P_{t+\delta}) & \textit{if liquidity provider sells} \\ ln(P_{t+\delta}) - ln(P_t) & \textit{if liquidity provider buys} \end{cases} \tag{2.4}$$

where a positive *realized spread* implies a profit for a trader/account k providing liquidity that occurred at time t. The time horizon δ of Equation 2.4 represents the length of time at which the subsequent (traded) price is observed, on the opposite side of the book, in a way that the *realized spread* is calculated conditionally of the side of the transaction. If the liquidity provider has to sell the stock, then to evaluate the profit or loss of the trade, I assume that the trader has to liquidate his position: the price considered is the buy-initiated trade. If there are no prices available on the other side, the realized spread is not calculated. Huang and Stoll (1996) and

Bessembinder and Venkataraman (2010) employ values of δ equal to five and thirty minutes. The measure of the realized spread by Colliard and Hoffmann (2017) is close to the one suggested by Bessembinder and Venkataraman (2010), that uses quoted midprice instead of the traded price after ten seconds, 5 minutes, and 30 minutes.[22] Given the technological improvements and the presence of HFTs, I introduce three additional values of δ: I consider 1 second, 10 seconds, and 1 minute in addition to 5 and 30 minutes. I report in Panel B of Table 2.1 only the value for the 5-minute interval, where I see that the only two categories that have, on average, positive realized spread are the HFT-MMs and the HFT-Others. HFT-Others are much less active in the market, according to all the metrics considered so far, but the resulting strategy could be very profitable. It is interesting also to compare the five-minute realized spread of HFT-MMs with the rebate provided by the exchange (0.20 bps): on average HFT-MMs can get the same value for both passive and aggressive execution. This potentially doubles the HFT-MMs profits when they execute passive orders and then close the position within five minutes.

In 2010, the U.S. Securities and Exchange Commission (SEC) presented a list of characteristics to define HFTs (U.S. Securities and Exchange Commission (2010)). I focus on the last item of the list, regarding the inventories: “Ending the trading day in as close to a flat position as possible (that is, not carrying significant, unhedged positions overnight).” Inventory management has been a crucial point in the economics of market making for decades, and has become one of the strengths of the HFT algorithms. As well explained in O’Hara (2015), because electronic market makers are just algorithms, an effective risk management of the positions can be achieved by limiting the amount of holdings on one stock or in a portfolio of stocks. The difficult part is the trade-off between the risk management boundaries and the profitability of the strategy. Effective inventory management is still crucial for a successful market-making stragegy. As for the end-of-day inventory positions, there is mixed empirical evidence. Menkveld (2013) finds that his representative market maker starts and ends most of the trading days with a zero net position. Malinova and Park (2016), in their Canadian dataset, find that there are several HFT-MMs that hold inventories, in some cases more than 70% of the daily trading value. They also quote Stephen Cavoli from Virtu, who claims that “Virtu hedges with related securities when they accumulate an inventory so that they would end the day ‘flat’ in terms of risk — but not necessarily in terms of their position.” Both papers analyze endogenous liquidity providers that apply market-making strategies, rather than DMMs as in my sample. However, I expect that the group of market makers is managing actively and effectively its inventories for risk management and profitability purposes.

I first aggregate the inventory positions at stock level, and then at traders’ group level for HFT-MMs and MIXED-MMs. I measure the relative inventory position for each stock-day-trader, calculated as the end-of-day inventory (number of shares) divided by the total number of shares sold and bought, in a way that the inventory position goes from -1 to +1. Since I cannot track the behavior of a single HFT firm, the results have to be interpreted with some caveat. The aggregation across the groups of market makers, however, yields some very interesting insights, presented graphically in Figure 2.1.

[22] Colliard and Hoffmann (2017) use the 10 seconds interval for price impact and realized spread, but they merge two databases (Bedofih and Thomson Reuters Tick History for the mid prices), and the way in which they calculate the realized spread differs from the measure presented in this paper.

FIGURE 2.1: **End of day net position**

This figure represents the daily relative inventories position, calculated as the end-of-day inventories (number of shares) divided by the total number of shares sold and bought, for HFT-MM and MIXED-MM. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.

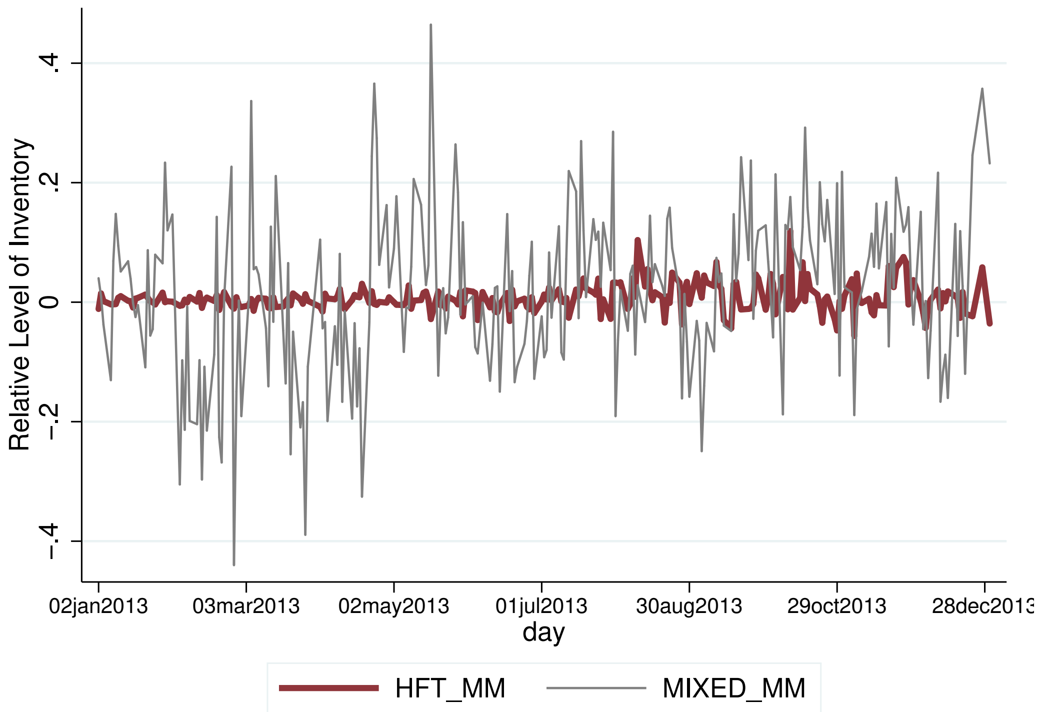


Figure 2.1 undoubtedly shows that HFT-MMs have a level of inventories that is impressively low compared to the MIXED-MMs. Occasionally the HFT-MM could have long or short positions, but on 95% of the cases, inventories are around ± 10% of the daily trading value. The other traders, including the MIXED-MMs, have a wider range.[23] The average stock-day inventory position, aggregated across all HFT-MMs, is 0.37%. I confirm that the MIXED-MMs do not manage their inventories as efficiently as HFT-MMs do.

2.5.2 The impact of the SLP Program

The aim of the following section is to provide an overall assessment of the performances of the liquidity providers, analyzing only the metrics that are considered by the exchange to provide a rebate on the passive execution. Without having traders' individual identifiers, I rely on aggregate measures of time presence in the order book and quantity displayed. Rule number (1) requires a presence in the order book for at least 95% of the time. The aggregate values of Table 2.1 show that on average HFT-MMs as a group are present for 99.2% of the time in the first 5 prices and MIXED-MMs for 97.6%. The aggregate measure of the requirements n. (2) and (3) yields many interesting graphical insights. Under rule n. (2), market makers are required to quote at least 5,000 euros at the best limit, as a simple monthly average

[23]Additional statistics on the inventory position can be found in the Internet Appendix, Table B.4

across all the securities in the basket, per side (see NYSE-Euronext (2012b)). On aggregate, the average daily quantity is around five times larger for the HFT-MMs, and three times larger for MIXED-MMs. The time series evolution of the average displayed volume of Figure 2.2 shows that on average for each stock-day, the total displayed order value for both market makers categories almost never goes under the 10,000 euros.

Interestingly, their quoting behavior changed dramatically after the introduction of the new SLP program on June 3, 2013. For the HFT-MMs, the amount goes from an average cumulative display order value of 32,134 euros (July 3) to an average of 27,313 euros, a remarkable drop of 15% in one day. All in all, on average across stock-days, HFT-MMs decrease their displayed order value by 25%, while MIXED-MMs increase it by about 44%.

Rule n. (3) initially required a 10% time presence for each stock at the best of the book, which was amended in the new SLP program during 2013. Figure 2.3 plots the time series of the presence in the order book. Altogether, the HFT-MMs have a stable average presence at the top of the book for more than 40% of the time, while the MIXED-MMs's average presence in the initial part of the sample is between 10 and 20% of the time. The explanation for this behavior is probably related to the fact that there are two liquidity provision programs in place, and only the SLP program has requirements regarding time presence. However, starting April 2, 2013, the time presence of the MIXED-MMs almost doubles, going from an average of 17% of the main phase time to 29%. Their presence then becomes stable around 30% of the time. In the aftermath of the introduction of the new SLP requirements, HFT-MMs mildly decrease their presence, going from an average time of 58% to 53%.

An additional requirement is related to the combined executed volume of NYSE-Euronext, Chi-X, BATs and Turquoise (0.70% in percentages of the aggregate monthly volume traded). This requirement aims to reduce the fragmentation of the French stock market, generated by the introduction of new trading venues by the MiFID regulation in 2007.[24] Increase in the market share of NYSE Euronext against the rise of other venues is one of the main reasons the SLP program has been implemented. Figure 2.4 provides a monthly snapshot of the trading activity in the four different venues during 2013. As a group, HFT-MMs provide an average of 15% of passive execution in the NYSE Euronext, while MIXED-MMs provide only around 3.5%.

[24]Boussetta, Lescourret, and Moinas (2017) describe in detail the fragmentation of the French stock market, albeit in the context of the pre-opening period.

FIGURE 2.2: **Average displayed order value for HFT-MM and MIXED-MM**

This figure shows the average displayed order value (volume multiplied by price in euro) for each day in the sample. The shaded area represents the 95% confidence interval of the average value. The vertical bar is drawn at the introduction date of the new SLP program (June 3, 2013), and the dotted red lines represent the average displayed value for the two subperiods. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.

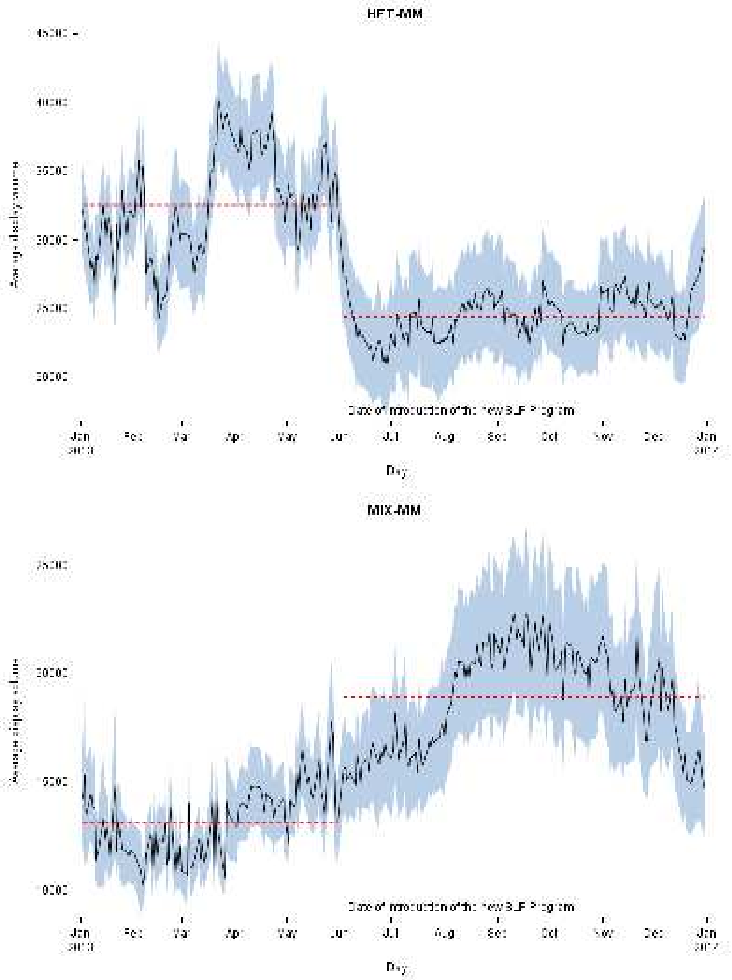


FIGURE 2.3: **Average time presence at the best bid and ask price for HFT-MM and MIXED-MM**

This figure shows the average presence for each day in the sample. The presence is calculated as the number of seconds where there are quotes available for trading, divided by the total number of seconds in the trading session. The shaded area represents the 95% confidence interval of the average value. The vertical bar is drawn at the introduction date of the new SLP program (June 3, 2013), and the dotted red lines represent the average presence time for the two subperiods. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.

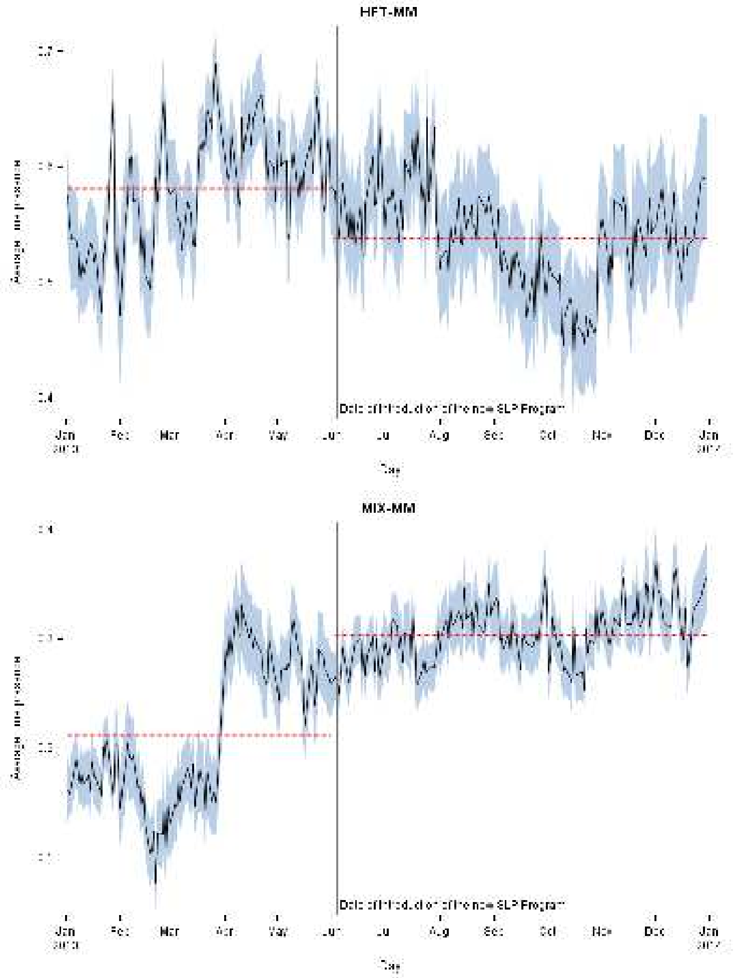
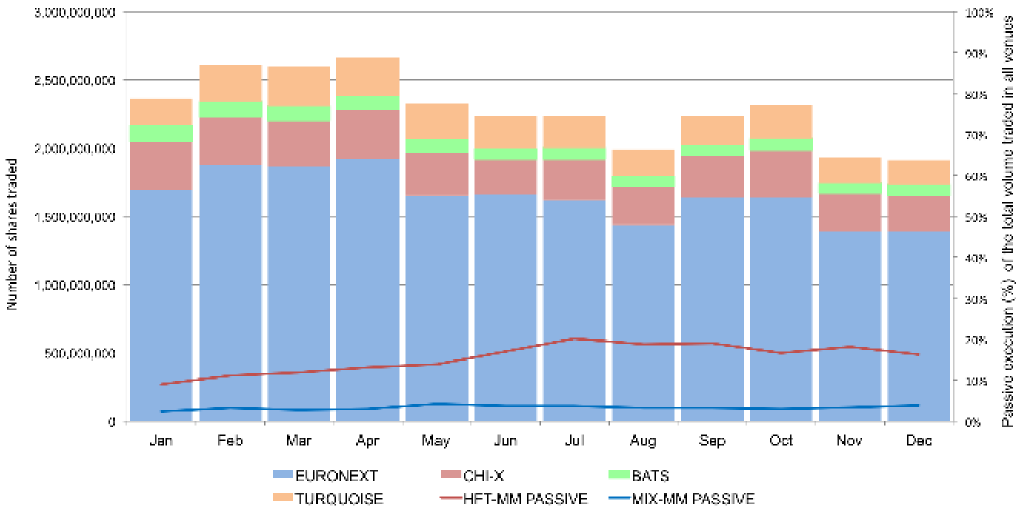


FIGURE 2.4: **Total traded value in 2013 for Euronext, Bats Chi-X, and Turquoise**

This figure shows the total amount traded (in number of shares) for Euronext, Chi-X, Bats, and Turquoise for the year 2013. The sample is reduced to 33 stocks of the CAC40 that are traded in all the venues. The two lines represent the number of shares passively traded, i.e., traded to provide liquidity, from HFT-MM and MIXED-MM. The source of data is Bloomberg for the volume of the venues, and BEDOFIH for the passive trades.



In the following sections I investigate the three main Hypotheses on liquidity provision, adverse selection, and competition.

2.5.3 Liquidity provision

Hypothesis 1. *HFT-MMs provide liquidity to the market, but strategically avoid providing liquidity to other HFTs*

Are HFT-MMs, in general, effective as liquidity providers? They generate a remarkable traffic in their labeled liquidity provision activities, but are they consistently providing liquidity across stocks and days? Are they selectively providing liquidity only to some categories of traders? The descriptive statistics of Table 2.1 show that HFT-MMs provide on average roughly one-third of liquidity and consume a considerable fraction of it. Their NLP is on average positive across stocks and days in the sample. MIXED-MMs have a negative NLP and consume more liquidity than they provide. Is this behavior constant across stocks and days? What are the differences between trader groups?

FIGURE 2.5: **Distribution of Net Liquidity Provision in the full sample**

This figure shows the density histogram of the net liquidity provision (NLP) as defined in Section 2.5.1 for 3 trader groups (HFT, MIXED, NONHFT) and 2 account types (MM and Other) during the main trading phase. The red vertical line represents the average value, also reported in the caption of the graphs. The sample period is the year 2013 for the 37 French stocks of the CAC40 index traded on NYSE Euronext Paris. Order flow data, with trader group and account flags, are from BEDOFIH.

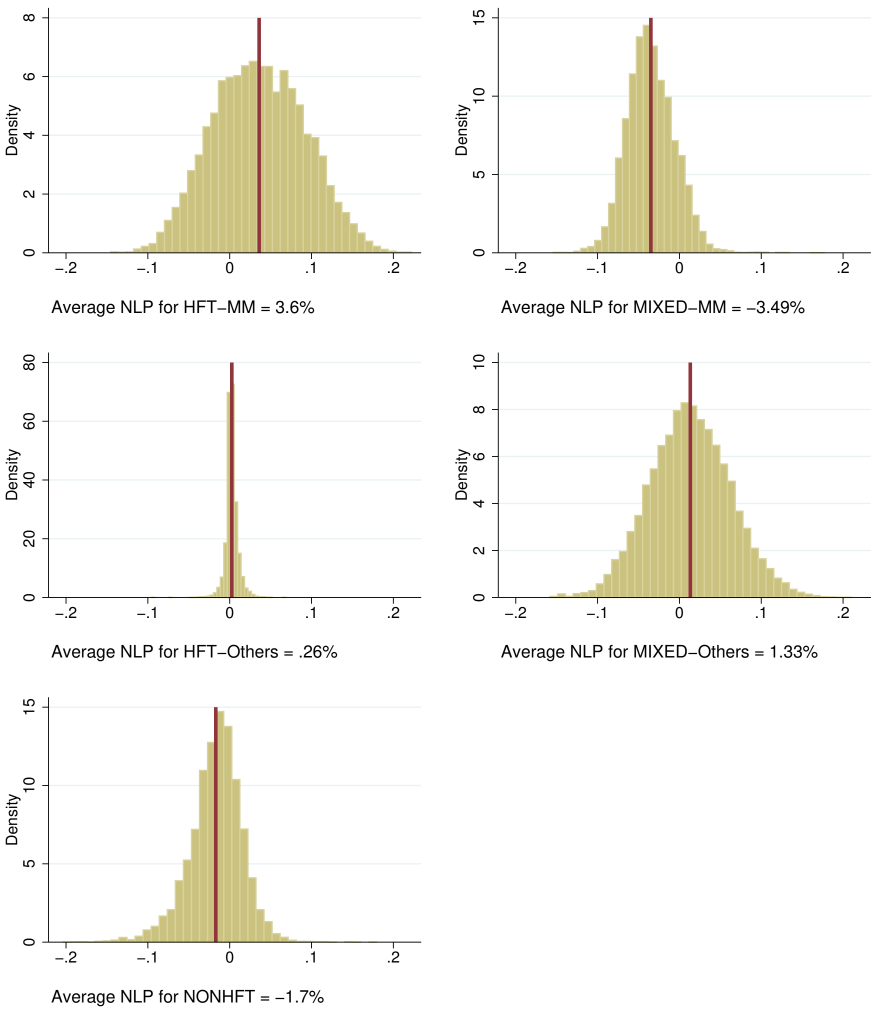


Figure 2.5 Panel A shows the distribution across stock-days of the NLP for the entire sample.[25] The histograms show that the behavior of the traders is very different. The distribution for HFT-MMs ranges from around -10% to +20%, indicating that on aggregate in some stock-days they are net liquidity providers to the market, while on some other days they are liquidity takers. The distribution of MIXED-MMs is more concentrated around the average value of NLP (-3.49%) and shows that they are more frequently liquidity takers rather than liquidity providers. The same applies for NONHFTs. MIXED-Others have a more symmetric distribution centered around

[25]Additional statistics on the distribution of NLP are presented in the Internet Appendix, Table B.2

Table 2.2: **Total Liquidity Provision**

This table shows the total liquidity provision in number of shares for three trader groups (HFT, MIXED, NONHFT) and two account types (MM and Others) during the main trading phase. The liquidity provider is defined as the trader that does not initiate the trade, and the liquidity demander as the trader that initiates the trade. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.

			Liquidity Takers					
			HFT		MIXED		NON HFT	
			MM	Other	MM	Other	Other	Total
Liq. Providers	HFT	MM	4.80%	0.46%	3.01%	12.98%	6.41%	27.65%
		Other	0.59%	0.05%	0.23%	0.94%	0.61%	2.43%
	MIXED	MM	1.01%	0.06%	0.50%	2.01%	0.81%	4.39%
		Other	9.24%	0.80%	4.32%	18.48%	10.40%	43.23%
	NON HFT	Other	6.02%	0.57%	2.94%	7.19%	5.59%	22.31%
	Total		21.66%	1.93%	11.00%	41.60%	23.81%	

zero. Since most of the HFT activity is carried out through the MM flag, the NLP distribution of HFT-Others ranges only between -0.80% and +1.52% (at the P5 and P95).

Therefore, in summary, the results show that HFT-MMs do provide liquidity to the market, in line with the first part of hypothesis 1. To verify the second part of Hypothesis 1, that is, that they strategically avoid trading against other HFTs, I investigate the flow of liquidity. Who is taking the liquidity from whom, and, conversely, who is providing liquidity to whom?

The matrices reported in Table 2.2 provide an overview on the total and average proportion of shares that can be assigned to all the trading-account activities. Panel A of Table 2.2 shows that HFT-MMs provide most of their liquidity to MIXED-Others (12.98%) and NON HFT (6.41%). In relative terms, 70% of their liquidity goes to these two categories. The remaining fraction of liquidity provided by HFT-MMs goes mostly to other HFT-MMs and MIXED-MMs, exposing them to the risk of being adversely selected. At first glance, the high presence in the order book for the two groups of market makers could lead to a higher trading activity with each other. However, it seems that HFT-MMs try to limit the provision of liquidity to other HFT-MMs and MIXED-MMs. The statistics on the average liquidity provision are in line with the one presented for the total amounts.[26]

To verify if the average numbers reported in Table 2.2 are statistically significant across stocks and days, I define the liquidity provision (LP) for trader/account k to trader/account m for stock i on day j during the main trading phase as follows:

$$LP_{i,j,k,m} = \frac{\text{Number of shares traded}_{i,j,k,m} \mid \text{Trader/Account } k \text{ provides liqudity to } m}{\text{Total traded volume in the main tradin phase}_{i,j}} \tag{2.5}$$

[26]Table B.3 in the Internet Appendix reports the average liquidity provision across stocks and days.

TABLE 2.3: **Liquidity Provision Regression**

This table shows the results of the linear regression where the HFT-MM (Panel A) or the MIXED-MM (Panel B) provide liquidity to other traders during the main trading phase. Standard errors are in parentheses. The results are presented per group, and ***, **, * correspond to 1%, 5%, and 10% significance levels. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.

Panel A: HFT-MM Liquidity Provision

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
To HFT-MM	0.00516* (0.00268)					0.00929*** (0.00289)	0.00933*** (0.00290)
To HFT-Others		-0.0409*** (0.000398)				-0.0350*** (0.000645)	-0.0350*** (0.000639)
To MIXED-MM			-0.00305 (0.00215)			0.00144 (0.00240)	0.00152 (0.00238)
To MIXED-Others				0.108*** (0.00420)		0.107*** (0.00440)	0.108*** (0.00438)
To NON HFT					0.0120*** (0.00200)	0.0159*** (0.00221)	0.0158*** (0.00218)
Stock Realized Volatility							-0.000549*** (0.000191)
VCAC							-0.000037 -0.000032
Log of Stock Volume traded							-0.00142*** (0.000165)
Stock average Bid-Ask Spread							-0.000383*** (0.000112)
Constant	0.0422*** (0.000288)	0.0439*** (0.000227)	0.0425*** (0.000254)	0.0378*** (0.000239)	0.0419*** (0.000258)	0.0380*** (0.000480)	0.0673*** (0.00352)
# obs	215,904	215,904	215,904	215,904	215,904	215,904	215,220
Adj R^2	0.000313	0.0180	0.000106	0.138	0.00172	0.156	0.157
Standard Errors	Clustered by stock and day						

and run the following regression:

$$LP_{i,j,k,m} = a_0 + \sum a_{MM,m} * I_{MM,m} + Controls_{i,j} + e_{i,j,k,m} \tag{2.6}$$

where $LP_{i,j,k,m}$ is the measure of liquidity provision by trader/account k to trader/account m for stock i, day j. $I_{MM,m}$ is a dummy variable that equals 1 when a MM provides liquidity to trader/account m. I add also three stock-day control variables (the stock realized volatility, the log of the total volume traded, and the average bid-ask spread) and an additional measure of the systematic volatility, the VCAC, that measures the daily volatility of the CAC40 Index. Standard errors are double clustered on both stock and day as suggested by Petersen (2009).[27] The results are presented in Table 2.3.

Table 2.3 shows that HFT-MMs are very careful not to provide liquidity to other HFTs, but suddenly they are executing passive orders against them, as confirmed by the positive but small value of the coefficient *To HFT-MM*. However, when they face the HFT-Others, they are acting opportunistically and take liquidity from them.

[27] I also estimate a model with standard error clustered on day and adding stock dummies, and the results are very similar to the one presented in Table 2.3.

TABLE 2.3: **Liquidity Provision Regression (cont.)**

Panel B: MIXED-MM Liquidity Provision							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
To HFT-MM	-0.0301*** (0.00144)					-0.0359*** (0.00155)	-0.0359*** (0.00155)
To HFT-Others		-0.0426*** (0.000239)				-0.0485*** (0.000417)	-0.0482*** (0.000392)
To MIXED-MM			-0.0365*** (0.000744)			-0.0420*** (0.000886)	-0.0420*** (0.000886)
To MIXED-Others				-0.0132*** (0.00161)		-0.0197*** (0.00171)	-0.0197*** (0.00169)
To NON HFT					-0.0321*** (0.000748)	-0.0378*** (0.000887)	-0.0378*** (0.000885)
Stock Realized Volatility							-0.000887*** (0.000183)
VCAC							-0.00006* (0.00004)
Log of Stock Volume traded							-0.00148*** (0.000208)
Stock average Bid-Ask Spread							-0.000349** (0.000137)
Constant	0.0437*** (0.000280)	0.0435*** (0.000196)	0.0439*** (0.000257)	0.0429*** (0.000265)	0.0437*** (0.000259)	0.0494*** (0.000365)	0.0803*** (0.00446)
# obs	215,904	215,904	215,904	215,904	215,904	215,904	215,220
Adj R^2	0.0108	0.0141	0.0157	0.00208	0.0123	0.0645	0.0648
Standard Errors	Clustered by stock and day						

Interestingly, even if the gross amount of liquidity provided to MIXED-MMs is not negligible, it is statistically equal to zero, confirming the intuition that they are strategically avoiding each other. Potentially, this is due to a different set of stocks where they are making the market, or a dedicated algorithm that could detect the presence of other market makers.

HFT-MMs consistently provide liquidity to MIXED-Others and to NONHFTs. The overall results confirm that HFT-MMs are providing liquidity mostly to liquidity-motivated traders (MIXED-Others and NONHFTs) but they take liquidity from other HFTs and do not provide significant liquidity to MIXED-MMs. The control variables for volatility, level of trading and overall liquidity have a negative and significant sign, indicating that the general level of liquidity provision worsens when the market conditions deteriorate. Panel B of Table 2.3 reports the same regression, but in this case when the MIXED-MMs provide liquidity to anyone else. All coefficients are negative and significant and characterize a very aggressive behavior. If they provide passive executions, the subsequent behavior more than offsets the first position. This result is, albeit not unexpected given the previous analysis, somehow singular for a DMM.

In summary, consistently with the first part of Hypothesis 1, I find that HFT-MMs are strategically providing liquidity to liquidity-motivated traders (NONHFTs) and to MIXED-Others. I cannot confirm that they are avoiding all the HFTs, since the MIXED-Others includes investment banks with considerable high-frequency activity. I will exploit in the following section why HFT-MMs are consistently providing liquidity to them. The decision is, also in this case, strategic and related to the potential profits that they can make. Finally, although on occasion they provide liquidity to other HFT-MMs, statistically they do not provide systematic liquidity to MIXED-MMs.

2.5.4 Adverse selection

Hypothesis 2. *HFT-MMs are most likely to be adversely selected by other HFTs.*

A well-established result of the theoretical (e.g., Glosten and Milgrom (1985)) and empirical (among others, Hasbrouck (1988) and Huang and Stoll (1996)) market microstructure literature is that the market makers run the risk that the price can move against them after a trade. In other words, the price can rise after the market-maker sale or fall after the market-maker buy. The market maker can increase his spread to offset this potential loss, which requires canceling the previous quotes and replacing them at different price levels. If the market maker is not fast enough to do so, most likely the stale quote will be sniped by a fast trader. The market maker is then "picked-off" and the losses are due to the adverse selection mechanism. One of the most-used metrics for adverse selection is the realized spread, introduced in Section 2.5.1. Instead of verifying if the market makers are canceling their quotes after a trade (as in Malinova and Park (2016)), I evaluate the risk of being adversely selected by looking at the realized spread in different time intervals. In other words, I verify what the gain or the loss of a market-making strategy would be when the market maker can revert the trade in the opposite side. As the theoretical literature has stressed, the source of adverse selection is no longer related to the degree of informativeness, but depends on how fast the trader is able to react after a signal, changing the quotes or trading aggressively. Thus, I expect that the risk of being adversely selected is more pronounced among fast traders. On the other side, a fast MM should be able to swap the cost of adverse selection to slower traders. The profitability of the business depends on the difference between these two concurrent activities.

Table 2.4 reports the average realized spread, calculated as presented in Section 2.5.1 for the trades where HFT-MMs are providing liquidity. A positive realized spread implies a profit, while a negative realized spread implies that HFT-MMs have been "picked-off". Panel A of Table 2.4 reports the trade-by-trade realized spread. The statistics show that HFT-MMs suffer most adverse selection costs when they are providing liquidity to other HFT-MMs. The value of the realized spread against other HFT-MMs monotonically decreases with the time, confirming the theoretical prediction that their quotes are sniped by other HFTs. On the other side, providing liquidity to NONHFTs yields a systematically positive realized spread, higher compared to the cost faced against the faster traders. The statistics show that they have a positive realized spread also when they provide liquidity to MIXED-Others, but the value is by far smaller compared to NONHFTs.

TABLE 2.4: **Realized spread statistics**

This table shows the average realized spread as defined in Equation 2.4 of Section 2.5.1. A positive realized spread implies a profit for an HFT-MM providing liquidity to the other groups. Panel A represents the average realized spread per trade. Panel B shows the cumulative realized spread per day, averaged across stocks. Panel C displays the number of valid observations where the spread is calculated, and Panel D the coverage, i.e., the number of times where the spread can be calculated over the total number of trades. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.

HFT-MM		**Panel A: average realized spread (bps)**				
provide liquidity:		1 sec.	10 sec.	1 min.	5 min.	30 min.
TO HFT	MM	-0.719	-0.787	-0.624	-0.508	-0.571
	Other	0.008	-0.024	0.044	-0.006	-0.151
TO MIXED	MM	-0.157	-0.292	-0.292	0.199	1.138
	Other	0.066	0.100	0.132	0.055	0.042
TO NONHFT		0.868	1.003	1.256	1.418	1.393

HFT-MM		**Panel B: average cumulative realized spread**				
provide liquidity:		1 sec.	10 sec.	1 min.	5 min.	30 min.
TO HFT	MM	-0.420%	-1.565%	-2.196%	-2.012%	-2.138%
	Other	0.001%	-0.006%	0.016%	-0.002%	-0.054%
TO MIXED	MM	-0.033%	-0.171%	-0.290%	0.218%	1.149%
	Other	0.075%	0.389%	0.883%	0.407%	0.285%
TO NONHFT		0.429%	1.928%	4.525%	5.767%	5.303%

Table 2.4: **Realized spread statistics (cont.)**

HFT-MM provide liquidity:		**Panel C: number of trades** 1 sec.	10 sec.	1 min.	5 min.	30 min.
TO HFT	MM	539’429	1’846’870	3’267’217	3’678’719	3’678’719
	Other	52’988	186’445	310’151	337’423	337’423
TO MIXED	MM	172’072	533’897	920’838	1’011’743	1’011’743
	Other	1’045’582	3’608’421	6’233’989	6’872’015	6’872’015
TO NONHFT		454’199	1’785’091	3’345’587	3’777’427	3’777’427

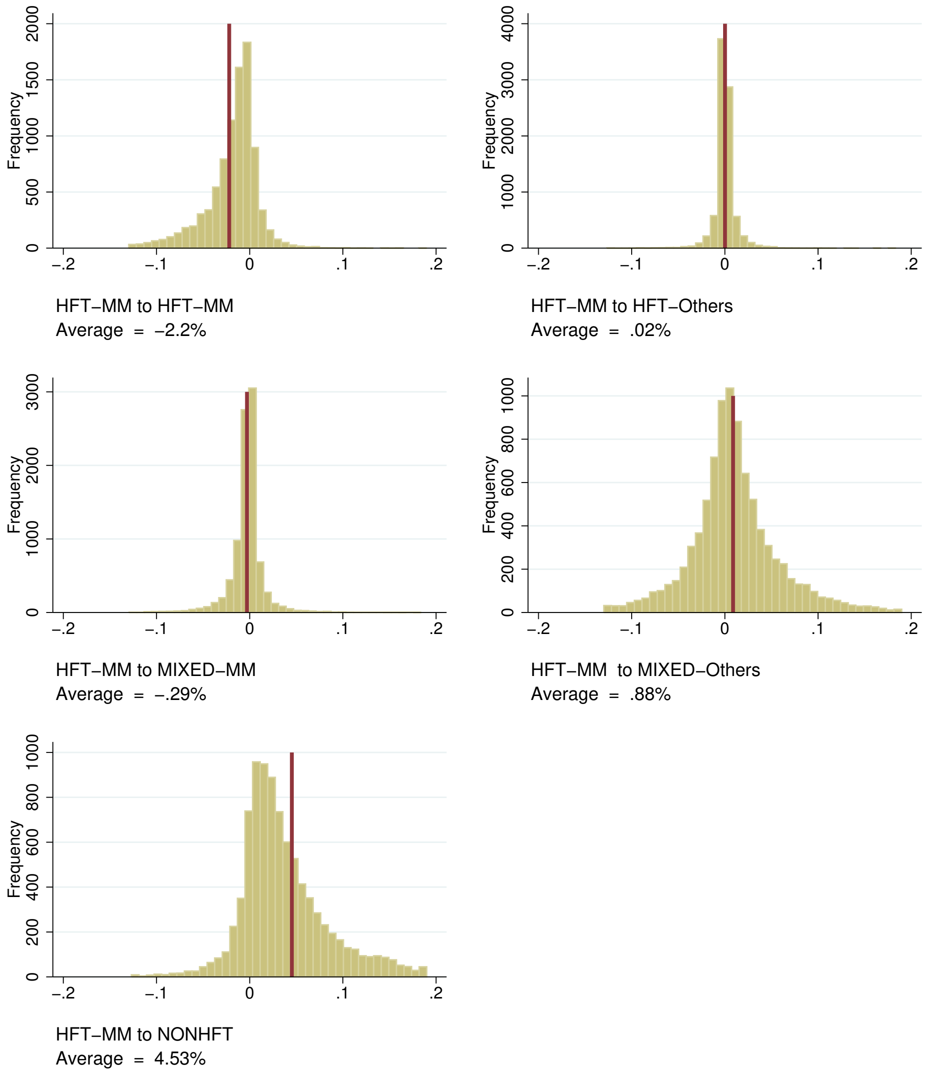
HFT-MM provide liquidity:		**Panel D: coverage** 1 sec.	10 sec.	1 min.	5 min.	30 min.
TO HFT	MM	14%	49%	88%	100%	100%
	Other	15%	54%	90%	100%	100%
TO MIXED	MM	17%	52%	90%	100%	100%
	Other	15%	51%	89%	100%	100%
TO NONHFT		12%	46%	87%	100%	100%

I aggregate the realized spread trade-by-trade for each stock-day-trader, and I report the average values per stock-day in Panel B of Table 2.4. Aggregating the values shows how severe the adverse selections costs can be for a market-making strategy. Against other HFT-MMs, the cumulative average realized spread is already -1.5% after one minute and goes more than 2% in the following minutes. Panel B of Table 2.4 also shows the potential source of profits, that is to provide liquidity to MIXED-Others and to NONHFTs. The automated market-making strategies can capture on average, 0.8 basis point 1 second after an HFT-MM provides liquidity to a NONHFT, gross of rebates and fees. The average cumulative return for a very simple strategy (i.e., provide liquidity to a NONHFT and then revert the position after 1 second at the current market price) yields a daily average 0.42% cumulative return per stock, gross of fees and rebates (Panel B). Panels C and D of Table 2.4 depict the number of trades where a realized spread could be calculated across the time interval, and the coverage is in percentage values. After 10 seconds, around one-half of the trades can be reverted, and after 5 minutes it is possible to find a match for all the initial trades.

To emphasize the asymmetric distribution of the realized spread, I use the one-minute time interval as a benchmark, and I plot on Figure 2.6 the histogram of the frequencies.

Figure 2.6: **Realized spread distribution after 1 minute**

This figure represents the distribution of the averaged daily cumulative realized spread where the HFT-MMs are providing liquidity to one of the other traders. The time horizon considered is one minute. The red vertical line represents the average value, reported in a footnote. For better visibility, the frequency histograms include only the values between the 1st and the 99th percentile of the total distribution. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.



The distribution of the realized spread confirms the dichotomy of the HFT-MMs when they provide liquidity to other HFT-MMs or NONHFTs. With the former, most of the realizations are negative, while the opposite is true for the latter. The distributions when HFT-MMs provide liquidity to HFT-Others and MIXED-MMs are very similar, with a very low dispersion around zero. The reason for this could be related to the speed of trading and the small size of the orders. A small trade usually does not have a big impact on the current market prices: most likely the bid-ask spread does not move at all, or moves only by a couple of ticks, resulting in a

TABLE 2.5: **Regressions on trade-by-trade realized spread**

This table shows the results of the trade-by-trade regressions where the dependent variable is the realized spread by HFT-MM (in basis points) when they provide liquidity to HFT-MM, MIXED-MM, MIXED-Others, and NONHFT. The base category is the HFT-Others. I consider five different time horizons to compute the realized spread, as explained in Section 2.5.4. Standard errors are double clustered on both stock and day. ***, **, * correspond to 1%, 5%, and 10% significance levels. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.

	Realized spread (bps)				
	1 second	10 seconds	1 minute	5 minutes	30 minutes
To HFT-MM	-0.727***	-0.763***	-0.668***	-0.502***	-0.420**
	(0.0988)	(0.0753)	(0.0751)	(0.0918)	(0.201)
To MIXED-MM	-0.165	-0.268*	-0.335***	0.206	1.289***
	(0.170)	(0.160)	(0.0877)	(0.128)	(0.453)
To MIXED-Others	0.0582	0.124**	0.0878	0.0613	0.193
	(0.0908)	(0.0617)	(0.0651)	(0.0819)	(0.192)
To NON HFT	0.860***	1.027***	1.212***	1.424***	1.544***
	(0.0817)	(0.0849)	(0.107)	(0.157)	(0.220)
Constant	0.00794	-0.0242	0.0437	-0.00627	-0.151
	(0.0899)	(0.0653)	(0.0733)	(0.1000)	(0.199)
# obs	2,264,270	7,960,724	14,077,782	15,677,327	14,571,672
Adj R^2	0.0143	0.0105	0.00473	0.00140	0.000343
Standard Errors	Clustered by stock and day				

realized spread close to zero. The distribution of the realized spread when HFT-MMs provide liquidity to the MIXED-Others has a long positive tail, that reflects in a higher number of profitable trading opportunities.

To verify on the one hand how severe the adverse selection problem can be for the HFT-MMs, or on the other hand if the market-making activity could be very profitable, two different analysis has been performed. The first considers all the trades where a realized spread can be calculated. The formal estimated model is:

$$realized\ spread_{i,j,k,m}(\delta) = \alpha_0 + \beta_1 * I_{MM,m} + e_{i,j,k,m} \tag{2.7}$$

where $realized\ spread_{i,j,k,m}$ is the realized spread when the HFT-MMs provide liquidity to the trader m for stock i on day j for trade k. $I_{MM,m}$ is a dummy variable that equals 1 when the HFT-MM is not the initiator of the trade and provides liquidity to the trader m. I estimate the regression for five different time intervals δ. I use as a base case the HFT-Others category: according to Table 2.4, panel C, the number of trades where they are facing each other is one-third of the trades against MIXED-MMs, and twenty times smaller the number of trades against MIXED-Others. Standard errors are double clustered on both stock and day as suggested by Petersen (2009). This first regression is aimed to verify the statistical significance of the average realized spread presented in Table 2.4, panel A.

The results confirm the theoretical prediction that HFT-MMs are more likely to be picked off by other HFT-MMs. The coefficient of the realized spread is negative and significant for all the time horizons considered. The highest coefficients belong to the shortest time intervals, one second and ten seconds, consistent with the notion that other bandits, or snipers, capture the stale quotes of HFT-MMs.

Regarding the other traders, the coefficient is only marginally significant when they provide liquidity to MIXED-MMs and MIXED-Others. The evidence presented so far (Section 2.5.3 on liquidity provision) indicates that HFT-MMs try to avoid providing liquidity to MIXED-MMs. However, when they do so, most likely the price does not move away from the initial trade, in a way that the resulting realized spread is statistically equal to zero. For similar reasons, the realized spread against the MIXED-Others is statistically equal to zero. The main difference is related to the number of trades, which is from five to nine times larger. All in all, providing liquidity to MIXED-Others seems to be a zero-sum game, where the primary source of profit for a liquidity provider is the rebate paid by the exchange. The main source of profit for HFT-MMs seems to be the provision of liquidity against liquidity-motivated NONHFTs. About one-quarter of the passive trades is with them and, according to the sign, magnitude, and significance of the coefficients presented in Table 2.5, there is no risk of adverse selection for HFT-MMs when they provide liquidity to NONHFTs but, on the contrary, a consistent source of profits.

The second analysis considers the cumulative realized spread for all the trades where the HFT-MMs provide liquidity. Using Equation 2.7 I also estimate the cumulative value, for the same time intervals, using as a base case the HFT-Others. The results, presented in Table B.5 almost mirror the sign and significance of the trade-by-trade analysis of Table 2.5: HFT-MMs are picked-off by other HFT-MMs and realized a positive profit when they provide liquidity to NONHFTs.

Introducing also the stock realized volatility as a proxy for the idiosyncratic risk, I find that an increase in the risk exacerbates the magnitude of realized spread in both ways: market makers can lose even more money when they are picked-off, but can also increase their profits when they are trading against liquidity-motivated traders.[28]. To summarize the results, I find that HFT-MMs are most likely to be adversely selected by other HFTs, and specifically by other HFT-MMs. These findings reveal the dual role played by the HFT-MMs: they could be both market makers and snipers, based on the market conditions.

2.5.5 Market Making agreements and Competition

Hypothesis 3. *Increasing competition among market makers:*

3A) *Increases the liquidity provision and reduce the bid-ask spread*

3B) *Reduces the presence in the book of HFT-MMs*

3C) *Reduces the adverse selection risk for slow traders*

During the 2013, the renewal of the SLP program introduced new rules for the liquidity providers, presented in Section 2.5.2. Despite the new requirements in terms of time presence in the order book, the new program brings two changes that affect the competition for the provision of liquidity under the agreement. The first is the possibility for other firms to join the program. The second is related to the basket composition. Although the CAC40 stocks were initially split into four different

[28]Detailed results of the regression are reported in Internet Appendix, Section B.4

Table 2.6: **Regressions on daily cumulative realized spread**

This table shows the results of the regressions where the dependent variable is the cumulative realized spread, calculated by aggregating the realized spreads across stock and days, and multiplied by 100, in order to have a percentage value. I consider five different time horizons to compute the realized spread, as explained in Section 2.5.4. In Panels B and C two additional variables are introduced, the realized volatility and the log of the total volume traded, both stock-day specific (see Section 2.5.1 for a description). The realized spread is calculated only for HFT-MMs, when they provide liquidity to HFT-MM, MIXED-MM, MIXED-Others, or NONHFT. The base category is the HFT-Others. Standard errors are double clustered on both stock and day. ***, **, * correspond to 1%, 5%, and 10% significance levels. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.

Panel A: realized spread					
	1 second	10 seconds	1 minute	5 minutes	30 minutes
To HFT-MM	-0.421***	-1.560***	-2.211***	-2.009***	-2.084***
	(0.0638)	(0.205)	(0.246)	(0.236)	(0.319)
To MIXED-MM	-0.0333	-0.165*	-0.306***	0.220*	1.204***
	(0.0316)	(0.0911)	(0.0933)	(0.125)	(0.458)
To MIXED-Others	0.0738	0.394**	0.867***	0.410	0.339
	(0.0454)	(0.170)	(0.300)	(0.332)	(0.639)
To NON HFT	0.429***	1.934***	4.509***	5.769***	5.358***
	(0.0849)	(0.381)	(0.702)	(0.870)	(0.908)
Constant	0.000686	-0.00560	0.0157	-0.00240	-0.0544
	(0.00778)	(0.0149)	(0.0265)	(0.0383)	(0.0717)
# obs	42,113	45,034	45,752	45,942	45,880
Adj R^2	0.0496	0.113	0.151	0.0827	0.0136
Standard Errors	Clustered by stock and day				

baskets, beginning on June 3, 2013, all the CAC40 components belong to the same basket.

Most likely, some firms could have been appointed as SLP for one basket, and not for another. Another possible situation is that the competition among HFT-MMs was limited only on a single basket of the most liquid stocks. Collapsing all the stocks into one basket imposed an important change on the market-making algorithms, now forced to make the market in more stocks and against other MMs.

In the previous sections, I investigate the liquidity provision and the adverse selection risk in the entire sample. Is the market quality affected by the change in the scheme and by the competition? How are the results of Hypothesis 1 and 2 affected by narrowing down the period around the event? In this section, I aim to answer these questions, given the theoretical prediction of Aït-Sahalia and Sağlam (2017a) model on competition among high-frequency market makers. This analysis also shed light on the presence of a structural break, that could affect the estimations in the entire sample.

The tender of application for a new SLP scheme was announced on May 9, 2013, and the began on June 3, 2013. Almost in the same period (beginning June 17, 2013), a new set of high-capacity market data channels for equities, ETFs, and bonds went live.[29] To characterize the pre- and post-change conditions, I narrow the sample period from April 2, 2013, to July 31, 2013, that is, two months before and two months after the inception date. The choice of being a member of the SLP program requires a trade-off between being present and active in a significant proportion of the trading day, or selectively trading when there is an opportunity to make a profit. In both cases, the traders have to use their own funds, but in one case there will be a rebate and a reduction in fees, while in the other the standard fees apply. Table 2.7 provides the mean and the standard deviation across stocks and days of both traders' characteristics and order book measures presented in Table 2.1, for the two subsamples.

Table 2.7 shows that there are some remarkable differences in the two-month period. Regarding HFT-MMs (Table 2.7 Panel A), the most relevant changes are an increase in the trading activity (TAR goes from 18% to 22%), a decrease in the aggressiveness ratio (from 49% to 39%), a decrease in the display order value at the best price levels (from 34'571 to 23'236, a 33% decrease) and an almost doubled average realized spread. The MIXED-MMs (Table2.7 Panel B) experienced an increase of quoting activity (from 23.8% to 32.7%) , aggressiveness ratio (from 66.4% to 70.6%), and a reduction of the quoted spread (from 4.7 ticks to 4.2 ticks).

To measure the statistical significance of these changes and to assess the aggregate impact on the market quality of both the increase in the competition and the new contractual requirements, in the spirit of Riordan and Storkenmaier (2012), I estimate a panel regression with stock fixed effect. For each trader/account, i, for each stock j and day k I estimate the following model:

$$y_{i,j,k} = \alpha_i, j + \beta_1 SLP_{i,j,k} + \beta_2 VCAC_k + \epsilon_{i,j,k} \tag{2.8}$$

where y is one of the variables defined in Section 2.5.1, SLP is a dummy that is equal to one after the introduction of the new SLP requirements, and $VCAC_k$ is a measure of the daily volatility for the CAC40 Index, as in Hendershott and Moulton (2011),

[29] The Details are presented in Euronext, Info Flash of June 14, 2013. This upgrade was announced in February and then postponed from May 20 to June 17. Most likely, the spike that I observe in Figure 2.3 for the MIXED-MMs is due to the testing of the new channels.

TABLE 2.7: **Summary Statistics on the reduced sample**

This table presents the average values of the variables included in the analysis presented in Section 2.5.5, for the reduced sample, which goes from April 2 to July 31, 2013. Standard deviations are in parentheses. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index. Order flow data, with trader group and account flags, are from BEDOFIH.

	Panel A: HFT-MM			**Panel B: MIXED-MM**		
	Averages		**Diff.**	**Averages**		**Diff.**
	Before	**After**	**(SD)**	**Before**	**After**	**(SD)**
Quoting activity ratio (QAR)	34.66	35.88	1.22 (0.56)	23.8	32.76	8.96 (0.4)
Trading Activity Ratio (TAR)	18.14	22.87	4.73 (0.46)	8.21	9.66	1.45 (0.25)
Cancellation ratio	96.4	95.84	-0.56 (0.12)	97.71	97.82	0.11 (0.08)
Aggressiveness ratio	49.32	39.2	-10.12 (0.76)	66.45	70.67	4.22 (1.21)
Display order value (at best bid and ask)	34'571	23'236	-11335 (441)	14'413	16'325	1912 (200)
Time presence 5 price levels	99.28	99.52	0.24 (0.07)	99.65	99.77	0.12 (0.04)
Time presence 3 price levels	97.78	97.5	-0.28 (0.18)	91.34	98.23	6.89 (0.28)
Time presence at Best Bid-Ask	60.62	57.24	-3.38 (0.68)	28.13	28.43	0.30 (0.46)
Time presence Top of the book (priority)	14.24	19.54	5.30 (0.58)	2.41	2.89	0.48 (0.11)
Gross Liquidity Provision (LP)	23.82	35.41	11.59 (0.75)	6.58	6.83	0.25 (0.46)
Gross Liquidity Consumption (LC)	22.5	22.9	0.40 (0.44)	11.91	15.72	3.81 (0.27)
Net Liquidity Provision (NLP)	0.66	6.26	5.60 (0.38)	-2.66	-4.44	-1.78 (0.27)
Quoted spread (ticks)	3.8362	3.7934	-0.04 (0.055)	4.6949	4.2783	-0.42 (0.061)
Effective spread (ticks)	1.1867	1.1169	-0.07 (0.042)	1.2385	1.1347	-0.10 (0.043)
Realized spread (bps)	0.1372	0.2562	0.12 (0.04)	-0.0677	-0.0894	-0.02 (0.081)

Table 2.7: **Summary Statistics on the reduced sample (cont.)**

	Panel C: HFT Others			**Panel D: MIXED Others**		
	Averages		**Diff.**	**Averages**		**Diff.**
	Before	**After**	**(SD)**	**Before**	**After**	**(SD)**
Quoting activity ratio (QAR)	16.78	13.87	-2.91 (0.45)	21.96	14.96	-7.00 (0.39)
Trading Activity Ratio (TAR)	1.34	1.04	-0.3 (0.06)	54.77	50.38	-4.39 (0.5)
Cancellation ratio	97	95.42	-1.58 (0.36)	90.6	87.66	-2.94 (0.3)
Aggressiveness ratio	32.93	30.56	-2.37 (1.59)	46.04	50.59	4.55 (0.47)
Display order value (at best bid and ask)	10’549	11’754	1205 (479)	14’672	13’063	-1609 (271)
Time presence 5 price levels	21.64	24.61	2.97 (1.31)	56.47	44.42	-12.05 (0.85)
Time presence 3 price levels	9.19	11.66	2.47 (0.62)	35.77	26.23	-9.54 (0.7)
Time presence at Best Bid-Ask	1.05	0.46	-0.59 (0.14)	12.14	9.73	-2.41 (0.32)
Time presence Top of the book (priority)	0.13	0.1	-0.03 (0.01)	4.09	3.1	-0.99 (0.16)
Gross Liquidity Provision (LP)	1.95	1.49	-0.46 (0.11)	53.31	43.02	-10.29 (0.82)
Gross Liquidity Consumption (LC)	0.85	0.69	-0.16 (0.06)	45.56	44.17	-1.39 (0.48)
Net Liquidity Provision (NLP)	0.55	0.41	-0.14 (0.06)	3.87	-0.57	-4.44 (0.47)
Quoted spread (ticks)	8.8347	10.1591	1.32 (0.353)	4.4734	4.6239	0.15 (0.065)
Effective spread (ticks)	2.042	2.1347	0.09 (0.099)	1.0578	0.9845	-0.07 (0.035)
Realized spread (bps) - 5 Minutes	0.9816	1.123	0.14 (0.329)	-0.1043	-0.1153	-0.01 (0.062)

Riordan and Storkenmaier (2012) and Megarbane, Saliba, Lehalle, and Rosenbaum (2017). Standard errors are double clustered on both stock and day as suggested by Petersen (2009). I report the results of the regressions in Table 2.8.

Table 2.8 shows that there have been no significant changes in the quoting activity ratio for the HFT-MMs. Instead, they trade more, cancel less, and are less aggressive. Their display order value decreases significantly, as already pointed out before, by more than 11'000 euros per stock/day at the best bid and ask. Their presence at the top of the book increase by roughly 5%, which translates to 25 more minutes on average per stock/day. They significantly provide more liquidity (NLP goes to 5% from zero, i.e., a strategy where they provide more liquidity and enjoy the rebate more frequently). All these changes did not statistically affect their quoted, effective, and realized spread, which remains at the same level in the two periods. I confirm the increase in the quoting activity for the MIXED-MMs, together with the aggressiveness and the display order value. However, in terms of market quality, they consume even more liquidity, but they quote a significantly lower spread. Potentially, a different set of strategies applied by MIXED-MMs affect the effective spread negatively, but not the realized spread after 5 minutes.

The results indicate that, on the one hand, there has been a strong reduction in the quantity available at the best bid and ask by quoted HFT-MMs, which is not completely compensated by other market participants. On the other hand, HFT-MMs are more present at the top of the book and provide more liquidity. Mixed-MMs, however, change their behavior significantly. They submit more messages, they are more aggressive, and they consume more liquidity. They quote a significantly lower spread, apparently without harming their realized spread performances. If I compare the differences between the MIXED-MMs and the MIXED-Others in the two periods, some metrics appear to have a symmetric change.

The QAR goes from 23.8% to 32.76% for the MIXED-MMs, while for the MIXED-Others it goes from 21.96% to 14.86%. The display order value increases by roughly 2'000 euros for MIXED-MMs, and decreases by more than 1'500 euros for MIXED-Others. Further, the gross liquidity consumption for MIXED-MMs increases by 5%, while the gross liquidity provision by MIXED-Others reduces by 10%. I can infer from these changes that some investment banks decided to join the new SLP program and move their proprietary trading activities under the SLP program to enjoy the rebate scheme and the fees reduction.

The above findings are consistent with the prediction of Aït-Sahalia and Sağlam (2017a): the liquidity provision increases, the (quoted) bid-ask spread narrows down, and HFT-MMs reduce their displayed order value compared to the previous regime. I argue that the reduction of the displayed liquidity available could be due to two concurrent factors. The first is to protect themselves from the risk of being adversely selected because a minor quantity displayed in the book could be managed more effectively. The second is that the increase in the competition forces the HFT-MMs to quote no longer on ten stocks in a basket, but on forty. Both risk management and inventory issued could have changed the logic of the market-making algorithm.

I also investigated at the basket level the adjustments, in order to provide additional evidence of the competition effect. If the adjustments are due to an increase in the competition, I should observe heterogeneity in the trading behavior for each basket, resulting in different coefficient adjustments after the transition from the first to the second period. If the adjustments are not due to the competition, the variables should have all the same sign and (possibly) a comparable magnitude across baskets. I estimate regression 2.8 for each basket for the two groups of market makers.

Table 2.8: **Regression on the introduction of the new SLP program**

This table shows the regression coefficients of the following panel regression:

$$y_{i,j,k} = \alpha_i, j + \beta_1 SLP_{i,j,k} + \beta_2 VCAC_k + \epsilon_{i,j,k} \quad (2.9)$$

where y is one of the 13 measures listed below, SLP is a dummy that is equal to one after the introduction of the new SLP requirements, and $VCAC_k$ a measure of the daily volatility for the CAC40 Index. Standard errors are in parentheses and double clustered by stock and date. ***, **, * correspond to 1%, 5%, and 10% significance levels. The sample period goes from April 2 to July 31, 2013, for the 37 French stocks of the CAC40 index traded on NYSE Euronext Paris. Order flow data, with trader group and account flags, are from BEDOFIH.

	HFT MM	**HFT Others**	**MIXED MM**	**MIXED Others**
Quoting activity ratio (QAR)	0.0150	-0.0272***	0.0886***	-0.0737***
	(0.0105)	(0.00676)	(0.00931)	(0.0105)
Trading Activity Ratio (TAR)	0.0478***	-0.00271***	0.0143***	-0.0459***
	(0.00672)	(0.000684)	(0.00291)	(0.00613)
Cancellation ratio	-0.00573***	-0.0175**	0.00140	-0.0309***
	(0.00197)	(0.00883)	(0.00127)	(0.00467)
Aggressiveness ratio	-0.107***	-0.0362	0.0352**	0.0501***
	(0.0118)	(0.0223)	(0.0139)	(0.00626)
Display order value (at best bid and ask)	-11,626***	1,646***	2,046***	-1,496***
	(1,473)	(561.8)	(586.9)	(498.9)
Time presence up to 5 price levels	0.00250***	0.0294	0.00130***	-0.120***
	(0.000904)	(0.0192)	(0.000495)	(0.0181)
Time presence up to 3 price levels	-0.00195	0.0274	0.0703***	-0.0937***
	(0.00346)	(0.0170)	(0.0111)	(0.0153)
Time presence at Best Bid-Ask	-0.0349**	-0.00539***	-0.00005	-0.0223***
	(0.0139)	(0.00178)	(0.0119)	(0.00473)
Time presence at the Top of the Book	0.0536***	-0.000320*	0.00416**	-0.00888***
	(0.00803)	(0.000167)	(0.00190)	(0.00209)
Net Liquidity Provision (NLP)	0.0584***	-0.000956	-0.0161***	-0.0494***
	(0.00612)	(0.000670)	(0.00290)	(0.00571)
Quoted spread (ticks)	-0.0989	1.533***	-0.468***	0.105
	(0.0904)	(0.473)	(0.107)	(0.0896)
Effective spread (ticks)	-0.0765	0.127	-0.112**	-0.0808*
	(0.0561)	(0.103)	(0.0559)	(0.0467)
Realized spread (bps) - 5 minutes	0.0967	0.289	0.00154	0.0104
	(0.0614)	(0.306)	(0.0983)	(0.0665)
Standard Errors	Clustered by stock and day			
N. of Stocks / Days	37 stocks / 85 days			

TABLE 2.9: **Regression on Baskets of stocks**

This table shows the estimation of regression 2.8 for the HFT-MM (Panel A) and the MIXED-MM (Panel B). The description of the variables is presented in Section 2.5.1. Standard errors are in parentheses and double clustered by stock and date. ***, **, * correspond to 1%, 5%, and 10% significance levels. The sample period goes from April 2 to July 31, 2013, for the 37 French stocks of the CAC40 index traded on NYSE Euronext Paris. Order flow data, with trader group and account flags, are from BEDOFIH.

Panel A: HFT-MM	**Basket 1**	**Basket 2**	**Basket 3**	**Basket 4**
Quoting activity ratio (QAR)	0.0243	0.0276*	0.0442***	-0.0380**
	(0.0154)	(0.0164)	(0.0140)	(0.0183)
Trading Activity Ratio (TAR)	0.0571***	0.0518***	0.0604***	0.0217***
	(0.00973)	(0.0118)	(0.00883)	(0.00814)
Cancellation ratio	-0.00110	-0.00535	-0.00285	-0.0133***
	(0.00179)	(0.00404)	(0.00287)	(0.00231)
Aggressiveness ratio	-0.115***	-0.129***	-0.110***	-0.0720***
	(0.0150)	(0.0179)	(0.0248)	(0.0162)
Display order value (at best bid and ask)	-12,179***	-14,998***	-9,414***	-9,221***
	(1,633)	(2,836)	(3,601)	(2,268)
Time presence up to 5 price levels	0.00253*	0.00240**	0.00458***	0.000530
	(0.00141)	(0.00117)	(0.00159)	(0.00166)
Time presence up to 3 price levels	0.00150	-0.00644	0.00464	-0.00613
	(0.00591)	(0.00799)	(0.00375)	(0.00528)
Time presence at Best Bid-Ask	-0.0384**	-0.0616**	0.0135	-0.0478*
	(0.0160)	(0.0277)	(0.0174)	(0.0263)
Time presence at the Top of the Book	0.0557***	0.0699***	0.0690***	0.0165
	(0.0117)	(0.0127)	(0.00969)	(0.0101)
Net Liquidity Provision (NLP)	0.0686***	0.0679***	0.0557***	0.0401***
	(0.00930)	(0.0105)	(0.0114)	(0.00760)
Quoted spread (ticks)	-0.127	0.0534	-0.425***	0.0676
	(0.163)	(0.161)	(0.154)	(0.0966)
Effective spread (ticks)	0.149	-0.111**	-0.291***	-0.0208
	(0.152)	(0.0487)	(0.0837)	(0.0812)
Realized spread (bps) - 5 minutes	-0.112	0.255***	0.0147	0.173**
	(0.169)	(0.0865)	(0.0788)	(0.0832)
Standard Errors	Clustered by stock and day			
N. of Stocks / Days	8	11	9	9

TABLE 2.9: **Regression on Baskets of stocks (cont.)**

Panel B: MIXED-MM	**Basket 1**	**Basket 2**	**Basket 3**	**Basket 4**
Quoting activity ratio (QAR)	0.137***	0.0393***	0.133***	0.0608***
	(0.00950)	(0.00827)	(0.0121)	(0.0108)
Trading Activity Ratio (TAR)	0.0250***	0.00906***	0.0163***	0.00915***
	(0.00503)	(0.00340)	(0.00303)	(0.00353)
Cancellation ratio	0.00305*	-0.00181	0.00443**	0.000787
	(0.00174)	(0.00163)	(0.00172)	(0.00306)
Aggressiveness ratio	0.0755***	0.0205	0.0636***	-0.0113
	(0.0206)	(0.0187)	(0.0180)	(0.0112)
Display order value (at best bid and ask)	2,485***	-913.6**	5,543***	1,771**
	(516.9)	(433.4)	(1,394)	(738.6)
Time presence up to 5 price levels	0.00368***	-0.000469	0.00280***	-0.000193
	(0.000938)	(0.000340)	(0.000705)	(0.000236)
Time presence up to 3 price levels	0.136***	0.0324***	0.106***	0.0213***
	(0.0209)	(0.00494)	(0.0237)	(0.00717)
Time presence at Best Bid-Ask	0.0736***	-0.0614***	0.0545***	-0.0457***
	(0.0120)	(0.0103)	(0.0147)	(0.0113)
Time presence at the Top of the Book	0.0159***	-0.00510**	0.00839***	0.000717
	(0.00205)	(0.00237)	(0.00223)	(0.00235)
Net Liquidity Provision (NLP)	-0.0268***	-0.0123***	-0.0205***	-0.00668**
	(0.00434)	(0.00343)	(0.00403)	(0.00316)
Quoted spread (ticks)	-0.841***	-0.116	-0.947***	-0.0826
	(0.0991)	(0.135)	(0.198)	(0.0880)
Effective spread (ticks)	0.120	-0.162***	-0.257***	-0.114
	(0.156)	(0.0503)	(0.0694)	(0.0958)
Realized spread (bps) - 5 minutes	-0.0805	0.268	-0.196	-0.0517
	(0.148)	(0.168)	(0.132)	(0.147)
Standard Errors	Clustered by stock and day			
N. of Stocks	8	11	9	9

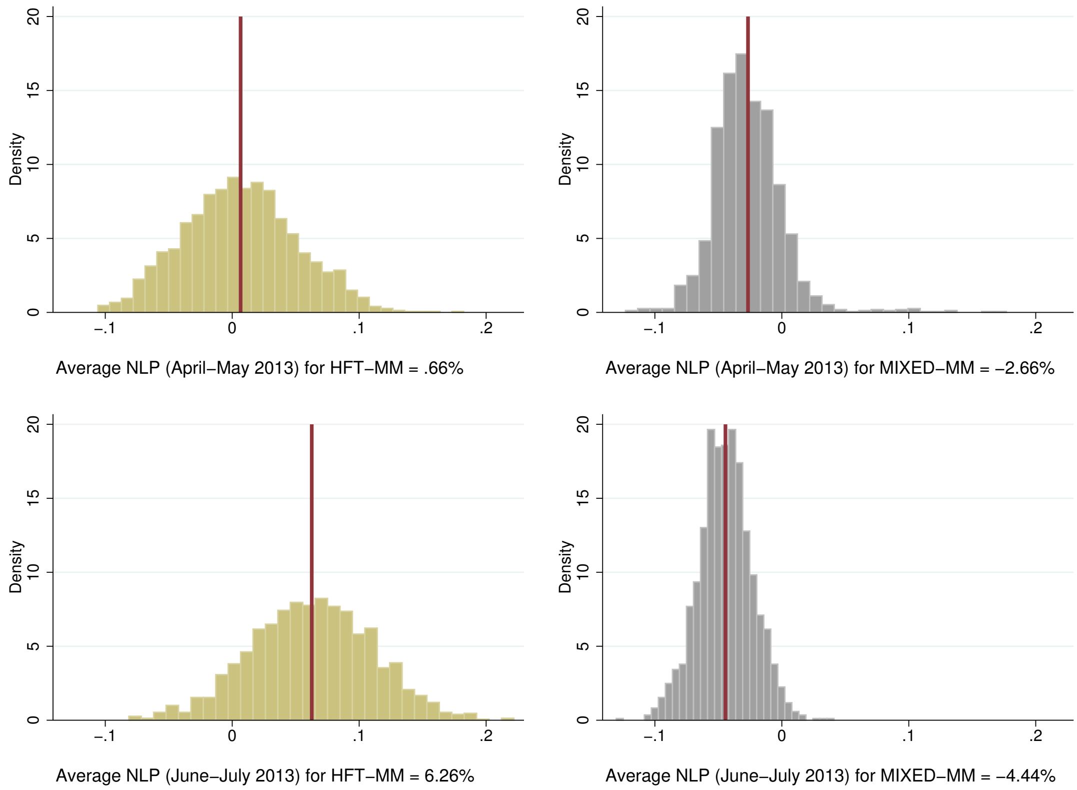
Table 2.9 Panel A reports the results for HFT-MMs. I notice that the quoting activity increases in baskets 2 and 3, while it decreases in basket 4. The increase in trading activity is less pronounced in basket 4, where there is also a reduction in the cancellation ratio and in the time presence at the best bid and ask. Basket number 3 displays the highest increase in quoting and trading activity, and a significant reduction of both quoted spread and realized spread. Table 2.9 Panel B shows the same estimation for MIXED-MMs. The main differences across baskets are the aggressiveness ratio, the display order value, and the quoted and effective spread. MIXED-MMs become more aggressive in baskets 1 and 3, where they also increase their displayed volume and reduce the quoted and effective spread significantly. Given the different coefficients across baskets, I confirm that the adjustments are due to an increase in the competition.

In Section 2.5.3, I establish for the entire sample that HFT-MMs do provide liquidity, and strategically try to avoid other HFT-MMs. I document that the level of liquidity provided by the market makers changed before and after the introduction of the new program. A closer look at the liquidity metrics presented in Table 2.7 provides some interesting facts. First, the gross LP of HFT-MMs goes from an average value of 23.8% to 35.4% (a remarkable +12.4%), almost without increasing their gross LC. The exact opposite situation is present for the MIXED-MMs, which increase their gross LC by +4% without increasing their LP.

Focusing on the NLP, Figure 2.7 shows that there is a remarkable change in the behavior of the two groups of market makers. HFT-MMs become more often net liquidity providers, while MIXED-MMs become more aggressive and consume even more liquidity. The average values go from 0.66% to 6.26% for the HFT-MMs, and from -2.66% to -4.44% for the MIXED-MMs.

FIGURE 2.7: **Distribution of Net Liquidity Provision Before and After the new SLP agreement**

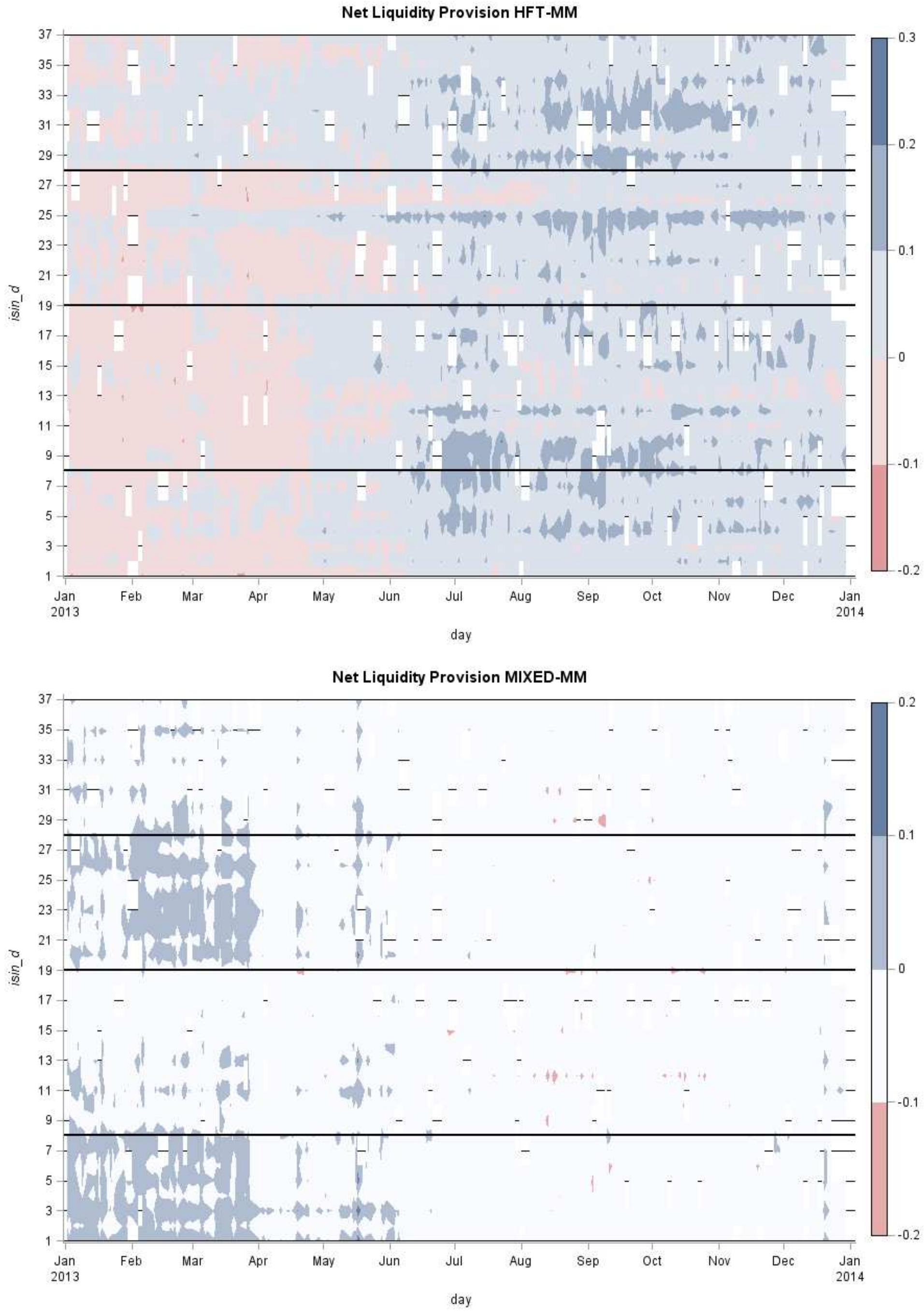
This figure shows the density histogram of the net liquidity provision (NLP) as defined in Section 2.5.1 for the two groups of market makers (HFT-MM and MIXED-MM) for two months before (left graphs) and for two months after (right graphs) the introduction of the new SLP agreement. The red vertical line represents the average value, also reported in the caption of the graphs. The sample data includes 37 French stocks of the CAC40 index traded on NYSE Euronext Paris. Order flow data, with trader group and account flags, are from BEDOFIH.



To exploit graphically the time series characteristics of the NLP, I use the "heat-map" representation across stocks and days for the liquidity providers, presented in Figure 2.8. The top panel shows that in the first period of the year, HFT-MMs were slightly net liquidity consumers, while the behavior remarkably switched to a positive net liquidity provision on almost all stocks beginning in June 2013. The bottom panel of Figure 2.8 represents the cross-section and time-series behavior of the MIXED-MMs. Even in this case, their behavior remarkably switches, but in the opposite direction. In the first period, they are mildly providing liquidity in some stocks, but in the second part of the sample, their NLP position is close to zero, or negative.

FIGURE 2.8: **Net Liquidity Provision Heatmaps for HFT-MM and MIXED-MM**

This figure shows the heatmaps of the net liquidity provision, defined in Equation 2.2 of Section 2.5.1 for the two groups of market makers (HFT-MM and MIXED-MM). The X-axis represents the date, while the Y-axis represent the stocks in the sample. The horizontal lines identify the four baskets of stocks active until May 2013. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags, are from BEDOFIH.



I formally test the changes in the liquidity-provision behavior, estimating equation 2.6 for the two subsamples (two months before and two months after the kick-off date

Table 2.10: **Liquidity Provision and SLP**

This table shows the estimation of regression 2.6 where the HFT-MM and the MIXED-MM provide liquidity to other traders, two months before (PRE-SLP) and two after (POST-SLP) the introduction of the new SLP agreement. Standard errors are in parenthesis and double clustered by stock and date. ***, **, * correspond to 1%, 5%, and 10% significance levels. The sample period goes from April 2nd to July 31st, 2013, for the 37 French stocks of the CAC40 index traded on NYSE Euronext Paris. Order flow data, with trader group and account flags are from BEDOFIH.

Liquidity Provision Pre and Post SLP

	HFT-MM provide liquidity		MIXED-MM provide liquidity	
	PRE-SLP	POST-SLP	PRE-SLP	POST-SLP
To HFT-MM	-0.00343 (0.00354)	0.0312*** (0.00388)	-0.0340*** (0.00209)	-0.0332*** (0.00200)
To HFT-Others	-0.0382*** (0.000752)	-0.0326*** (0.000739)	-0.0477*** (0.000442)	-0.0489*** (0.000470)
To MIXED-MM	-0.00909*** (0.00248)	0.0205*** (0.00355)	-0.0412*** (0.00114)	-0.0404*** (0.00134)
To MIXED-Others	0.0839*** (0.00568)	0.139*** (0.00562)	-0.0162*** (0.00327)	-0.0189*** (0.00200)
To NON HFT	0.00632** (0.00258)	0.0237*** (0.00240)	-0.0360*** (0.00122)	-0.0384*** (0.000977)
Constant	0.0401*** (0.000594)	0.0348*** (0.000594)	0.0484*** (0.000368)	0.0495*** (0.000444)
# obs	38,598	34,940	38,598	34,940
Adj R^2	0.0974	0.289	0.0556	0.0675
Standard Errors	Clustered by stock and day			

of the new SLP program) and for the two groups of market makers. The results are presented in Table 2.10.

Table 2.10 depicts the effects of the competition on the liquidity provision strategies by the market makers. For the HFT-MMs, in the pre-SLP period, they successfully avoid providing liquidity to other HFT-MMs. The coefficient of *To HFT-MM* is negative and not significant. However, the same coefficient in the post-SLP become positive and highly significant, implicating that they are no longer able to discriminate between market makers and liquidity-motivated traders. Another implication regards the liquidity provided to MIXED-MMs. In the pre-SLP period, not only were they not providing liquidity to MIXED-MMs, but they were consuming the liquidity supplied by the MIXED-MMs. The coefficient of *To MIXED-MM* switches from negative and significant to positive and significant. Regarding the other categories, HFT-MMs significantly provides more liquidity also to MIXED-Others and NONHFTs. Interestingly, the provision of liquidity by MIXED-MMs remains almost unchanged. The new competitive environment does not influence the liquidity provision strategies, but only their aggressiveness.

Finally, I statistically verify if the new program affects the adverse-selection risk for the HFT-MMs, estimating Equation 2.7 two months before and two months after the introduction of the program. Table 2.11 show the results for three representative time intervals (10 seconds, 1 minute, and 5 minutes).

The greater provision of liquidity to other HFT-MMs does not translate into a

Table 2.11: **Realized spread regression and SLP**

This table shows the estimation of regression 2.7 for HFT-MM traders only, two months before and two after the introduction of the new SLP agreement. Standard errors are in parentheses and double clustered by stock and date. ***, **, * correspond to 1%, 5%, and 10%significance levels. The sample period goes from April 2 to July 31, 2013, for the 37 French stocks of the CAC40 index traded on NYSE Euronext Paris. Order flow data, with trader group and account flags, are from BEDOFIH.

Realized spread (bps) Pre and Post SLP

	10 seconds		1 minute		5 minutes	
	PRE-SLP	POST-SLP	PRE-SLP	POST-SLP	PRE-SLP	POST-SLP
To HFT-MM	-0.758***	-0.686***	-0.701***	-0.684***	-0.696***	-0.442**
	(0.153)	(0.132)	(0.139)	(0.108)	(0.214)	(0.194)
To MIXED-MM	0.328	-0.372**	-0.436**	-0.335**	-0.0728	0.259
	(0.641)	(0.179)	(0.189)	(0.165)	(0.406)	(0.233)
To MIXED-Others	0.159	0.332***	0.0555	0.218**	-0.153	0.247
	(0.133)	(0.126)	(0.113)	(0.0925)	(0.209)	(0.174)
To NON HFT	1.264***	1.200***	1.417***	1.334***	1.563***	1.552***
	(0.136)	(0.119)	(0.152)	(0.113)	(0.296)	(0.141)
Constant	-0.177	-0.0283	-0.0141	0.122	0.0552	-0.0326
	(0.135)	(0.123)	(0.119)	(0.101)	(0.226)	(0.177)
# obs	1,453,238	1,530,252	2,599,721	2,697,979	2,890,607	2,957,059
Adj R^2	0.00965	0.0152	0.00521	0.00632	0.00172	0.00156
Standard Errors			Clustered by stock and day			

higher risk of being adversely selected: the realized spread, albeit negative in all the time intervals considered, is lower in the post-SLP period. The same applies when they are providing liquidity to MIXED-MMs. However, it seems that there are more sophisticated fast traders in the MIXED-MMs, since the risk of being picked off is more severe for short time intervals (10 seconds). The coefficients of the realized spread against *NONHFTs*, although all positive, are all smaller in the post-SLP period compared to the pre-SLP. This implies a reduction of the adverse selection risk for the slower traders, which pay a smaller price when they face an HFT-MM.

Taken together, all the empirical evidence presented in this section shows, as predicted by the theory, that increasing the competition and tightening the requirements is beneficial for market quality. The quoted spread decreases, the liquidity available in the market increases, and the adverse selection costs for the slow traders mildly decrease.

2.6 Conclusion

In this paper, I provide empirical evidence on the behavior of HFT-MMs in the context of three recent theoretical contributions on the new market microstructure models by Budish, Cramton, and Shim (2015), Menkveld and Zoican (2017), and Aït-Sahalia and Sağlam (2017a). I find that HFT-MMs are consistently but selectively providing liquidity to the market. Their algorithms are very efficient in intercepting the order flow of slow traders and avoiding other HFTs. This efficiency is justified by the fact that they run the risk of being adversely selected only when they are providing liquidity to other HFT-MMs. The liquidity provided to NONHFTs, on average, grants them a consistent and conspicuous return, even in short time intervals. In the tale of Menkveld and Zoican (2017), two types of HFTs, the HFT-MM and the HFT-Bandits, are racing "towards a carrot" and could assume both the role of MM or the bandit. I do find evidence that this is the case, and the race is most likely between two HFT-MMs that are selectively acting as liquidity providers or bandits.

The introduction of a new supplemental liquidity provision agreement (SLP) allows to test whether an increase in the competition changes the behavior of the market makers. Under the new rules, the provision of liquidity increases, the quoted bid-ask spread reduces, and the HFT-MMs become more conservative, drastically reducing their displayed quantity at the best prices. Further, I find that the adverse selection risk decreases for the liquidity-motivated traders (NONHFTs). The results show that the two categories of market makers in the sample, the HFT and the MIXED, behave in a very different way. While the former is very close to what the regulation expects from an electronic liquidity provider, the latter trade very aggressively and consume liquidity.

All in all, the analysis can be viewed as a preview of what will be the new trading environment after January 2018. Flash crashes, extreme price movements, and periods of high volatility are all "exceptional circumstances" foreseen explicitly in the MiFID II directive; therefore, they represent cases where one can expect a consistent drop in liquidity. What is potentially very important is to verify, under normal market conditions, if the HFTs can play the role of electronic market makers fulfilling the dictates of the future regulation. MiFID II put a spotlight on algorithmic trading and HFTs, *de facto* endorsing the automatic liquidity provision by electronic market makers. This paper offers some insights on this topic, looking at the behavior of a market-making flagged order flow of NYSE Euronext during 2013. The SLP program, introduced by NYSE Euronext and similar to a designated market makers model, encompasses most of the characteristics of the regime that will be in force starting from January 2018 under MiFID II: *(i)* it is designed to enhance liquidity provision by algorithmic market makers; *(ii)* there is a binding agreement between the exchange and the firm; *(iii)* there is a monitoring system to evaluate the performances of the liquidity providers.

The policy implication of this analysis is that algorithmic market-making strategies, together with a formal commitment to provide liquidity under an agreement with the exchange, could improve the market quality, given that the exchange imposes a sufficient competition among market makers. I show that the quoted bid-ask spread reduces and the provision of liquidity increases. However, HFTs still impose high adverse selection costs to slower traders. I provide evidence that these costs that form the profits of the market-making strategies could be marginally reduced by introducing greater competition. We await the full implementation of MiFID II to confirm these findings.

Chapter 3

Intraday Pricing and Liquidity of Italian and German Treasury Auctions

3.1 Introduction

The total amount of government debt for the Euro Area is about 9.7 trillions[1]: 70% of this amount (6.8 trillions) is composed by government securities, making the European sovereign bond market one of the largest in the world.[2] Among all the EU members, two countries are particularly relevant, for different reasons. The first is Italy, that has one of the highest amount of public debt in the world and an historically very liquid secondary bond market. The second is Germany, one of the strongest country in Europe in terms of economic growth and industrial output. The amount of sovereign debt for these two countries is relevant: 2.3 trillions for Italy, and about 1.3 trillions for Germany. Together, they account for roughly half of the total European sovereign debt outstanding.

A sizable part of this debt is issued by the Treasury agencies via auctions, that is the main funding source for the Treasury to borrow money from the market and to roll-over the maturing debt. The recent financial crisis, the importance of a well functioning primary and secondary market for the sovereign bond and the size of the secondary market itself, motivates a careful analysis of the behavior of the market participants, especially during the auction days. Both the Italian and German market are characterized by the presence of a pool of financial institutions (mostly investment banks) that have specific duties: the primary dealers. Primary dealers are appointed to provide liquidity in the secondary market, acting as market-makers, and are also required to actively participate to the primary auctions submitting meaningful bids.

The purpose of this paper is to analyze the influence of the bond supply on the behavior of the primary dealers (or market-makers), and the impact in terms of market quality. Consistent with the theoretical models of Duffie (2010) and Sigaux (2017), I show empirically the presence of intraday price pressure and liquidity pattern around the auction time. Further, I find that liquidity in terms of bid-ask spread is better in the action days compared to non-auction days. This is motivated by the model of Bessembinder et al. (2016), that predicts higher liquidity before a scheduled event. However, the uncertainty around the auction push market-makers to reduce the total amount quoted in the auction days, and most importantly to widen the bid ask spread and withdrawn from the market. The sovereign bond crisis and the Public Sector Purchase Program (PSPP) have a different impact in the two countries. For Italy, the crisis amplify the liquidity issues, while the PSPP beneficially affects the behavior of the market makers, that remains in the secondary market during the auctions and do not withdraw their quotes.

[1] See Eurostat `http://ec.europa.eu/eurostat/web/euro-indicators/` for the EU 19 members.

[2] As a comparison, the US market is about 14 trillions, and the Japanese market 9.3 trillions.

The existent empirical literature on European Treasury auctions shows that government security supply affects secondary market prices. These temporary price movements, that usually starts days before the auction and reabsorb few days after, identify an inverted V-Shaped pattern of the yield. In other words, the bond yield rises before the auction and then fall in the days following days. Since the calendar of Treasury auctions is published well in advance, together with the time of the auction and the amount auctioned, these price movements are not due to unexpected events. While the general results are consistent with the previous evidence using daily data, I show that using intraday data it is possible to better understand the price dynamics and the behavior of market participants minutes before the auction take place. More precisely, the use of daily data capture a short-term effect that could be affected by strategies that involves different instruments (Future, Repo) or hedging using other bonds with similar maturities. While I am not denying this effect, the use of intraday data allows to capture almost "instantaneous" dynamics that are related to different reasons.

My main contribution is to shed light on the intraday linkages between price movements, dry-up of liquidity, and market-makers' behavior in the auctions' days. To the best of my knowledge, no prior research investigates this issue in a high-frequency setting for the European Sovereign bond markets. Compared to the empirical works of Beetsma et al. (2016a) with daily data for the European Bond market, and Fleming and Liu (2016) with intraday data on the U.S. Treasury, I am investigating the liquidity consequences of the behavior of the market-makers, in terms of bid-ask spread, participation, and total depth of the market. In a two-stage analysis, I show that the uncertainty around the auction push market-makers to reduce the amount quoted. Market-makers also widen the bid-ask spread very close to the auction time to protect themselves from adverse selection costs. The explanation of this intraday behavior is due to the high risk aversion of the market makers. Price and liquidity patterns are not observed on non-auction days, suggesting that the auctions themselves influence the behavior of the market participants.

In the last seven years, many factors influenced the sovereign bond prices in the secondary market. The most important is the 2011 debt crisis and the ECB interventions. Pelizzon et al. (2016) analyze the dynamic relation between credit risk and liquidity in the Italian sovereign bond market during the 2011 crisis, finding that credit risk drives the liquidity. They also analyze the liquidity of the Italian sovereign bond market after the initial intervention by the ECB, showing that the increased liquidity available to the banks disconnect the link between credit risk and market liquidity. However, I show that there are peculiar intraday liquidity dynamics during the auction dates, that are exacerbated by the 2011 crisis and attenuated by the PSPP intervention.

One the one hand, a cheaper funding is beneficial for both the market-makers, that could participate more effectively in the primary auction, and for the Treasury. On the other hand, the empirical evidence suggests that dealers also exploit the secondary market channel, short selling the auctioned bond (or a bond with similar characteristics, i.e., the previous on-the-run bond) before the auction, to push the price down. Moreover, in a high frequency setting, the price pressure is present also the quoting activity, and mainly driven by the liquidity channel. The Treasury potentially pays an additional cost for the issuance. The empirical analysis is aimed to address this concerns about liquidity and price movements. A better understanding of this relationship could improve the effectiveness of Treasury auctions, reduce the costs, and improve the liquidity in the secondary market.

The outline of the paper is as follows. Section 2 provides a literature review on sovereign bond market, price pressures, and liquidity. Section 3 describes the primary auctions details for Italy and Germany, and explains the institutional structure of trading on MTS and the data. The empirical evidences about price pressures, liquidity, sovereign bond crisis and PSPP is presented in Section 4. Section 5 concludes.

3.2 Literature Review

The analysis of market-makers' behavior in the fixed income, especially in the treasury market outside the U.S., received attention only on recent years, due to the availability of the data and the development of electronic trading platforms. Market-makers' behavior in the sovereign bond market is very important, since the securities auctioned by the Treasuries are underwritten by the same primary dealers that are the market makers in the secondary market.

The earliest literature focused on how public information drives the price movements in the treasury market. The work of Fleming and Remolona (1997) summarize the earliest contributions, concluding that there is a significant impact of the macroeconomic announcement on bond prices. Together with Ederington and Lee (1993), albeit the latter in the derivative market, they pioneered the intraday analysis of price behavior not in the stock markets. In their work, Fleming and Remolona (1997) shows that the sharpest price movements of the five-year U.S. Treasury note are related to just-released macroeconomic announcements. This issue has been deeply investigated in Fleming and Remolona (1999), where they analyze the quotes of the market makers, rather than only the trades. They find an almost instantaneous price movement at the time of the macroeconomic release, relating this finding to the theoretical model of French and Roll (1986), i.e., the reaction to the public information is anticipated by the quotes, and do not require trading activity. Fleming and Remolona (1999) suggest that the effect on the bid-ask spread is related to the inventory management of the market makers, that withdrawn their quotes anticipating the price changes.

The issue of the market makers' inventories has been analyzed by Fleming and Rosenberg (2008). Using weekly net position of the primary dealers in government securities, they find that dealers include in their balance sheets a large part of the sovereign bond supply, maintaining it until the maturity. Most importantly for the purpose of this paper, their analysis shows that dealers are compensated for the inventory risk they run in the week of the auction, suggesting that dealers buy sovereign bonds in the auction week when the prices are lower, and sell the securities late when the price is higher.

The recent empirical literature focuses on the secondary market movements mainly using daily data. Lou, Yan, and Zhang (2013) shows that the US treasury bond prices decrease significantly five days before the auctions and then shortly recover, linking their results to the limited risk-bearing capacity of the dealers and imperfect capital mobility of end users. A similar pattern is also detected by Beetsma et al. (2016a). In their paper, they study the auction effect for Italy and Germany, in the context of the financial crisis. They find that the auction effect is stronger in Italy, and exacerbates during the crisis. They identify the volatility as the main driving factor for Italy, and the limited risk-bearing capacity of the dealers for Germany.

In a broader sample composed by six European countries Beetsma et al. (2016b) finds evidence of spillover effects across countries in sovereign auctions' days. In contrast to this empirical evidences, Cafiso (2015) do not find evidence of auction cycles for Italy in a reduced sample of auctions, after comparing the result of the auction with the contemporaneous market quotes. However, all the European contributions on this topic use daily data. The only empirical contribution that analyzes the intraday movement around the US Treasury auctions, and close to this work, is by Fleming and Liu (2016). They do find evidence of price pressure effect, not present in non-auction days. They also show that the liquidity tends to deteriorate at the time of the auction and recover thereafter. They conclude that the price pressure could be explained by the limited risk-bearing capacity of the dealers.

Several theoretical papers attempt to explain the V-Shaped pattern and the price overshooting. Brunnermeier and Pedersen (2005) explain that the sharp price movements and subsequent recovery are due to predatory trading. In their model, the strategy consists of a predator that sell the asset before another trader, that has to liquidate a position, enter the market. The price thus will move down. Further, the predator will realize the profit reversing their position. This practice damages the market quality.

Duffie (2010) introduces a model of price impacts and reversal. He related his model not only to unanticipated shocks, but also to anticipated shocks like the treasury auctions. The main empirical implications of this model are that, after a shock, the (slow) mobility of the capital, or additional searching costs, affect the price reversal. As soon as the investors have additional capital, the price shock is reabsorbed. This model is particularly designed for markets where the trading is infrequent, such as the bond market.

Boyarchenko, Lucca, and Veldkamp (2016) deal with information sharing, and how it affects the primary dealer, the customers, and the U.S. Treasury during the auctions. Besides the results related to the degree of informativeness, in their model the do allow post-auction appreciation due to private information of the bidders. Thus, the appreciation is the return awarded to the auction participants that submit competitive bids.

The theoretical model of Beetsma et al. (2016a) related the price effect to the inventory position of the dealers: the larger the amount issued in the auction, the larger the inventory risk and thus the price effect. A financial crisis influence the variance of the return of a bond, the price effect and also the risk aversion of the dealers. The recent contribution by Sigaux (2017) introduces a model aimed to explain the auction pattern, also assuming that the price gradually decreases due to the uncertainty about the (net) size of the trade. The main implication of the model that the author also verify empirically in a sample of Italian auction is that investors face the trade-off about speculating on the difference between the prices before and at the auction, or hedge the uncertainty regarding the supply, buying more bonds before the auction takes place. One additional corollary regards the trading activity and the short-selling of the issued note that are usually higher and increase close to the auction. The author also verify empirically their prediction, in a broad sample that goes from 2000 to 2015 and includes the reopenings of the Italian sovereing bonds with maturity between 2 and 30 years.[3] He also finds the inverted V-shaped pattern of the yield difference, but he shows that the meeting between dealers an the Treasury, and the auction announcement are able to explain 2.4 basis point of the increase in yield.

The model of Bessembinder et al. (2016) specifically deal with the liquidity around predictable trades, in their case the roll-over of crude oil future contracts. The model is close, in the spirit of the one by Brunnermeier and Pedersen (2005), but they allow transitory effects on the prices, rather than permanent. The framework is particularly suitable also for the Treasury auctions, where the date is known in advance. They

[3]The author use daily data from Datastream and secondary trades and Repo from MTS.

find, both theoretically and empirically, that the liquidity is higher during the event day (the roll-days), and this effect is due to the liquidity provision role that the monopolistic trader assume. Under a set of assumption, the strategic trader acts beneficially for the market given that the price impact is not too large and temporary.

3.3 Data and Methodology

3.3.1 Primary Market Auctions

The data for the primary auctions are collected directly from the official web sites of the respective Debt Management offices: Banca d'Italia and the Deutsche Finanzagentur. The focus of the empirical analysis is only on the coupon-bearing Sovereign bonds, issued by the Italian and the German Treasuries. As described in Pelizzon et al. (2016), the majority of the Italian bonds exchanged in the MTS market are coupon-bearing Treasury bonds, or Buoni del Tesoro Poliennali (BTP). In line with previous works, albeit using daily data (for instance, Beetsma et al. (2016a)) the maturity selected are the 3, 5 and 10 years BTP. For the German sovereign bond market, the sample consists of the 2 years Schatz, the 5 years Bobl and the 10 years Bund. Table 3.1 provides an overview of the auctions data, distinguishing between new issues (new on-the-run bonds), subsequent issues of the same on-the-run bond (On the run) and re-open specific bonds in order to improve the liquidity in the secondary market, or following the request from the primary dealers (re-opens). The strategy of reopening off-the-run bonds is applied only by the Italian Treasury, especially for the 10Y maturity. Starting from October 2012, the Italian Treasury auctioned only new on-the-run, or increase the quantity of the current on-the-run. For the Italian sample, only the regular auctions are considered, excluding the supplemental auctions reserved to the specialists that take place one business day after the regular auctions.[4]

[4]The amount offered varies from 10% to 30% of the amount allotted at the auction, and only the Specialist with at least one valid offer in the main auction can subscribe for an additional quantity, at the marginal price fixed at the auction.

TABLE 3.1: **Auctions' results**

This table presents the summary statistics for the 2, 3, 5 and 10 year government bonds issued by Italy and Germany, from June 2011 to December 2016. The source of data are the website of the national Treasury Authorities (The Italian Treasury for Italy, and the Deutsche Finanzagentur for the German issues).

Panel A: Result of Italian Auctions (June 2011-December 2016)

	3Y			5Y			10Y		
	New issues	On the run	Re open	New issues	On the run	Re open	New issues	On the run	Re open
Number of Auctions	14	44	1	13	52	6	11	56	18
Amount bidded (avg. M€)	5613	4407	1773	5144	3729	1483	5650	3751	1594
Amount allotted (avg. M€)	3785	2916	779	3788	2590	653	4023	2687	918
Bid-to-cover ratio (average)	1.48	1.53	2.28	1.36	1.45	2.37	1.40	1.41	1.79
Average Yield (%)	2.25	1.81	4.29	2.62	2.30	4.11	3.43	3.45	5.54

Panel B: Result of German Auctions (June 2011-December 2016)

	2Y		5Y		10Y	
	New issues	On the run	New issues	On the run	New issues	On the run
Number of Auctions	20	47	13	47	13	53
Amount bidded (avg. M€)	7252	7087	5726	5413	5369	4812
Amount allotted (avg. M€)	4213	3729	3926	3211	4040	3429
Retention Quote (avg. M€)	937	760	1074	725	1114	798
Bid-to-cover ratio (average)	1.74	1.91	1.47	1.70	1.32	1.41
Average Yield (%)	-0.06	0.00	0.47	0.32	1.29	1.10

Table 1 Panel shows that the number of auctions is quite similar between the two countries across maturities, as well as the average amount bidden and allotted, in particular for the 5 and 10 years maturities. The average yield is very different, reflecting the riskiness of the two countries: Germany, as a "safe heaven", displays a lower yield, on average negative for the shorter maturity. The difference of the yield in the two countries is around 2% across maturities. The total number of auctions is higher for Italy, that has a higher number of re-openings compared to Germany and mostly concentrated in the 10 years maturity. The bid-to-cover ratio (the ratio between the total amount of bids and the maximum amount announced by the Treasuries) varies across auction types. In general, the value is higher for the auctions that follow the first. For the on-the-run bonds, the values are on average from 1.36 to 1.53 for Italy, and from 1.41 to 1.91 for Germany. The re-opens for the Italian bonds displays the highest bid-to-cover ratio among maturities, indicating a high demand for these bonds. For the German auctions, the retention quote is higher for the new issues, around 10%-20% of the bid quantity.

3.3.2 Secondary market data and variables definition

The dataset of secondary market data is composed of all quotes, orders, and trades for the MTS European sovereign bond market platform, from June 2011 to December 2016. Data have milliseconds timestamp and, from the beginning of 2013, the timestamp is at the microsecond level. The starting point of the sample coincide with the availability of tick-by-tick data.[5] MTS also offers co-location facilities and low-latency connectivity.

[5]For the period before June 2011, only the best bid and ask quotes are available from MTS

TABLE 3.2: **Descriptive statistics**

This table shows the summary statistics for the sample of Treasury coupon bonds included in the intraday analysis, only for the auction dates, for Italy (Panel A) and Germany (Panel B). The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

Panel A: ITALY

	3Y				**5Y**				**10Y**			
	Mean	STD	P5	P95	Mean	STD	P5	P95	Mean	STD	P5	P95
Midprice	101.82	2.52	97.88	106.00	104.36	4.20	96.84	110.26	107.17	9.29	91.76	122.11
Yield (%)	1.44	1.54	-0.04	4.80	1.54	1.63	-0.03	5.02	2.46	2.03	0.10	5.92
Yield Difference (bps)	-0.99	5.59	-9.30	3.90	-1.52	4.52	-9.10	3.00	-1.56	4.13	-8.50	3.40
Depth (M €)	124.34	33.46	53.00	165.75	122.07	32.31	54.00	162.25	116.93	31.59	49.50	156.25
N. Proposals	19.99	5.32	8.00	27.00	20.14	5.40	8.00	27.00	20.05	5.46	8.00	27.00
Bid-Ask Spread	0.11	0.42	0.01	0.30	0.12	0.27	0.02	0.34	0.19	0.38	0.03	0.63
Daily Volume Traded (M €)	542.57	141.86	309.50	822.50	499.76	226.78	84.50	961.50	289.57	206.23	54.50	673.00
Daily N. Trades	97.32	26.40	53.00	144.00	97.94	43.90	17.00	182.00	64.04	41.35	12.00	139.00
Bonds	15				15				18			
Days	58				68				77			

Panel B: GERMANY

	2Y				**5Y**				**10Y**			
	Mean	STD	P5	P95	Mean	STD	P5	P95	Mean	STD	P5	P95
Midprice	100.41	0.50	99.80	101.29	102.19	2.00	99.57	106.21	106.24	6.13	98.57	118.34
Yield (%)	-0.09	0.32	-0.68	0.27	0.02	0.42	-0.64	0.69	0.77	0.84	-0.54	1.91
Yield Difference (bps)	-0.11	0.87	-1.50	1.10	-0.07	1.23	-1.90	1.90	-0.36	1.94	-3.50	2.40
Depth (M €)	69.42	27.18	22.00	110.00	69.58	22.44	25.00	100.00	71.38	23.23	25.00	105.00
N. Proposals	7.91	2.63	3.00	12.00	8.32	2.59	3.00	12.00	9.21	2.88	3.00	13.00
Bid-Ask Spread	0.05	0.21	0.02	0.08	0.06	0.09	0.03	0.10	0.08	0.52	0.03	0.13
Daily Volume Traded (M €)	50.75	57.29	5.00	155.00	41.40	40.20	5.00	110.00	35.65	34.56	2.50	120.00
Daily N. Trades	4.45	5.89	0.00	16.00	3.38	4.93	0.00	15.50	4.67	6.01	0.00	21.00
Bonds	15				15				15			
Days	60				60				65			

In the MTS market, two types of traders exist: primary dealers (market makers) and other dealers (market takers). The primary dealers have market-making obligations that requires them to post on both sides of the market and to maintain a spread close to the average spread of the other primary dealers. The MTS also allows the use of iceberg orders, where the traders can display only a portion of the quantity that they are willing to trade. The trading hours goes from 8:00 a.m. to 5:30 p.m. Anonymity is preserved until the trade is executed; if the trade is centrally cleared, also the two counterparties of the trade are anonymous.

The bonds considered in the sample are only coupon bearing bonds, quoted in price per €100 of face value. The sample is restricted only to bonds that have been auctioned during the sample period. The descriptive statistics of the sample, only for the auction dates, are provided in Table 3.2.

Several order book measures are calculated directly from the high-frequency quotes, extracting snapshots of the order book every minute. The *midprice* is calculated as a simple average of the best bid and best ask prices available. If one of the two prices (bid or ask) is not available, then the midprice is not calculated. Table 3.2, Panel A shows the average midprice for each Italian bonds is higher than the correspondent

German bond for the same, or similar, maturity (Table 3.2, Panel B). The standard deviations and the two reported percentiles (P5 and P95) characterize a higher dispersion of the distribution. The *yield* of each bond is calculated directly from the quotes, taking into account the different rules for the coupon payments (semiannual for the Italian Bonds, annual for the German Bonds). The average yields numbers are in line with the values presented in Table 3.1 for the auction results. The average yield for the shortest maturity (2Y) for Germany is negative, reflecting the effects of the ECB quantitative easing and the low-interest rate environment in the aftermath of the financial crisis.

Following Fleming and Liu (2016), to analyze the impact of the Treasury auctions on the secondary market, I calculate the yield difference, i.e., the simple difference between the yield of the bond in a certain period after and before the auction, and the yield in the secondary market at the auction. The yield difference is calculated as:

$$\textit{Yield difference}_{i,t,d} = Y_{i,d,TA-\epsilon} - Y_{i,d,TA} \tag{3.1}$$

Where $Y_{i,d,TA-\epsilon}$ is the yield measured in one-minute increments ϵ minutes away from the auction time, for bond i and day d, and $Y_{i,d,TA}$ is the yield measured at the time of the auction. The auction time are 11:00 a.m. and 11:30 a.m for Italy and Germany, respectively. The time series evolution of the yield difference is presented in Section 3.4.

Table 3.2, Panel A and B shows the average yield difference (in basis points) for the entire day. The values across countries reflect the different yields of the underlying bonds. On average, the value is negative, and Italy displays higher values of these differences. To measure the liquidity of the bonds, I consider three different liquidity measures. The first is the total *depth* of the market, calculated for each one-minute interval as the average quantity at the bid and ask, quoted in the entire order book and measured in millions of euros (par value). Table 3.2, Panel A shows that the depth across maturities for Italy is comparable and, on average, around 120 millions of euros. Panel B shows that the average depth for the German market is roughly one half compared to Italy, around 70 millions of euros across maturities. The second is the number of proposals (*N. Proposals*) available for trading, for each minute. Every quote, or "proposal" in the database can be tracked throughout the trading day and is representative of one single dealer. A high number of proposals indicates that the dealers are available to trade, and the market is therefore liquid. Table 3.2 shows that the average number of proposals is higher for Italy (20) compared to Germany (8), mainly for two reasons. The first is that the number of participants is smaller for MTS Germany. The second is that other competing venues have a considerable market share for the German Sovereign bonds; besides, a substantial number of trades is conducted over-the-counter. According to MTS, there are 56 participants for MTS Italy, and 36 for MTS Germany.[6] Crossing the two lists, there are 22 dealers that operate as market makers in both markets. Among them, three are Italians (Banca IMI, Banca Sella, and Monte dei Paschi) and one is German (Deutsche Bank). One interesting difference between Italy and Germany is that the Bank of Italy is recognized as a dealer only for the Italian market, while the Finanzagentur is not present in both lists.

The third liquidity measure is the *Bid-Ask Spread*, calculated as the difference between the best ask price and the best bid price available in a given minute. Table

[6]The List of market participants, for both Market Makers and Takers, is available on the MTS website for Italy and Germany

3.2 Panel A shows that the Bid-Ask Spread for the Italian bonds ranges, on average, from 0.11 euros (maturity of 3 years) to 0.19 (maturity of 10 years). These figures are almost halved for the German Bid-Ask spread, reflecting the lower risk and the high liquidity of the German bonds (Panel B).

The bottom part of Table 3.2 provides an overview of the trading activity during the auction days. The daily volume traded for the Italian bonds (Panel A) is higher for the shortest maturities: the 3 years BTP display an average of 542 millions of euros, while for the 10 years, the average value is 289 million. On average, the number of daily trades is around 97 for the 3 and 5 years maturity, and 64 for the 10 years maturity. Panel B shows that the volume traded and the number of trades for the German bonds is more than an order of magnitude smaller. Finally, the number of bonds and auction days considered in the analysis are similar for the two countries.

In the MTS market, there is also the possibility to trade a bond that has been announced by the Treasury, but not yet issued. This is usually referred as the "grey market" or the "when-issued market". Sovereign bonds traded on the grey market will be settled following the settlement conditions of the issued bond. The grey market activity in the sample is particularly relevant for the newly issued bonds, which will be the new on-the-run after the auction. There is evidence of quoting activity for both Italy and Germany in the grey market. However, trading activity is present only for the Italian Sovereign bonds. Figure 3.1 plot the time-series evolution of the traded volume, for the 3, 5 and 10 years Italian notes and represent the traded volume of the current on-the-run bond, i.e., each bar corresponds to the total quantity traded (on both buy and sell side) for the current on-the-run bond. The red bars represent the volume traded in the grey market before a new on-the-run bond is issued. The trading activity in the grey market usually appears around three days before the auction, since the Treasury has to announce the full details of the auctioned bond (ISIN Code, maturity, and coupon). For the US Treasury market, Fabozzi and Fleming (2000) document that the volume traded in the grey market accounts for around six percent of the total volume of Treasury securities traded electronically. Figure 3.1 shows that there is a non-negligible volume traded before the auction for all the maturities. Figure 3.2 shows that the trading activity for the German bonds appears seldomly. Especially during 2013, across maturities, there is a reduction of the trading volume, which increase afterward starting from January 2014, particularly for the 10 years Bund. As pointed out before, there is no trading activity in the grey market for the German bonds.

FIGURE 3.1: **Trading volume and Grey Market for the Italian Sovereign Bonds**

This figure shows the total trading activity only for the respective on-the-run bond in the sample period. The red bars represents the quantity traded in the grey market, before the official issuance of the new on-the-run bond. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

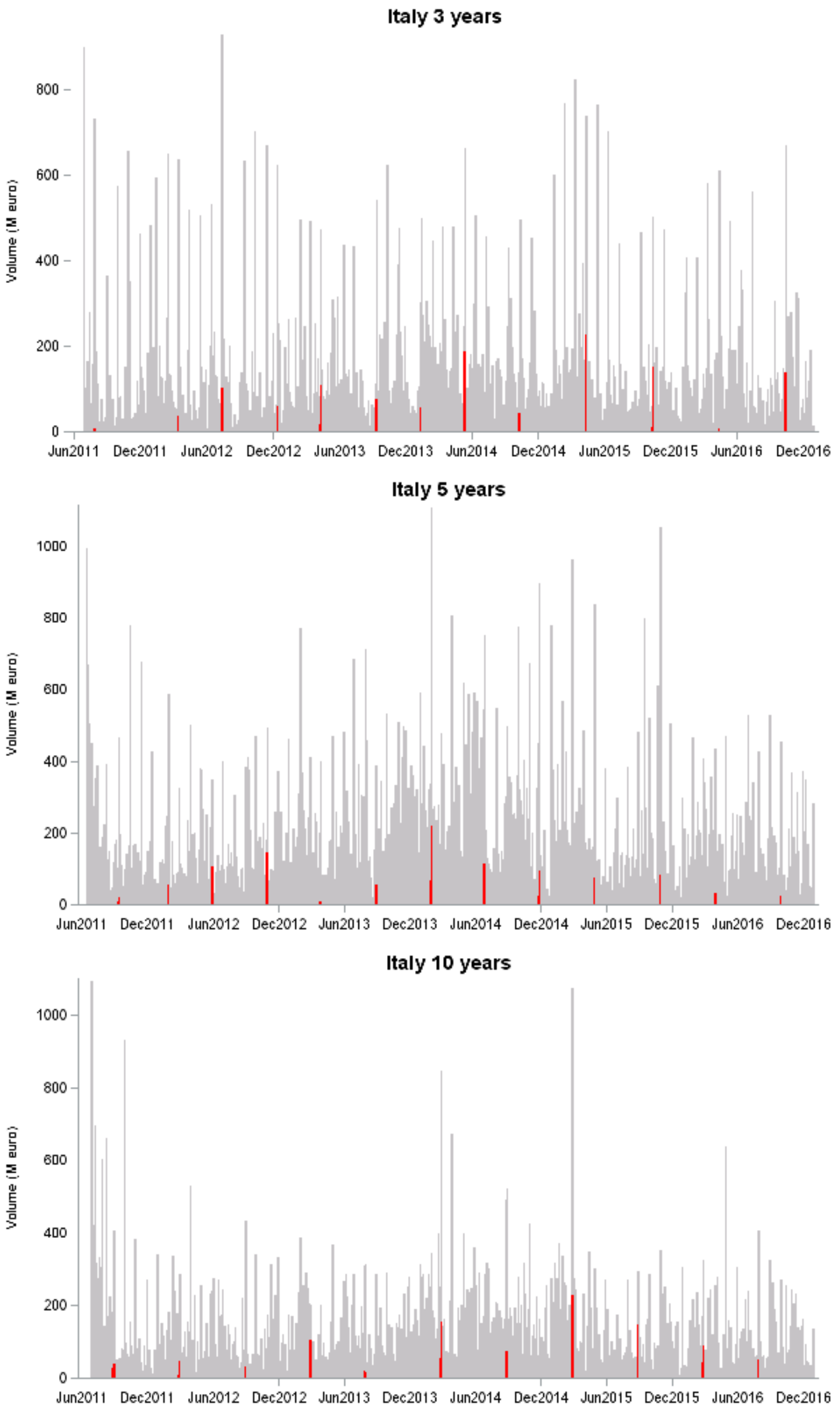
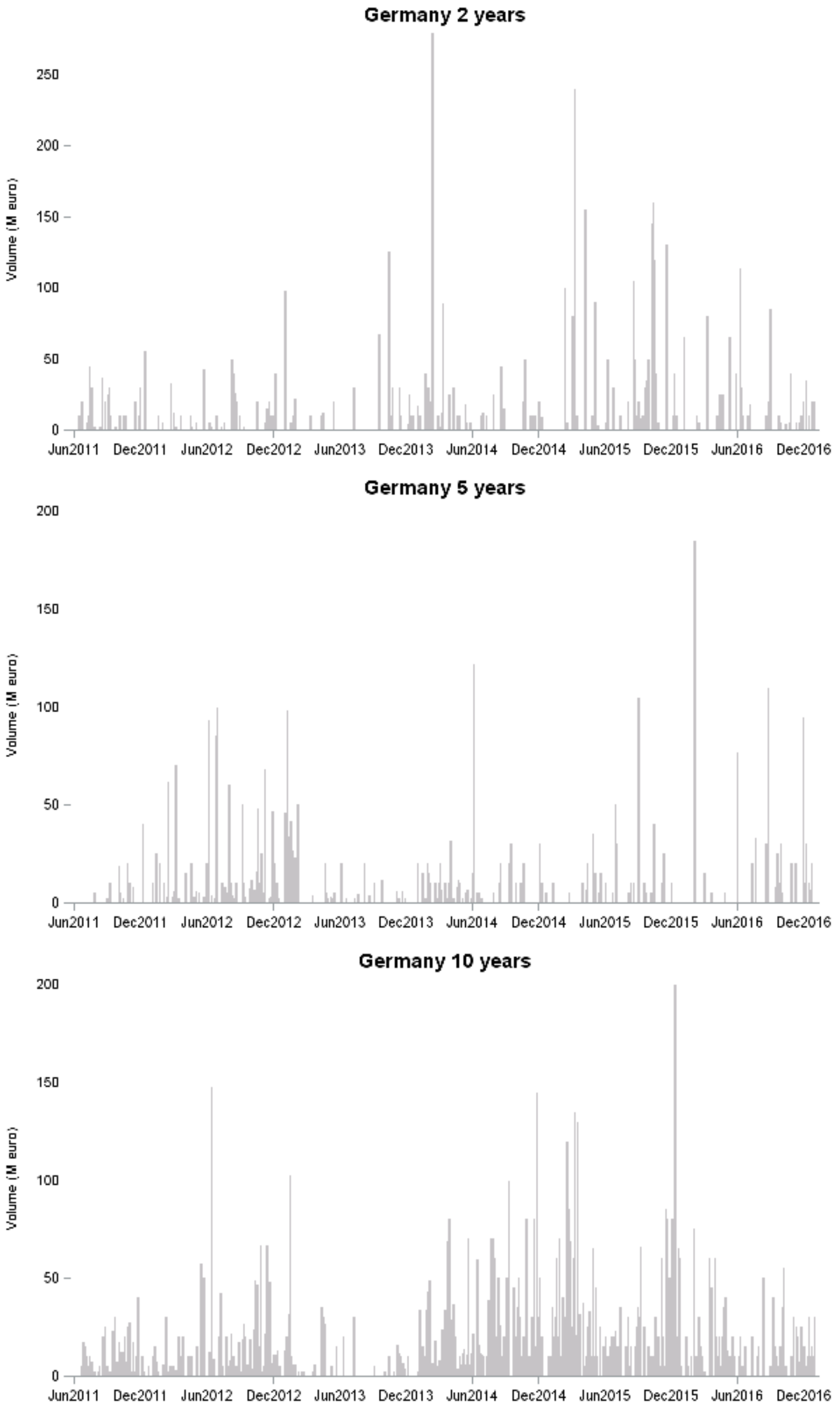


FIGURE 3.2: **Trading volume for the German Sovereign Bonds**

This figure shows the total trading activity only for the respective on-the-run bond in the sample period. The database is composed by fixed coupon sovereign bonds for Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).



3.4 Empirical Evidence

3.4.1 Price Pressures

The aim of this section is to provide intraday empirical evidence that the Treasury auctions are the source of temporary price movements in the secondary market. To do so, following Fleming and Liu (2016), I calculate the Yield difference as defined in Equation 3.1, for each auctioned bond, for Italy and Germany. The yield difference is measured in the window from two hours before the auction to two hours after the auction, in a way that the value of ϵ of Equation 3.1 ranges from -120 to +120 minutes.[7] Thus, the time of the auction is always zero.

The main analysis considers only the auction days of the on-the-run bonds, excluding the days where the new on-the-run is issued. As a robustness check, I also repeat the same analysis also for the auctions of the newly issued bonds, which includes the quotes in the grey market and, and only for Italy, the analysis of the re-openings for off-the-run bonds. The analysis is presented in the appendix. Table 3.3 reports the average yield difference for Italy and Germany, only for the on-the-run bonds, for different intervals ranging from 2 hours before to 2 hours after the auction.

A negative yield difference implies that the yield at the time of the auction is higher compared to the yield before and after the issuance time. Panel A of Table 3.3 shows the results for the Italian bonds where, for almost all the times considered in the analysis, the difference is negative for all the maturities, especially for the 5Y and 10Y notes. For the 3Y bonds, the yield difference is statistically significantly different from zero starting from 100 minutes before the auction, but twenty minutes after the auction, it is no longer significant. For the 5Y and 10Y Italian bonds, the yield difference is always negative and significant in the entire estimation window. The effect is almost symmetric for the 5Y notes: two hours before the auction, the yield difference is around 1.6 basis points. Two hours after, the same difference is around 1.77, indicating that the price of the bond return to the initial value before the auction. The pattern is similar also for the 10Y bonds. This symmetric pattern is not present for the 3Y bonds, where, after a significant movement in the 10 minutes after the auction, the yield remains statistically the same in the following two hours.

Panel B of Table 3.3 reports the same analysis for the German bonds. In this case, the shortest maturity (2Y) does not display a consistent significant pattern around the auction, albeit the yield difference is negative for almost all the time intervals. The yield difference for the 5Y German bonds is statistically different from zero starting from twenty minutes before the auction and remains significantly different up to one hour after. The 10Y Bund display the strongest auction effect in the pool of German bonds. The yield difference is negative and statistically significant starting from 100 minutes before the auction and remains different from zero for the rest of the time window. The effect is, also in this case, almost symmetric. A graphical evidence of the inverted V-shaped pattern for Italy and Germany is provided in Figure 3.3. The solid line represents the average yield difference (in basis points), the shaded area displays the 95% confidence intervals, and the dashed line shows the yield difference calculated, for the same set of bonds, when there are no auctions.

[7] Fleming and Liu (2016) use a larger time window, that goes from minus four hours to plus for hours of the auction time. There are two reasons why I choose a smaller window. The first is related to the auction time of Italy and Germany (11 a.m. and 11:30 a.m.). The second is related to the high price volatility and bid-ask spread at the beginning of the day. This effect is due to the fact that not all the dealers' quotes are present immediately after market opening.

Table 3.3: **Yield Difference On the run**

This table shows the average yield difference, or the yield change from t minutes before the auction to the time of auction ($t = 0$), for the re-openings of on-the-run bonds. The auction times are 11:00 a.m. for Italy, and 11:30 a.m. for Germany. The midpoint is converted into yields using the respective conventions. The number of observations corresponds to the number of auctions for each country and maturity (Panel A for Italy, and Panel B for Germany). *, **, and *** denote significance at the 10, 5, and 1% levels using a t-test to verify if the values are statistically different from zero. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

Panel A: Italy On-the-run bonds

	3Y		**5Y**		**10Y**	
t	Avg. Yield Diff.	Tstat	Avg. Yield Diff.	Tstat	Avg. Yield Diff.	Tstat
-120	-1.530	-1.594	-0.958	-1.314	-1.550**	-2.408
-100	-2.011**	-2.337	-1.609**	-2.289	-2.016***	-3.275
-80	-2.104***	-2.980	-2.105***	-3.389	-2.015***	-3.754
-60	-1.888***	-3.061	-2.18***	-4.306	-1.856***	-4.168
-30	-1.497***	-3.829	-1.483***	-4.062	-1.071***	-3.492
-20	-1.020***	-3.480	-1.276***	-3.716	-0.861***	-3.223
-10	-0.5**	-2.519	-0.570**	-2.469	-0.293*	-1.711
10	-0.675***	-2.993	-0.701***	-2.982	-0.877***	-3.838
20	-0.172	-0.403	-1.116***	-3.347	-1.051***	-2.704
30	0.147	0.274	-1.389***	-3.609	-1.018**	-2.528
60	-0.065	-0.112	-1.041**	-2.463	-1.101***	-3.237
80	0.238	0.324	-1.172**	-2.512	-0.936**	-2.264
100	0.136	0.166	-1.583***	-3.475	-0.980**	-2.302
120	-0.236	-0.311	-1.770***	-3.420	-1.322***	-3.190
Obs	44		52		56	

Panel B: Germany On-the-run bonds

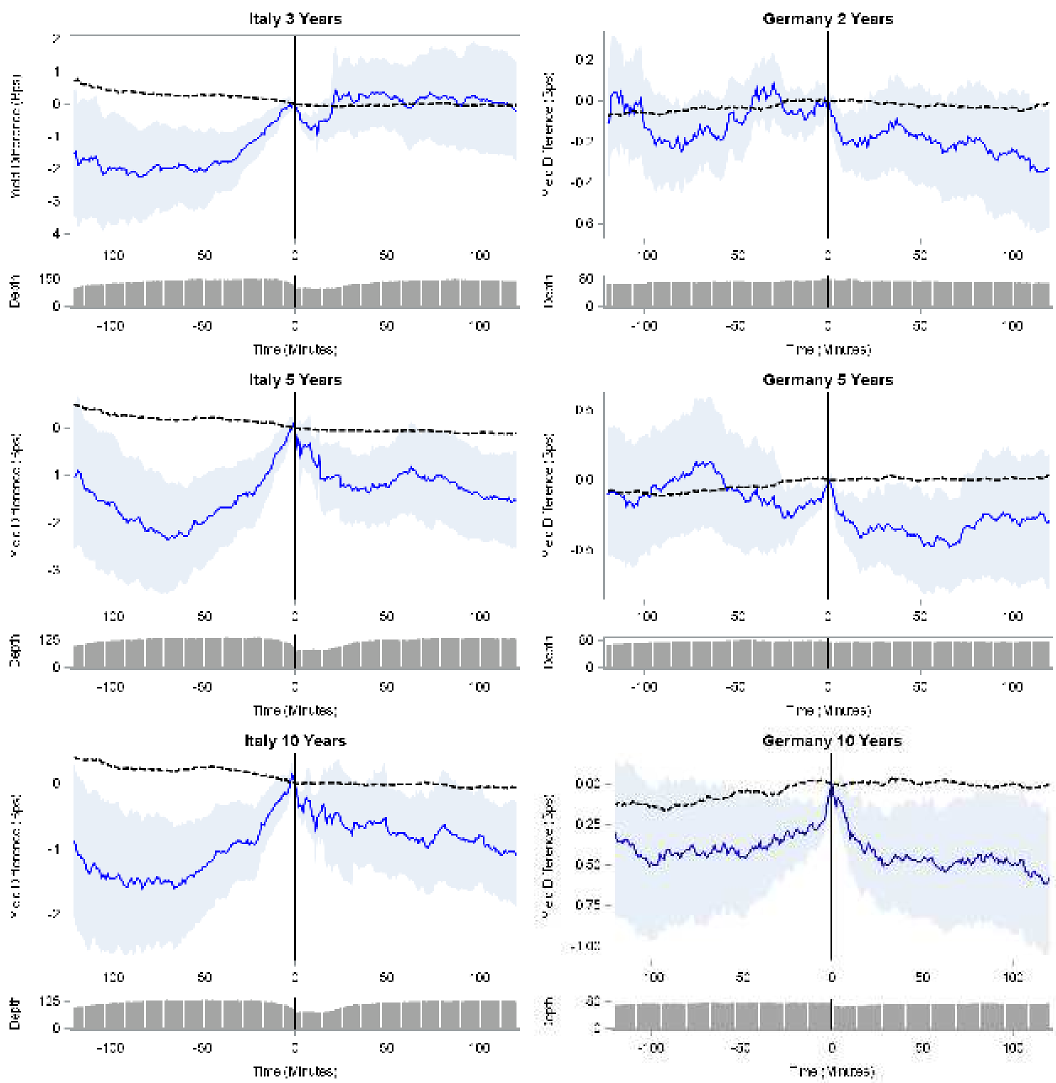
	2Y		**5Y**		**10Y**	
t	Avg. Yield Diff.	Tstat	Avg. Yield Diff.	Tstat	Avg. Yield Diff.	Tstat
-120	-0.111	-0.796	-0.102	-0.445	-0.303	-1.302
-100	-0.132	-1.168	-0.112	-0.534	-0.486**	-2.057
-80	-0.247**	-2.443	0.034	0.164	-0.401*	-1.897
-60	-0.173*	-1.785	0.058	0.277	-0.363*	-1.871
-30	0.085	1.067	-0.121	-0.648	-0.336***	-2.770
-20	-0.046	-0.822	-0.270***	-2.745	-0.286***	-2.764
-10	-0.059	-1.113	-0.142**	-2.169	-0.278***	-4.018
10	-0.210***	-2.928	-0.287***	-3.241	-0.338***	-2.983
20	-0.185*	-1.856	-0.389***	-3.062	-0.369***	-2.903
30	-0.146	-1.499	-0.365***	-2.983	-0.5***	-3.440
60	-0.202*	-1.731	-0.421**	-2.410	-0.530***	-2.911
80	-0.178	-1.306	-0.314	-1.595	-0.461**	-2.332
100	-0.234	-1.585	-0.295	-1.286	-0.501**	-2.316
120	-0.331**	-2.301	-0.291	-1.219	-0.575**	-2.602
Obs	47		47		53	

As expected from the previous analysis, Figure 3.3 shows that the auction effect is particularly pronounced for the Italian 5 and 10Y bonds, and for the 10Y German Bund. In addition, Figure 3.3 shows that the auction effect is not present in non-auction days.

However, the results are not directly comparable with the work of (Beetsma et al., 2016a), that use daily data from Bloomberg. They report, for Italy, a yield daily movement up to 3.5 basis points for the 5Y and 10Y Italian bond. I do find intraday

FIGURE 3.3: **Yield difference for the On-the-run bonds**

This figure plot the average yield difference (top panel) and the total depth available in the market (bottom panel, in Millions of €), for the re-openings of on-the-run bonds during the auction dates. The shaded area represents the 95% confidence interval around the sample mean, and the black dashed line represents the average yield difference on non-auction dates. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).



quote movement up to 2 basis points across maturity, roughly comparable to the results of daily yield movements in the US treasury market reported in Lou, Yan, and Zhang (2013). For Germany, the average yield differences across maturities are smaller and comparable with the intraday data on the US treasury notes reported in Fleming and Liu (2016). The maximum average intraday yield difference is about 0.5 basis points.

The bottom of Figure 3.3 also reports for each panel the evolution of the average total depth. There is a remarkable difference between Italy and Germany. For Italy, the quoted depth sharply decrease few minutes before the auction and then takes

TABLE 3.4: **Return for the on-the-run Bonds**

This table shows the Average Δ Return, or the cumulative return before and after the auction as defined in Equation 3.2, during the auction dates for the re-openings of on-the-run bonds. The number of observations corresponds to the number of auctions for each country and maturity (Panel A for Italy, and Panel B for Germany). *, **, and *** denote significance at the 10, 5, and 1% levels using a t-test to verify if the values are statistically different from zero. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

Panel A: Italy On-the-run bonds						
	3Y		**5Y**		**10Y**	
Time (minutes)	Avg. Δ Return	Tstat	Avg. Δ Return	Tstat	Avg. Δ Return	Tstat
10	3.050***	3.918	5.187***	3.465	6.201***	3.308
20	3.177**	2.524	9.783***	4.445	10.686***	2.796
30	3.561**	2.229	11.638***	4.492	12.416***	3.249
60	5.164**	2.367	14.196***	4.413	18.004***	4.209
80	5.027*	1.853	14.337***	4.011	16.523***	3.188
100	5.092	1.560	13.117***	3.268	17.372***	3.232
120	4.749	1.372	11.406**	2.597	15.329***	2.754
Obs	44		52		56	

Panel B: Germany On-the-run bonds						
	2Y		**5Y**		**10Y**	
Time (minutes)	Avg. Δ Return	Tstat	Avg. Δ Return	Tstat	Avg. Δ Return	Tstat
10	0.530**	2.665	2.085***	3.498	5.621***	4.321
20	0.461*	1.828	3.227***	4.081	5.957***	3.946
30	0.139	0.471	2.383**	2.269	7.712***	4.643
60	0.738**	2.475	1.890	1.404	8.123***	3.437
80	0.873***	2.750	1.444	0.972	7.681***	3.022
100	0.711*	1.837	2.002	1.448	8.799***	3.055
120	0.953**	2.375	1.979	1.249	8.231***	2.782
Obs	47		47		53	

several minutes to recover. For Germany, the average depth mildly changes only for the 10Y bond. The evolution of the depth is analyzed explicitly in Section 3.4.2.

Following Lou, Yan, and Zhang (2013) and Fleming and Liu (2016), I introduce an additional measure that integrate the impact before and after the auction, the Δ *return* for bond i, day d, and time ϵ, defined as follows:

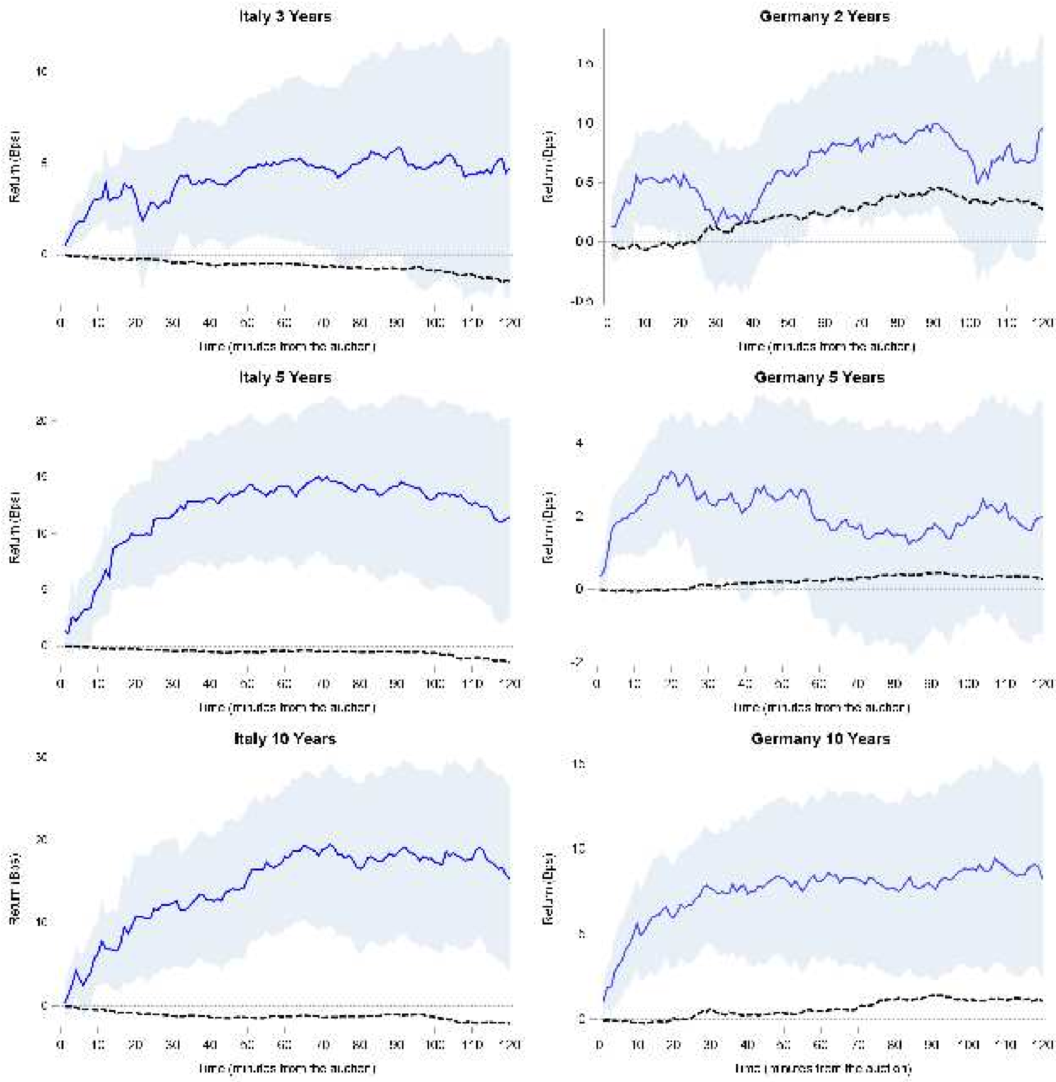
$$\Delta \ return_{\ i,d,\epsilon} = \left(\frac{Midquote_{\epsilon} - Midquote_{TA}}{Midquote_{TA}}\right) - \left(\frac{Midquote_{TA} - Midquote_{-\epsilon}}{Midquote_{-\epsilon}}\right) \tag{3.2}$$

where *Midquote* represents the average of the bid and ask quote for each minute snapshot, and ϵ represents the time (in minutes) before and after the auction where the return is calculated. The first ratio of Equation 3.2 represent the return after the auction, while the second fraction is the return before the auction.

As shown in Panel A of Table 3.4, the cumulative return for an Italian 10Y on-the-run bond thirty minutes after the auction is, on average 12.41 bps higher than the return of the same bond thirty minutes before the auction, statistically significant at the 1% level. The Δ *return* for the 5Y bond displays a slightly lower value (11.63 bps). For the 3Y bonds, the difference between return is always positive, but significant only up to 80 minutes before and after the auction. Panel B of Table 3.4 shows the value of Δ *return* for the German bonds. The results are mixed for the 2Y and 5Y bonds, and does not allows to drawn conclusions. For the 10Y bond, the difference between the two return is always positive and significant at the 1% level, with values halved compared to the Italian bonds. Thirty minutes after the auction, the return is, on average 7.71 bps higher than the return thirty minutes before the auction. Figure 3.4 plot the values of Δ *return* for the entire estimation window, for both Italy and Germany, depicting the summary results presented on Table 3.4. Further, the pattern of the Δ *return* is specific for the auction days: the dashed line in Figure 3.4 shows that the return is close to zero or negative during non-auction days.

FIGURE 3.4: **Cumulative Return for the On-the-run bonds**

This figures plot the cumulative average Δ return, or the cumulative return before and after the auction as defined in Equation 3.2, during the auction dates for the re-openings of on-the-run bonds. The shaded area represents the 95% confidence interval around the sample mean, and the black dashed line represents the average cumulative return on non-auction dates. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).



3.4.2 Liquidity

The statistics presented in Table 3.2 shows that, especially for the German sovereign bonds, the daily number of trades is quite low. Thus, one has to rely on different measures of liquidity, as described in Schneider, Lillo, and Pelizzon (2016). In addition, according to the model of French and Roll (1986), the reaction of the market does not require trades but is anticipated and followed by the quoting activity.

Given the particular microstructure of the MTS market, I consider three measures of liquidity, described in Section 3.3: the *Bid-ask spread*, the total *depth* of the market, and the number of proposals (*N. Proposals*) available in the market. These three measures are closely related to each other: the higher the number of proposals available in the market, the higher is usually the depth, and the lower is the bid-ask spread.[8]

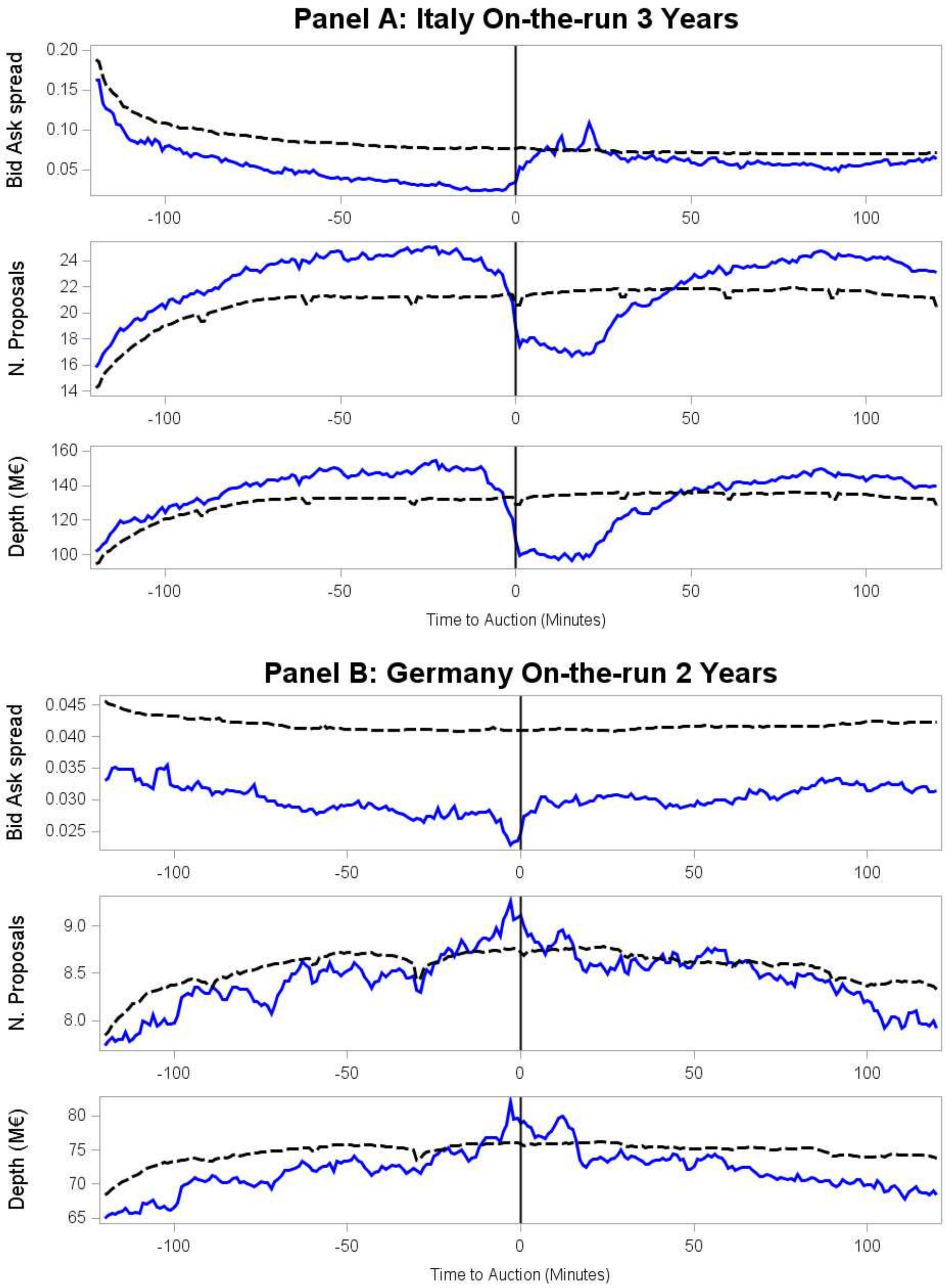
Primary dealers are required to participate in the auction, submitting bids and clearly devoting resources to the auction. If they have to incorporate the new issuance into their balance sheets, then one would expect that their behavior surrounding the auction is very risk adverse. Theoretically, I should observe an effect on the general liquidity of the day, a reaction close to the auction time, and a recovery of the liquidity measures after some time. According to the model of Bessembinder et al. (2016), the best strategy for a strategic trader is to provide liquidity when some other traders have to liquidate their position. This implies that, generally, the liquidity during the event days should be higher compared to the non-event day. However, the shocks (the auctions in our case) affects the price and also the behavior of the dealers. In Duffie (2010), dealers have capital constraint and, after a shock, the slow mobility of the capital affect the speed of reversal.

The graphical representation of the three liquidity measures, presented in Figure 3.5 for each group of bonds-country, allows to outline an initial assessment of the liquidity effect induced by the Treasury auctions. In almost all the considered panels, and for at least one measure, there is a significantly different behavior of the market participants. For a straightforward comparison, the black dashed line represents the average values of the metrics in non-auction days. Non-auction days are defined as days where there are no auctions for both the Italian and the German Treasury, for any maturity and any bonds. In most of the cases, there is a sharp adjustment very close to the auction time (time 0 in the plots), with a subsequent adjustment that could last, when present, one hour. For this reason, I introduce a two-stage analysis in the spirit of Fleming and Remolona (1999). The first stage uses minute-by-minute time interval from five minutes before the auction, to five minutes after the auction, in order to analyze the response of the liquidity measures to in the time immediately surrounding the auction. Since the auction, like the macroeconomic news in Fleming and Remolona (1999), are announced well in advance, I expect a comparable reaction in a very short time frame. The second stage takes into account the subsequent adjustments that occur after the announcement of the auction results. Graphically, figure 3.5 shows that the adjustment could take a significant amount of time. For this reason, I use ten-minutes intervals from one hour before to one hour after the auction.

[8]Pelizzon et al. (2014) and Schneider, Lillo, and Pelizzon (2016) consider three measures of liquidity, the bid-ask spread, the total quoted volume (or total depth) and the inverse depth, that reflects the cost of immediacy. I include only the first two measures in my analysis, since I am interested in the liquidity shocks due to the auction, rather than due to potential trading activity.

FIGURE 3.5: **Liquidity Measures**

This figures plot the average Bid-Ask spread, the number of proposals and the total depth (in Millions of €) as defined in Section 3.3.2, for each one-minute interval for the re-openings of on-the-run bonds. The black dashed line represents the average value of the measures on non-auction dates. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).



3.4.2.1 First stage analysis

The minute-by-minute analysis allows evaluating the short-term impact of the auction. Table 3.5 presents the bid-ask spread, the number of proposals and the total depth, for every minute from 10:55 to 11:05 for the Italian bonds, and from 11:25 to 11:35 for the German bonds. I find that the only general result across bonds is that the bid-ask spread is lower in the five minutes prior to the auction compared to non-auction days. Panel A of Table 3.5 examine the liquidity measures for the 3Y Italian BTP. The bid-ask spread is significantly lower in auction days, but this gap closes quickly five minutes after the auction time, where the spread is statistically equal to the non-auction days. The number of proposals in the market significantly drop exactly in the time of the auction and remains at a lower level for the entire time window. On average, from 1 to 3 dealers are withdrawing their quotes. In terms of total depth, the quantity available starts dropping by around 10 millions two minutes before the auction and reaches the lowest peak three minutes after. Panel B of Table 3.5 examine the liquidity measures for the 2Y German bond. In this case, the only significant effect is related to the bid-ask spread, that is significantly lower for the entire time window. No significant effects are present for the number of proposals and the depth: both remains comparable to the non-auction days.

Panel C of Table 3.5 shows the results for the 5Y Italian bond. In this case, the bid-ask spread before the auction is lower than usually, but exactly at the time of the auction, it starts increasing sharply, becoming six basis point higher than the normal three minutes after the auction. In this case, the dealers start withdrawing their quotes four minutes before the auction, and continue up to two minutes after the auction. The number of dealers that exit from the market is six: on average, only around 15 traders are quoting during the auction, compared to 22 in non-auction days. The same effect is present also in the total depth, that is systematically lower than usual for the entire time window. The results for the 5Y German bonds, presented in Panel D of Table 3.5, show that the bid-ask spread is around one basis point lower than non-auction days, significant only up to one minute after the auction.

The 10Y tenor presents very clear results in terms of liquidity, for both countries. Panel E of Table 3.5 shows that the bid-ask spread is lower before the auction, but exactly in the minute of the auction, it raises at the usual level. The behavior of the dealer is comparable to the one presented for the 5Y Italian tenor. Dealers start to withdrawn their quotes four minutes before the auction, and one minute after at least six dealers are no longer quoting. This clearly influences the total depth of the market, that is generally lower but sharply decrease at the time of the auction. For Germany, Panel F of Table 3.5 shows that for the 10Y maturity the behavior of the bid-ask spread is comparable to Italy, albeit the order of magnitude is smaller. Immediately after the auction, the bid-ask spread comes back to the normal values. At least one dealer withdrawn from the market, and the total depth steadily decreases during the entire time window.

In summary, the higher liquidity of the bonds in terms of bid-ask spread reflects the willingness of the traders to provide liquidity before the auctions take place. However, their inventory and capital constraint, due to the participation in the auction, force some dealers to withdrawn from the market minutes before the auction-time. However, even if the bonds are very liquid, the total quantity available for trading is lower compared to the non-auction days, also reflecting, in this case, the capital constraint due to the commitment to participate in a meaningful way to the auction.

Table 3.5: **Liquidity measures by One-minute Intervals**

This table shows the average values of the Bid-Ask spread, the Number of Proposals, and the total Depth, as defined in Section 3.3.2, for each one-minute interval for the re-openings of on-the-run bonds. The bid-ask spread is the difference between ask price and bid price. The Depth is reported in millions of Euros. Column (a) represents the average values, t minutes from the auction for non-auction days, while column (b) for the auction days only. Column (a-b) represents the difference between non-auction and auction days, for each country and maturity (Panel A, C and E for Italy, and Panel B, D and F for Germany). *, **, and *** denote significance at the 10, 5, and 1% levels using a t-statistic comparing means for non-auction and auction days assuming unequal variances. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

Panel A: Italy 3Y On-the-run

	Bid-Ask Spread			N. Proposals			Depth		
Minutes to auction	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-5	0.08	0.02	0.05***	21.33	23.32	-1.99**	132.55	138.19	-5.64
-4	0.08	0.02	0.05***	21.41	23.00	-1.59**	133.21	136.39	-3.17
-3	0.08	0.03	0.05***	21.41	22.11	-0.70	133.20	128.87	4.32
-2	0.08	0.03	0.04***	21.44	21.41	0.03	133.45	123.66	9.78**
-1	0.08	0.03	0.04***	21.39	20.75	0.63	133.04	120.59	12.45***
0	0.08	0.03	0.04***	20.63	18.89	1.74**	128.86	108.06	20.80***
1	0.08	0.05	0.02***	20.63	17.48	3.15***	128.91	99.19	29.71***
2	0.08	0.05	0.02***	21.30	17.95	3.34***	132.51	100.78	31.72***
3	0.08	0.06	0.01**	21.34	17.80	3.54***	132.85	101.16	31.68***
4	0.08	0.06	0.01**	21.39	18.11	3.27***	133.04	102.65	30.39***
5	0.08	0.07	0.00	21.49	18.11	3.37***	133.73	102.96	30.77***

Panel B: Germany 2Y On-the-run

	Bid-Ask Spread			N. Proposals			Depth		
	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-5	0.04	0.03	0.01***	8.76	9.06	-0.30	76.12	77.69	-1.56
-4	0.04	0.02	0.01***	8.75	9.13	-0.37	76.02	78.59	-2.57
-3	0.04	0.02	0.01***	8.75	9.26	-0.51	76.04	82.06	-6.01
-2	0.04	0.02	0.01***	8.76	9.06	-0.30	76.11	79.55	-3.43
-1	0.04	0.02	0.01***	8.76	9.09	-0.32	76.09	79.60	-3.50
0	0.04	0.02	0.01***	8.72	9.11	-0.38	75.86	78.89	-3.02
1	0.04	0.03	0.01***	8.69	9.00	-0.31	75.61	79.22	-3.61
2	0.04	0.03	0.01***	8.73	8.89	-0.16	75.82	78.40	-2.57
3	0.04	0.03	0.01***	8.74	8.91	-0.17	75.88	78.36	-2.47
4	0.04	0.03	0.01***	8.73	8.83	-0.09	75.82	76.81	-0.99
5	0.04	0.03	0.01***	8.75	8.83	-0.08	75.96	77.10	-1.13

Table 3.5: **Liquidity measures by One-minute Intervals (cont.)**

Panel C: Italy 5Y On-the-run									
	Bid-Ask Spread			N. Proposals			Depth		
Minutes to auction	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-5	0.09	0.04	0.05***	22.17	21.77	0.40	133.73	116.57	17.16***
-4	0.09	0.04	0.04***	22.26	20.98	1.27*	134.39	111.81	22.58***
-3	0.09	0.04	0.04***	22.30	20.42	1.88**	134.59	109.42	25.17***
-2	0.09	0.04	0.04***	22.33	19.60	2.73***	134.83	103.19	31.64***
-1	0.09	0.04	0.04***	22.24	18.85	3.39***	134.23	96.61	37.61***
0	0.09	0.07	0.02	21.41	17.08	4.32***	129.79	88.06	41.72***
1	0.09	0.11	-0.01	21.43	15.17	6.25***	129.89	77.53	52.35***
2	0.09	0.13	-0.04**	22.17	15.48	6.69***	133.78	80.21	53.56***
3	0.09	0.15	-0.06**	22.22	15.90	6.31***	134.05	81.98	52.06***
4	0.09	0.14	-0.05**	22.28	16.02	6.26***	134.39	81.74	52.65***
5	0.08	0.14	-0.05**	22.41	15.81	6.60***	135.22	81.02	54.20***

Panel D: Germany 5Y On-the-run									
	Bid-Ask Spread			N. Proposals			Depth		
	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-5	0.06	0.05	0.01**	9.25	9.66	-0.41	77.30	78.79	-1.49
-4	0.06	0.05	0.01**	9.23	9.68	-0.44	77.16	79.18	-2.01
-3	0.06	0.05	0.01**	9.25	9.62	-0.36	77.33	78.15	-0.82
-2	0.06	0.05	0.01**	9.26	9.64	-0.37	77.38	78.25	-0.86
-1	0.06	0.05	0.01	9.27	9.47	-0.19	77.49	77.29	0.19
0	0.06	0.04	0.01***	9.24	9.32	-0.08	77.35	75.79	1.56
1	0.06	0.05	0.01*	9.24	9.04	0.19	77.37	74.61	2.75
2	0.06	0.05	0.00	9.28	9.04	0.23	77.60	74.69	2.91
3	0.06	0.05	0.00	9.29	8.94	0.35	77.69	73.47	4.21
4	0.06	0.06	0.00	9.30	8.89	0.41	77.80	74.13	3.66
5	0.06	0.06	0.00	9.31	8.85	0.46	77.86	73.56	4.30

Table 3.5: **Liquidity measures by One-minute Intervals (cont.)**

Panel E: Italy 10Y On-the-run									
	Bid-Ask Spread			N. Proposals			Depth		
Minutes to auction	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-5	0.13	0.05	0.07***	22.13	22.09	0.04	127.99	108.38	19.60***
-4	0.13	0.06	0.06***	22.21	20.89	1.31**	128.58	102.45	26.13***
-3	0.13	0.05	0.07***	22.29	20.16	2.13***	129.03	96.81	32.22***
-2	0.13	0.06	0.06***	22.31	19.96	2.34***	129.14	96.63	32.51***
-1	0.13	0.07	0.06***	22.23	19.25	2.97***	128.59	91.04	37.55***
0	0.13	0.09	0.04***	21.35	17.21	4.13***	124.04	80.71	43.33***
1	0.13	0.13	0.00	21.40	15.50	5.89***	124.24	71.60	52.64***
2	0.13	0.14	-0.01	22.10	16.13	5.97***	127.92	75.09	52.83***
3	0.13	0.14	-0.01	22.16	16.50	5.66***	128.22	76.89	51.33***
4	0.13	0.15	-0.02	22.21	16.46	5.74***	128.46	76.76	51.69***
5	0.13	0.15	-0.02	22.32	16.41	5.90***	129.07	76.67	52.39***

Panel F: Germany 10Y On-the-run									
	Bid-Ask Spread			N. Proposals			Depth		
	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-5	0.07	0.05	0.01***	10.48	10.75	-0.27	80.89	76.21	4.68*
-4	0.07	0.05	0.01***	10.45	10.69	-0.24	80.58	75.90	4.68*
-3	0.07	0.05	0.01***	10.46	10.63	-0.17	80.72	74.76	5.95**
-2	0.07	0.05	0.01***	10.45	10.75	-0.29	80.69	75.73	4.96**
-1	0.07	0.05	0.01***	10.45	10.62	-0.16	80.72	74.65	6.07***
0	0.07	0.05	0.01***	10.41	10.17	0.24	80.55	71.48	9.07***
1	0.07	0.06	0.00	10.41	9.62	0.79***	80.59	68.11	12.48***
2	0.07	0.06	0.00	10.46	9.60	0.86***	80.85	67.66	13.18***
3	0.07	0.07	0.00	10.45	9.40	1.05***	80.84	66.73	14.11***
4	0.07	0.07	-0.00	10.47	9.29	1.17***	80.90	65.65	15.24***
5	0.07	0.07	-0.00	10.48	9.12	1.36***	80.99	64.98	16.01***

3.4.2.2 Second stage analysis

According to Duffie (2010), Bessembinder et al. (2016), and Sigaux (2017), the price pressure is temporary and should revert at least partially as soon as the information about the auction has been assimilated by the market participants. In this second stage, I analyze the subsequent adjustment, examining the behavior of the market at a higher interval, every ten minutes, and covering the time window that goes from one hour before, to one hour after the auction time. The results follow the same format of Table 3.5 and are presented in Table 3.6 for all the maturities and the two countries considered.

For the shortest maturity, Table 3.6 Panel A shows that the bid-ask spread returns to the value of non-auction days in the first ten minutes. In terms of participation, the number of proposals shows that the dealer that withdrawn from the market re-join at least thirty minutes before. Roughly in the same amount of time, the total depth returns to the average value of non-auction days. For Germany, Panel B of Table 3.6 shows that the effect is present only for the bid-ask spread, of the same magnitude presented in Panel B of Table 3.5.

For the 5Y maturities, Table 3.6 Panel C and D mirror the results of the 3Y bonds for the bid-ask spread and the participation of the dealers. The only difference is related to the total depth for the Italian 5Y bond: the depth available stats to decrease around ten minutes before the auction and does not completely recover after one hour, also indicating, in this case, most likely a higher risk aversion and capital constraint for the market participants.

Finally, Panel E and F of Table 3.6 show the results for the 10Y bonds for Italy and Germany, respectively. For Italy, the significance of the bid-ask spread display that the spike lasts more than ten minutes. In the following fifty minutes, the bid-ask spread is statistically comparable to non-auction days. The market participants that withdrawn from the market wait at least thirty minutes to start quoting again. The peak is reached after sixty minutes, where 24 members are, on average, joining the market simultaneously. Regarding market depth, it starts to decrease well before the auction, at least twenty minutes. It almost fully recovers after one hour. Regarding Germany, in terms of bid-ask spread the market is more liquid only before the auction, and then it is indistinguishable from non-auction days. The market maker that withdrawn from the market is probably responsible for the lower depth available in the market. However, for the 10Y German bonds, the quantity displayed is usually smaller starting from ten minutes before the auction, and do not recover completely thereafter.

Consistently with the theory and with the intraday evidence in the U.S. market of Fleming and Liu (2016), I do find that the auction dates the liquidity is better in terms of spread, also across maturities. However, in many instances the spread rise at the time of the auction, and usually remains at the level of non-auction days. There is strong evidence, especially for the Italian market, that dealers withdraw their quotes from the market and then come back to the normal level at least ten to twenty minutes later. There are remarkable differences between Italy and Germany, especially for the shortest maturities (2 and 5 years). To provide additional evidence of this behavior, the appendix reports the graphical behavior of the number of proposals for each year, in the two hours surrounding the auction. The effect is severe for Italy especially in the years 2012, 2013 and 2014, and for Germany only for the 10Y, and specifically for the years 2012, 2013 and 2015.

The interpretation of these results points into the direction of the high risk aversion of the dealers and the uncertainty related to the supply of the Treasury, at least for

TABLE 3.6: **Liquidity measures by Ten-minute Intervals**

This table reports the average values of the Bid-Ask spread, the Number of Proposals, and the total Depth, as defined in Section 3.3.2 for the re-openings of on-the-run bonds, for each ten-minute interval from one hour before to one hour after the auction. The bid-ask spread is the difference between ask price and bid price. The Depth is reported in millions of Euros. Column (a) represents the average values, t minutes from the auction for non-auction days, while column (b) for the auction days only. Column (a-b) represents the difference between non-auction and auction days, for each country and maturity (Panel A, C and E for Italy, and Panel B, D and F for Germany). *, **, and *** denote significance at the 10, 5, and 1% levels using a t-statistic comparing means for non-auction and auction days assuming unequal variances. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

Panel A: Italy 3Y On-the-run

	Bid-Ask Spread			N. Proposals			Depth		
Minutes to auction	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-60	0.08	0.04	0.04***	21.16	24.32	-3.16***	132.01	148.16	-16.14***
-50	0.08	0.04	0.04***	21.20	24.26	-3.05***	132.70	146.78	-14.08***
-40	0.08	0.03	0.04***	21.22	24.52	-3.29***	132.58	147.00	-14.42***
-30	0.08	0.03	0.04***	21.13	24.83	-3.69***	131.61	151.31	-19.69***
-20	0.08	0.03	0.05***	21.23	24.39	-3.15***	131.91	149.94	-18.02***
-10	0.08	0.03	0.05***	21.33	22.79	-1.46**	132.62	136.73	-4.10
0	0.08	0.06	0.01*	21.27	17.86	3.40***	132.48	101.46	31.02***
10	0.07	0.08	-0.00	21.64	17.11	4.53***	134.69	99.24	35.44***
20	0.07	0.08	-0.00	21.79	18.10	3.69***	135.51	108.90	26.60***
30	0.07	0.06	0.00	21.65	20.48	1.17**	134.80	124.22	10.57**
40	0.07	0.06	0.00	21.83	21.82	0.01	135.76	132.50	3.26
50	0.07	0.06	0.01	21.86	23.05	-1.18**	135.99	138.82	-2.83
60	0.07	0.06	0.01**	21.63	23.38	-1.74***	134.67	140.68	-6.01

Panel B: Germany 2Y On-the-run

	Bid-Ask Spread			N. Proposals			Depth		
	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-60	0.04	0.03	0.01***	8.67	8.43	0.23	75.41	71.96	3.44
-50	0.04	0.03	0.01***	8.71	8.40	0.30	75.71	71.79	3.91
-40	0.04	0.03	0.01***	8.66	8.49	0.16	75.26	72.26	2.99
-30	0.04	0.03	0.01***	8.57	8.55	0.02	74.60	73.52	1.08
-20	0.04	0.03	0.01***	8.71	8.77	-0.05	75.68	74.45	1.22
-10	0.04	0.03	0.01***	8.74	9.00	-0.26	75.95	78.00	-2.04
0	0.04	0.03	0.01***	8.73	8.85	-0.12	75.83	77.58	-1.75
10	0.04	0.03	0.01***	8.75	8.72	0.03	75.94	76.36	-0.41
20	0.04	0.03	0.01***	8.76	8.56	0.19	76.04	73.73	2.31
30	0.04	0.03	0.01***	8.66	8.57	0.08	75.38	73.53	1.85
40	0.04	0.03	0.01***	8.62	8.61	0.01	75.20	73.29	1.90
50	0.04	0.03	0.01***	8.61	8.71	-0.10	75.19	73.60	1.59
60	0.04	0.03	0.01***	8.60	8.59	0.01	75.27	72.11	3.16

Table 3.6: **Liquidity measures by Ten-minute Intervals (cont.)**

Panel C: Italy 5Y On-the-run									
	Bid-Ask Spread			N. Proposals			Depth		
Minutes to auction	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-60	0.09	0.07	0.02***	22.15	23.79	-1.64***	134.37	134.05	0.31
-50	0.09	0.06	0.02***	22.18	23.95	-1.76***	135.09	135.81	-0.71
-40	0.09	0.06	0.03***	22.17	23.96	-1.79***	134.62	135.89	-1.26
-30	0.09	0.05	0.03***	22.03	24.11	-2.08***	133.34	135.09	-1.75
-20	0.09	0.05	0.04***	22.15	24.04	-1.88***	133.77	133.08	0.68
-10	0.09	0.04	0.04***	22.21	21.46	0.75	134.04	115.25	18.78***
0	0.09	0.13	-0.04**	22.15	15.86	6.28***	133.82	82.09	51.72***
10	0.08	0.16	-0.07***	22.60	15.73	6.87***	136.43	81.85	54.57***
20	0.08	0.12	-0.04**	22.74	17.89	4.85***	137.24	96.38	40.85***
30	0.08	0.10	-0.01*	22.63	20.91	1.71***	136.66	116.74	19.92***
40	0.08	0.10	-0.01	22.83	22.30	0.53	137.72	124.88	12.83***
50	0.08	0.10	-0.02*	22.80	22.65	0.15	137.58	127.07	10.51***
60	0.08	0.10	-0.02	22.57	23.04	-0.47	136.09	128.10	7.99**

Panel D: Germany 5Y On-the-run									
	Bid-Ask Spread			N. Proposals			Depth		
	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-60	0.06	0.05	0.01***	9.19	9.53	-0.34	76.95	78.67	-1.71
-50	0.06	0.05	0.01***	9.26	9.73	-0.47*	77.45	80.60	-3.14
-40	0.06	0.05	0.01***	9.13	9.62	-0.48*	76.27	79.58	-3.30
-30	0.06	0.05	0.01***	8.94	9.35	-0.41	74.69	76.88	-2.18
-20	0.06	0.05	0.01***	9.16	9.56	-0.39	76.51	78.53	-2.02
-10	0.06	0.05	0.01**	9.22	9.63	-0.40	77.11	78.47	-1.36
0	0.06	0.05	0.00	9.28	8.98	0.30	77.64	74.48	3.15
10	0.06	0.06	0.00*	9.32	9.00	0.32	77.91	75.14	2.76
20	0.06	0.06	0.00	9.33	9.08	0.25	77.98	75.17	2.80
30	0.06	0.05	0.00**	9.21	9.14	0.06	77.16	75.75	1.41
40	0.06	0.05	0.00**	9.17	9.23	-0.06	76.96	76.91	0.05
50	0.06	0.06	0.00**	9.10	9.03	0.06	76.65	75.74	0.91
60	0.06	0.06	0.00*	9.07	9.09	-0.02	76.60	76.00	0.59

Table 3.6: **Liquidity measures by Ten-minute Intervals (cont.)**

Panel E: Italy 10Y On-the-run									
	Bid-Ask Spread			N. Proposals			Depth		
Minutes to auction	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-60	0.14	0.09	0.04***	22.13	24.62	-2.49***	128.73	128.50	0.22
-50	0.13	0.09	0.04***	22.28	24.98	-2.69***	129.66	130.30	-0.64
-40	0.13	0.09	0.04***	22.21	24.95	-2.73***	128.98	129.80	-0.81
-30	0.13	0.08	0.05***	21.99	24.83	-2.83***	127.44	128.57	-1.12
-20	0.13	0.07	0.05***	22.09	24.38	-2.29***	127.79	123.03	4.76**
-10	0.13	0.06	0.07***	22.15	21.60	0.55	128.17	106.00	22.16***
0	0.13	0.15	-0.02	22.09	16.46	5.62***	127.92	76.88	51.04***
10	0.12	0.18	-0.05**	22.55	16.21	6.33***	130.52	76.14	54.37***
20	0.12	0.14	-0.01	22.65	19.08	3.57***	130.99	94.06	36.92***
30	0.12	0.14	-0.02	22.53	21.66	0.86	130.30	110.67	19.63***
40	0.12	0.13	-0.01	22.73	22.81	-0.08	131.48	116.82	14.65***
50	0.12	0.13	-0.00	22.69	23.55	-0.85	131.40	121.43	9.97***
60	0.12	0.13	-0.00	22.45	24.00	-1.55***	129.93	123.97	5.96*

Panel F: Germany 10Y On-the-run									
	Bid-Ask Spread			N. Proposals			Depth		
	(a)	(b)	(a-b)	(a)	(b)	(a-b)	(a)	(b)	(a-b)
-60	0.07	0.06	0.01***	10.42	10.62	-0.19	80.49	75.41	5.07**
-50	0.07	0.05	0.01***	10.48	10.79	-0.31	80.87	76.40	4.46*
-40	0.07	0.05	0.01***	10.33	10.74	-0.40	79.71	76.67	3.03
-30	0.07	0.06	0.01***	10.07	10.50	-0.43	77.58	75.20	2.38
-20	0.07	0.06	0.01***	10.33	10.64	-0.31	79.56	75.89	3.67
-10	0.07	0.05	0.01***	10.43	10.65	-0.21	80.49	75.53	4.95**
0	0.07	0.07	0.00	10.46	9.42	1.04***	80.85	66.58	14.27***
10	0.07	0.07	0.00	10.50	9.50	1.00***	81.10	67.75	13.35***
20	0.07	0.06	0.00	10.51	9.88	0.63*	81.28	70.55	10.73***
30	0.07	0.06	0.00	10.35	10.15	0.19	80.38	73.03	7.35***
40	0.07	0.06	0.00	10.30	10.14	0.16	80.22	72.96	7.26***
50	0.07	0.06	0.00	10.27	10.13	0.14	80.06	73.02	7.03***
60	0.07	0.06	0.00	10.24	10.16	0.07	79.93	73.26	6.66**

Italy and for the 10Y German Bund. The information uncertainty resolves around ten to twenty minutes later when the results of the auction are fully incorporated not only in the prices but also in terms of liquidity in the market.

3.4.2.3 The Sovereign Bond Crisis and the PSPP Program

In previous sections, I presented evidence of price pressure around the auction time, due to different behavior of the dealer in auction versus non-auction days. This section aims to verify if both the price pressure and the liquidity are influenced by the recent Sovereign Bond Crisis and the intervention by the European Central Bank (ECB), through its Public Sector Purchase Program (PSPP). Specifically, under the PSPP program that began in March 2015, the ECB purchases a significant amount of public and private sector securities every month (around 60 billion monthly). The sovereign bond crisis and the extraordinary quantitative easing intervention by the ECB are very likely to have an impact on the behavior of the market makers during the auctions. For what concern the sovereign bond crisis only, Pelizzon et al. (2013) find that a fraction of the market makers withdraws their quotes from the market. Further, frequent update of quotes does not reflect into a higher level of liquidity.

This analysis is motivated by the graphical evidence of Figures 3.6 and 3.7, that plot the average year value of the *N. Proposals* for each minute. The number of market makers that withdraw their quotes from the market changes over time, suggesting that both the crisis and the PSPP have an impact on the behavior of the market makers.

To assess both the effects of the financial crisis and PSPP, I estimate a set of daily time-series regressions, where the dependent variables measure the price pressure, the behavior of the market makers and the liquidity in the market. Specifically, these variables are the daily cumulative Δ *return* as a measure of price pressure; the *N. of Withdraw* represents the difference between the maximum amount of dealers present in the two hours surrounding the auction, minus the minimum at the time of the auction. Intuitively, it represents the number of dealers that are more risk adverse and are canceling their quotes before the auction. The *Bid to Cover Ratio* represents how "successful" is the primary auction, and it is the ratio between the total amount of quantity bid by the primary auction participant, divided by the amount allocated at the auction. The higher the ratio, the more successful is the auction. Finally, the average *Bid-ask spread* and the average *depth* are calculated only during the two hours surrounding the auction.

Formally, for Italy and Germany, I estimate the following model:

$$y_t = \alpha_t + \beta_1 Crisis_t + \beta_2 PSPP_t + \beta_3 VIX + \epsilon_t \tag{3.3}$$

where y is one of the variables defined before, $Crisis$ is a dummy that is equal to one during the sovereign bond crisis (from November 9, 2011 to July 26, 2012, or the "whatever it takes" speech of Mario Draghi), $PSPP$ a dummy that is equal to one for the period of the asset purchase (from March 2015 until the end of the sample period), VIX is the well-know volatility index as a control variable for the general risk-aversion in the financial markets. Standard errors are robust for heteroscedasticity and clustered at bond level. The results of the regressions, which consider only the on-the-run bonds for the two countries, are reported in Table 3.7.

FIGURE 3.6: **Number of Proposals by year for Italy**

This figures plot the average number of proposals by year, as defined in Section 3.3.2, for each one-minute interval and for the re-openings dates of on-the-run bonds only. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

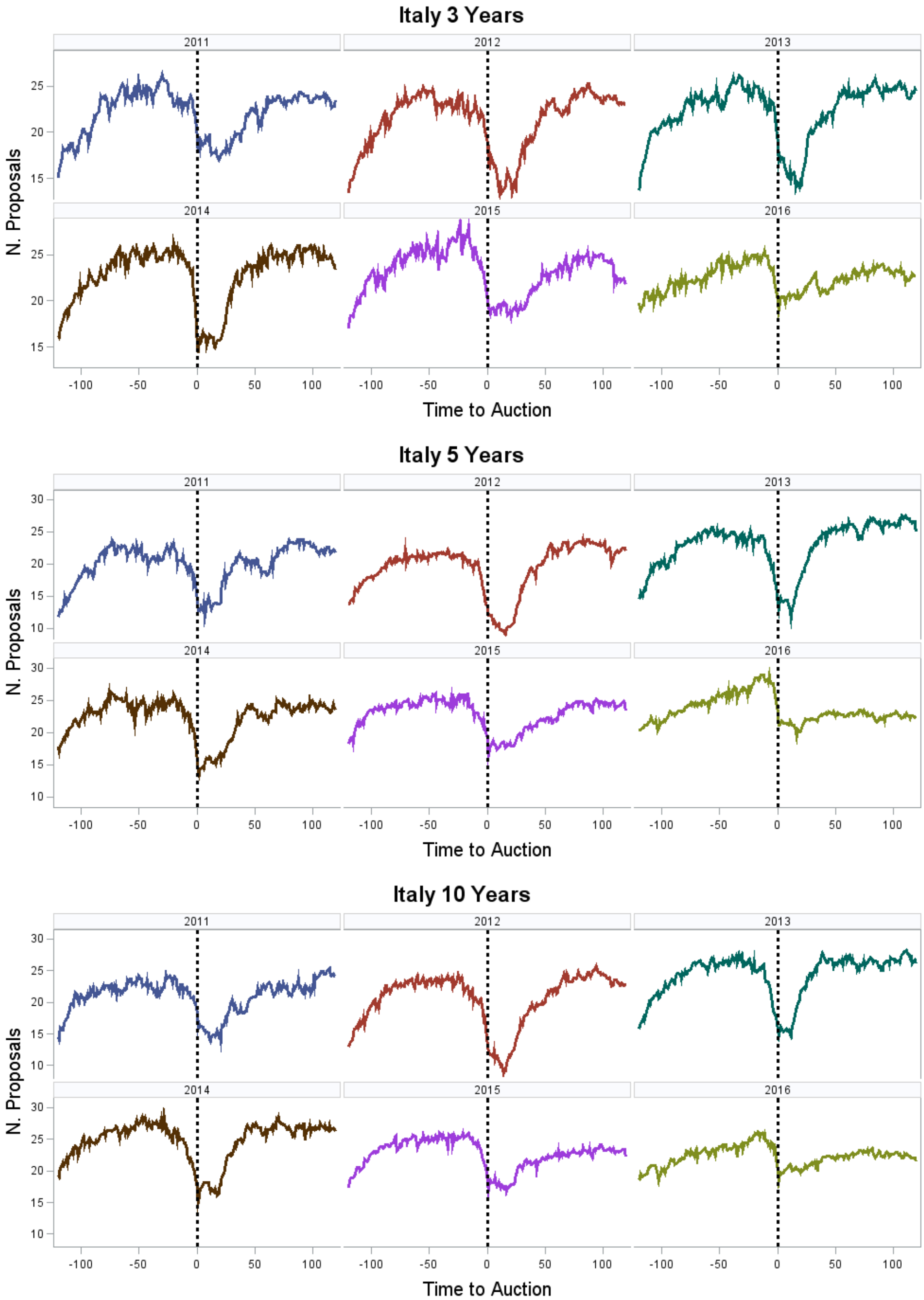
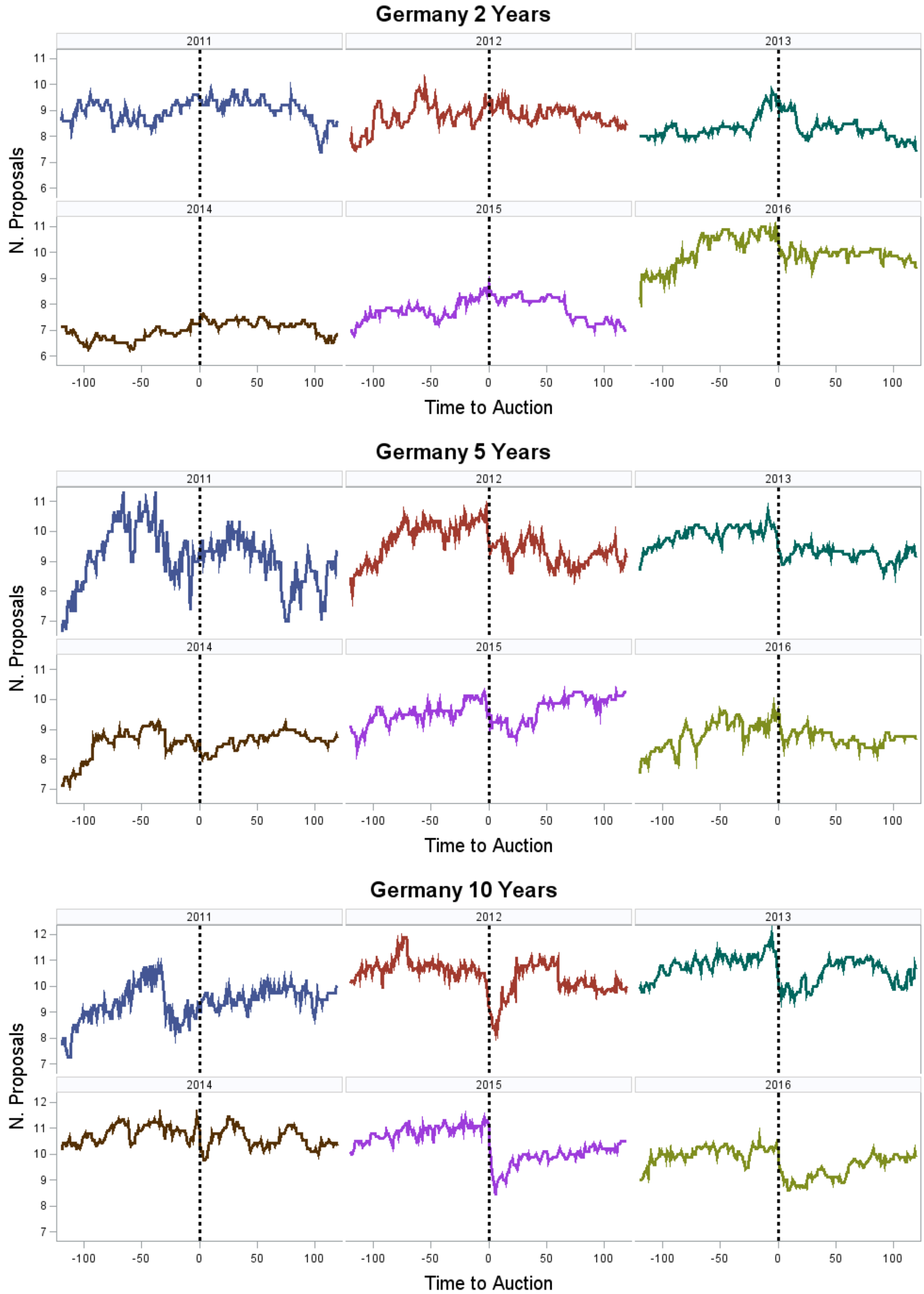


FIGURE 3.7: **Number of Proposals by year for Germany**

This figures plot the average number of proposals by year, as defined in Section 3.3.2, for each one-minute interval and for the re-openings dates of on-the-run bonds only. The database is composed by fixed coupon sovereign bonds for Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).



Panel A of Table 3.7 show that the cumulative Δ *return* is unaffected by the financial crisis, and is negatively affected by the PSPP program only for the 5Y bonds, showing that at least for this maturity the ECB program reduces the price pressures around the auction. About the behavior of the dealer, the analysis shows that for the 3Y and 5Y maturity the number of dealers that withdraw from the market increase significantly by more than two dealers. However, the PSPP program seems to reduce the risk aversion of the dealers, since the number of withdrawn reduces considerably for all the maturities. The results of the auction are positively affected by the PSPP since the bid to cover ratio has positive and significant sign across maturities. Finally, the two measures of liquidity, the average *Bid-ask spread* and the average *depth* are significant only for some maturities, but indicate that during the crisis the spread increase and the depth decrease, while the ECB intervention leads to a reduction in the spread and an increase of the total depth available during the auction.

About Germany, Panel B of Table 3.7 shows that there is a significant stronger price pressure for the 2 and 10 years bonds. Surprisingly, the coefficient of the cumulative Δ *return* is also positive for the 2 years bonds during the PSPP, indicating only for this maturity that the ECB program does not reduce the price pressure during the auction. Nevertheless, the price pressure for this note was not particularly strong (see Table 3.4). The market makers does not behave differently during the crisis or during the PSPP period, as they do not significantly withdraw quotes in general during the auctions. The bid to cover ratio is only mildly significant. The liquidity measures display interesting results. During the sovereign bond crisis, the bid-ask spread clearly increases, especially for the 5 and 10 years maturity. However, for the 10 Y bond, the spread increases also during the PSPP program, showing some potential scarcity problems for the bonds auctioned. About the depth available in the market, the coefficients of the dummies are significant and positive for the 2 years bond for the crisis and the PSPP, and only for the PSPP program for the 5 years bonds.

To summarize, the analysis shows that the crisis and the PSPP have a different impact on the two countries. For Italy, the crisis strongly affected the behavior of the dealers, that withdraw from the market and become more risk-averse. This results in a wider bid-ask spread and a lower quantity quoted in the market. The PSPP program seems to restore the confidence of the dealer, as all the measures improve substantially. The results for Germany are mixed, mainly because the sovereign bond crisis affected the peripheral countries. In this context, Germany is viewed as a “safe heaven”, the dealers’ behavior is thus not affected by this event. For the same reason, the PSPP seems to not affect the price pressures and liquidity measures.

TABLE 3.7: **The Sovereign Bond Crisis and the PSPP**

This table reports the results of the linear regression presented in Section 3.4.2.3, for Italy (Panel A) and Germany (Panel B). All variables are aggregated at daily level, considering only the two hours surrounding the auction. Standard error are robust for heteroschedasticity and clustered at bond level. *, **, and *** denote significance at the 10, 5, and 1% levels. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

Panel A: Italy

		Cum. ΔReturn	N. of Withdraw	Bid to Cover Ratio	Avg. Bid-ask Spread	Avg. Depth
3Y	Sov. Bond Crisis	15.72	2.206*	-0.0431	0.0943**	-22.43***
	PSPP	3.757	-4.000***	0.197**	-0.0402***	6.916
	VIX	0.253	-0.203	-0.00338	0.00165***	1.234**
	Constant	-3.059	17.14***	1.536***	0.0388**	96.39***
	Observations	43	43	43	43	43
	R-squared	0.066	0.341	0.323	0.613	0.186
5Y	Sov. Bond Crisis	-29.21	2.886***	0.0412	0.120***	5.169
	PSPP	-15.69**	-6.023***	0.0696*	-0.0591**	12.12**
	VIX	0.206	-0.151*	0.000910	0.00305	-0.640
	Constant	16.81**	17.80***	1.411***	0.0753**	110.9***
	Observations	52	52	52	52	52
	R-squared	0.104	0.461	0.064	0.385	0.091
10Y	Sov. Bond Crisis	34.70	-0.265	0.0679*	0.224	-27.28***
	PSPP	-8.359	-6.438***	0.0612*	-0.0208	-3.035
	VIX	0.484	-0.0709	-0.00490**	0.00694**	-0.556***
	Constant	6.172	16.91***	1.454***	0.0243	112.7***
	Observations	56	56	56	56	56
	R-squared	0.122	0.458	0.160	0.415	0.311

Table 3.7: **The Sovereign Bond Crisis and the PSPP (cont.)**

Panel B: Germany						
		Cum. ΔReturn	N. of Withdraw	Bid to Cover Ratio	Avg. Bid-ask Spread	Avg. Depth
2Y	Sov. Bond Crisis	3.661***	-0.194	-0.100*	0.00384	18.36*
	PSPP	1.400**	0.309	-0.106	0.00105	28.83***
	VIX	-0.0406	-0.0571**	-0.0131*	0.000836*	-0.598
	Constant	0.695	3.279***	2.204***	0.0145*	73.73***
	Observations	45	45	45	45	45
	R-squared	0.218	0.080	0.096	0.107	0.304
5Y	Sov. Bond Crisis	4.954	0.143	0.243*	0.0356**	-9.469
	PSPP	0.473	0.402	-0.245*	0.00665	10.33**
	VIX	-0.353	0.0442*	-0.0158	0.00213*	0.0634
	Constant	6.777	1.921***	1.994***	0.0145	72.44***
	Observations	47	47	47	47	47
	R-squared	0.042	0.044	0.210	0.447	0.140
10Y	Sov. Bond Crisis	15.35***	1.857	0.0544	0.0261**	-0.257
	PSPP	-3.284	0.386	-0.0276	0.0159*	3.687
	VIX	1.322**	-0.0369	-0.0107*	0.000249	-0.321
	Constant	-14.05	3.720***	1.595***	0.0513***	75.24***
	Observations	51	51	51	51	51
	R-squared	0.215	0.104	0.047	0.176	0.032

3.5 Conclusion

This paper provides intraday empirical evidence of the impact of Treasury auctions in the secondary market of sovereign bonds. Using data from the Mercato dei Titoli di Stato (MTS), I find price and liquidity patterns around auction dates, showing that these patterns are present not only in the days surrounding the auctions, as demonstrated in previous studies in the European Market but also in the hours around the auction times.

My main contribution is to shed light on the intraday linkages between price movements, dry-up of liquidity, and market-makers' behavior in the auctions' days. To the best of my knowledge, no prior research investigates this issue in a high-frequency setting for the European Sovereign bond markets.

I show that there is a statistically significant price pressure for the Italian coupon bonds with a maturity of 5 and 10 years and for the German 10 years Bund. Consistently with the model of Bessembinder et al. (2016), I find that liquidity in terms of bid-ask spread is better around the auction days. However, dealers tend to be risk-averse during the auction times, since a portion of them withdraw their quotes minutes before the auction time. In a two-stage analysis, I show that the uncertainty around the auction push dealers to reduce the amount quoted, reducing the total depth of the market. Dealers also widen the bid-ask spread very close to the auction time, to protect themselves from adverse selection costs. The explanation of this behavior is due to their capital constraint and their limited risk-bearing capacity, as demonstrated in the previous literature. These patterns are not observed on non-auction days, suggesting that the bond supply through primary auctions influence the behavior of the market participants in the secondary market.

The findings are complementary to the work of (Beetsma et al., 2016a), that use daily data and report a daily movement up to 3.5 basis point. However, I find that the order of magnitude, looking at the quotes in the secondary market, is quite large for Italy, up to 2 basis points across maturities. For Germany, the intraday movements are roughly comparable with the intraday US Treasury movements in Fleming and Liu (2016), where the yield difference is around 0.5 basis points. Using intraday data it is possible to capture the "instantaneous" dynamics related to the risk-aversion of the dealers.

Finally, the role of the crisis is substantial, as documented by previous works. However, at least for the most critical country in the sample, Italy, the ECB intervention through the PSPP contribute to reduce the consequences of the "auction cycle effect", especially for the liquidity and the participation of the market makers.

The analysis have policy implications. First, the role of market-makers is potentially due to risk aversion, but could also be the results of opportunistic behavior. Second, the ECB intervention trough the PSPP partially reduces the price pressures and the liquidity dry-ups. However, the program will be terminated soon and, in absence of specific agreements between the exchange and the market makers, the "auction cycle effect" could return at its initial magnitude. Future research will address this issue, once the ECB intervention will be terminated.

Appendix A

Internet Appendix for “Coming Early to the Party”

A.1 The opening auction procedure and related institutional details

The opening auction on NYSE Euronext Paris kicks off at 9.00 a.m. sharp during the period of our study.[1] During the accumulation period, orders not executed on the previous day populate the order book, and traders are also allowed to post new buy and sell orders. An order can be submitted with a validity of up to one year: these Good Till Cancelled orders remain active until the broker decides to cancel it or until the order is totally executed, up to one calendar year. This feature poses an additional issue in the rebuilding of the order book, i.e. keep track of the orders of the previous day, not or partially executed. These orders populate the order book at the beginning of the pre-opening phase, at 7.15 a.m., they do not usually cross and most of the time a midquote can be calculated, but not a theoretical opening price. The exchange disseminates the (predicted) opening price and the relative quantity available for trading every time there is a new order submission or cancellation that triggers a change in the auction price or quantity. The opening price is calculated by crossing the aggregate demand and supply curves, and selecting the prices that maximize the volume of shares traded at the call auction.

NYSE Euronext Paris disseminates two types of market data, throughout the NYSE Euronext Trading Platform. The first set of orders is called *Market by Orders*, and includes all buy and sell orders, the disclosed quantity and the displayed price. The second set of market data is called *Market by Limits*, and includes the ten best limits for buy and sell orders. For buy orders with prices higher than the theoretical price, and for sell order with prices lower than the theoretical price, the price limit displayed is the theoretical price, so that the most aggressive orders are not completely visible to subscribers.

Price priority is applied initially to market orders, buy orders with a limit price above the opening price and sell orders with a limit price below the open price - these orders are completely filled, including the hidden quantity. During both phases, the pre-opening phase and the main trading phase, traders are allowed to submit partially hidden (iceberg) orders. In fact, the theoretical opening price is calculated by also including the hidden quantity, but the hidden portion is not displayed to all market participants (orders can be partially but not completely hidden). In case of imbalances between demand and supply, orders with a limit price equal to the opening price are

[1] As of 19 August 2015, the opening time at NYSE Euronext Paris was randomized, but in the sample period considered, the auction occurred at exactly 9.00 a.m.

filled first, also following time priority. When an order is modified, it loses its time priority, except in cases where the volume of an existing order is decreased.[2]

During the main trading phase, the principle underlying order matching is, again, based on both price and time priority. Market participants can submit, modify and cancel different types of orders. Not all the order types contribute to the theoretical opening price, and some of them have a different behavior during the pre-opening phase and the main trading phase. In particular, the orders allowed are pure market and limit orders, stop-market, stop-limit and stop-on-quote orders, market-to-limit orders, and pegged orders. During the pre-opening phase, pegged orders are not allowed, market-to-limit orders are replaced by market-on-opening orders, and stop-orders are not taken into account in determining the opening price. To facilitate and incentivize HFT activity, NYSE Euronext Paris also offers co-location services and different connection speeds with the exchange's matching engine.

In order to enhance the liquidity of less liquid securities, NYSE Euronext Paris introduced a designated MM program in 1992, which was extended in 1994 to include more liquid stocks (Venkataraman and Waisburd (2007)). More recently, in 2011, NYSE Euronext Paris introduced the *Supplemental Liquidity Provision* (SLP) program dedicated only to the most liquid stocks, during the main trading phase.[3] By signing an agreement, a trader (including a HFT) agrees to post two-way quotes that obey minimum capital and maximum spread restrictions for a given stock (see Liquidity Providers and Market Makers on Euronext). Any member of NYSE Euronext Paris is eligible to participate in the program, but only with their *own* resources, excluding all orders coming from customers. A new SLP program, which commenced in 2013, rewards members with a financial rebate, if they execute passive orders.

As for taxation, France introduced two new taxes in 2012: a financial transaction tax and a HFT tax.[4] However, the latter tax is applicable only to HFTs registered in France, who are a minority of the HFTs operating on NYSE Euronext Paris. It is to be noted, that MMs are exempt from both these taxes. Therefore, when placing an order at NYSE Euronext Paris, market participants have to separate orders submitted as part of their MM activities from their proprietary activities. As a result of the financial transaction tax, the HFT tax, and MiFID II requirements, our data explicitly separates MM activities from OWN trading.

[2]For detailed rules of the opening call matching procedure and the order valid for the auction, please see the Euronext Trading Manual for the Universal Trading Platform, described in Euronext (2016)

[3]Technical details and the list of the securities included can be found in NYSE-Euronext (2011).

[4]Colliard and Hoffmann (2016) provide a detailed analysis of the introduction of the financial transaction tax with BEDOFIH data.

A.2 Quoting and trading activity

The aim of this part is to verify if the quoting activity is stable through time and across stocks. A first aggregate comparison can be found in Figure A.1 and Figure A.2, which show the quoting and trading activity across dates and stocks, respectively, for the three trader categories (PURE-HFTs, MIXED-HFTs and NONHFTs). Figure A.1 indicates that HFTs participate more selectively in the pre-opening phase, even if their trading activity is quite stable during the sample period. During the first 30-minutes of the main trading phase, HFTs' participation is very stable through time. The same picture across stocks is presented in Figure A.2, which shows that the participation at the stock level can vary across trading phases. The figure indicates that, even though there is a low average level of participation in the pre-opening phase, the participation during the first 30-minutes of the main trading phase improves significantly. For instance, for the last stock in the column, the average quoting activity is less than 5% in the pre-opening phase, but the average quoting activity in the first 30-minutes of the main trading phase rises to 38%.

A formal assessment of HFT behavior is provided in Table A.1. During the pre-opening phase, the median QAR for PURE-HFT-OWN is 25.17%, and ranges from 6.43% to 52.78%, indicating that HFTs participate intensively in the pre-opening phase, at least for some stocks, from their own account. This participation for the PURE-HFT-OWN category declines during the first 30-minutes of the main trading phase, given that HFTs switch most of their activity from their OWN account to the MM account. Similar conclusions can be drawn by looking at the distribution of trading activity, where the PURE-HFT-OWN group contributes to trading activity with a median TAR of 6.47% during the opening auction, ranging from zero to 44.25%, across stocks.

The proportions of quoting and trading activity, by account, are very different in the two phases analyzed. There is still good quoting participation by HFTs' proprietary trading in their OWN account in the pre-opening phase. In the first 30 minutes, almost all the activity switches to MM accounts, for both PURE-HFT and MIXED-HFT traders. The account identification provided by NYSE Euronext Paris reveals that, across stocks, there is a pronounced heterogeneity in the trader behavior. It is clear that traders from both the HFT and MIXED categories with the MM flag regularly post and trade orders only in the main trading phase, given the prevailing set of rules that does not offer them any advantage in terms of fee reduction in the pre-opening phase. A graphical representation of this behavior across stocks is provided in Figure A.3.

TABLE A.1: **Quoting and Trading activity distribution across stocks for HFTs and MIXED**

This table shows the distribution of the quoting activity (Panel A) and trading activity (Panel B) across stocks for PURE-HFTs and MIXED-HFTs across four account types (CLIENT, OWN, MM, RLP), for the pre-opening phase, opening auction and the first 30-minutes of the main trading phase. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A: quoting activity distribution for PURE-HFT and MIXED-HFT by account

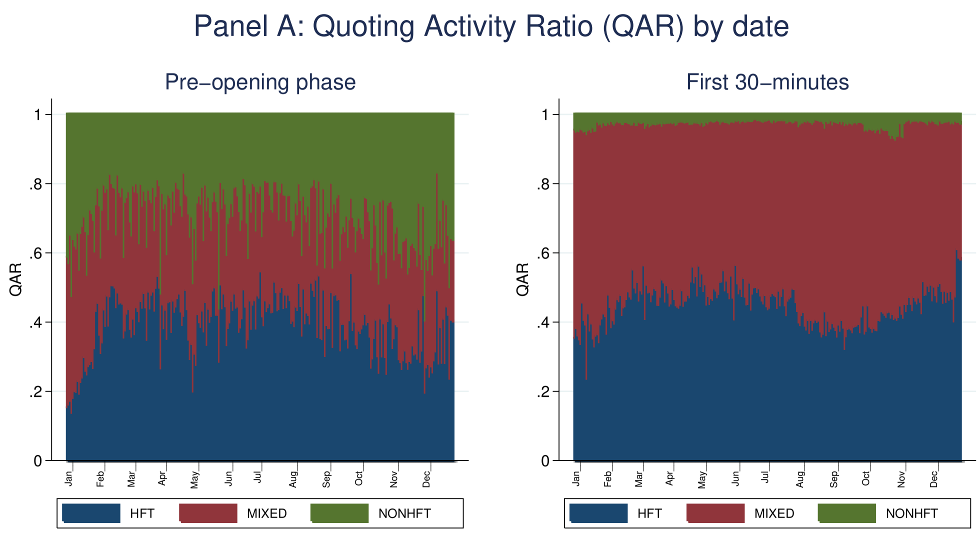
	Pre-opening period				First 30-minutes of continuous period			
	Median	SD	P5	P95	Median	SD	P5	P95
PURE-HFT CLIENT	0.13%	0.27%	0.00%	0.66%	0.04%	0.18%	0.01%	0.23%
PURE-HFT-OWN	41.05%	19.22%	0.73%	64.90%	3.92%	4.50%	0.39%	14.18%
PURE-HFT-RLP	0.00%	0.00%	0.00%	0.00%	10.83%	5.89%	4.27%	23.34%
PURE-HFT-MM	0.00%	0.98%	0.00%	0.30%	28.70%	7.62%	17.04%	41.52%
MIXED-HFT-CLIENT	6.39%	5.71%	2.43%	19.48%	2.12%	3.93%	0.56%	12.54%
MIXED-HFT-OWN	17.07%	9.26%	6.92%	36.67%	11.86%	7.25%	5.80%	29.06%
MIXED-HFT- RLP	0.00%	0.01%	0.00%	0.00%	4.95%	2.08%	2.78%	9.39%
MIXED-HFT- MM	0.56%	3.58%	0.00%	9.25%	27.41%	10.81%	7.57%	42.69%
MIXED-HFT-PARENT	1.47%	1.71%	0.29%	5.21%	3.84%	1.77%	1.29%	6.99%

Panel B: trading activity distribution for PURE-HFT and MIXED-HFT by account

	Opening auction				First 30-minutes of continuous period			
	Median	SD	P5	P95	Median	SD	P5	P95
PURE-HFT CLIENT	0	1.47%	0	1.35%	0	0.88%	0	1.55%
PURE-HFT-OWN	3.16%	5.48%	0.06%	15.90%	1.30%	2.06%	0	5.76%
PURE-HFT-RLP	0	0	0	0	0	0.06%	0	0
PURE-HFT-MM	0	0.42%	0	0.83%	20.20%	7.25%	9.69%	33.47%
MIXED-HFT-CLIENT	13.14%	10.87%	0.60%	34.83%	7.74%	6.17%	0.96%	20.40%
MIXED-HFT-OWN	34.68%	13.04%	14.48%	57.60%	34.41%	10.17%	19.44%	52.61%
MIXED-HFT- RLP	0	0	0	0	0	0.07%	0	0
MIXED-HFT- MM	2.00%	3.25%	0	8.66%	7.37%	4.45%	1.29%	15.51%
MIXED-HFT-PARENT	5.21%	5.73%	0	17.67%	6.34%	3.72%	1.49%	13.75%

FIGURE A.1: **Quoting and Trading activity ratio for each date**

This figure shows the total quoting (Panel A) and trading activity (Panel B), for each date, three trader groups (PURE-HFT, MIXED-HFT and NON-HFT) during the pre-opening phase, the opening auction, and the first 30 minutes of the main trading phase. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.



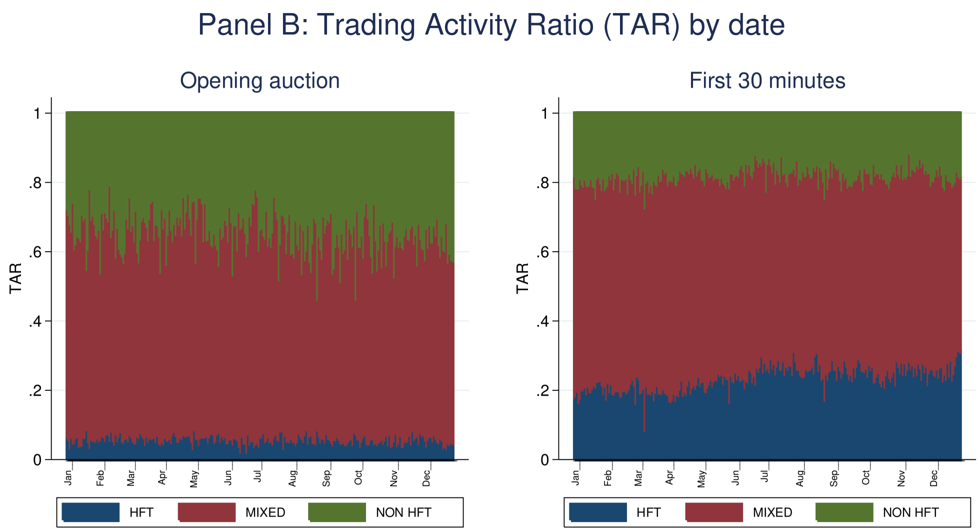


FIGURE A.2: **Quoting and Trading activity ratio for each stock**

This figure shows the total quoting (Panel A) and trading activity (Panel B), for each stock, three trader groups (PURE-HFT, MIXED-HFT and NON-HFT) during the pre-opening phase, the opening auction, and the first 30-minutes of the main trading phase. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

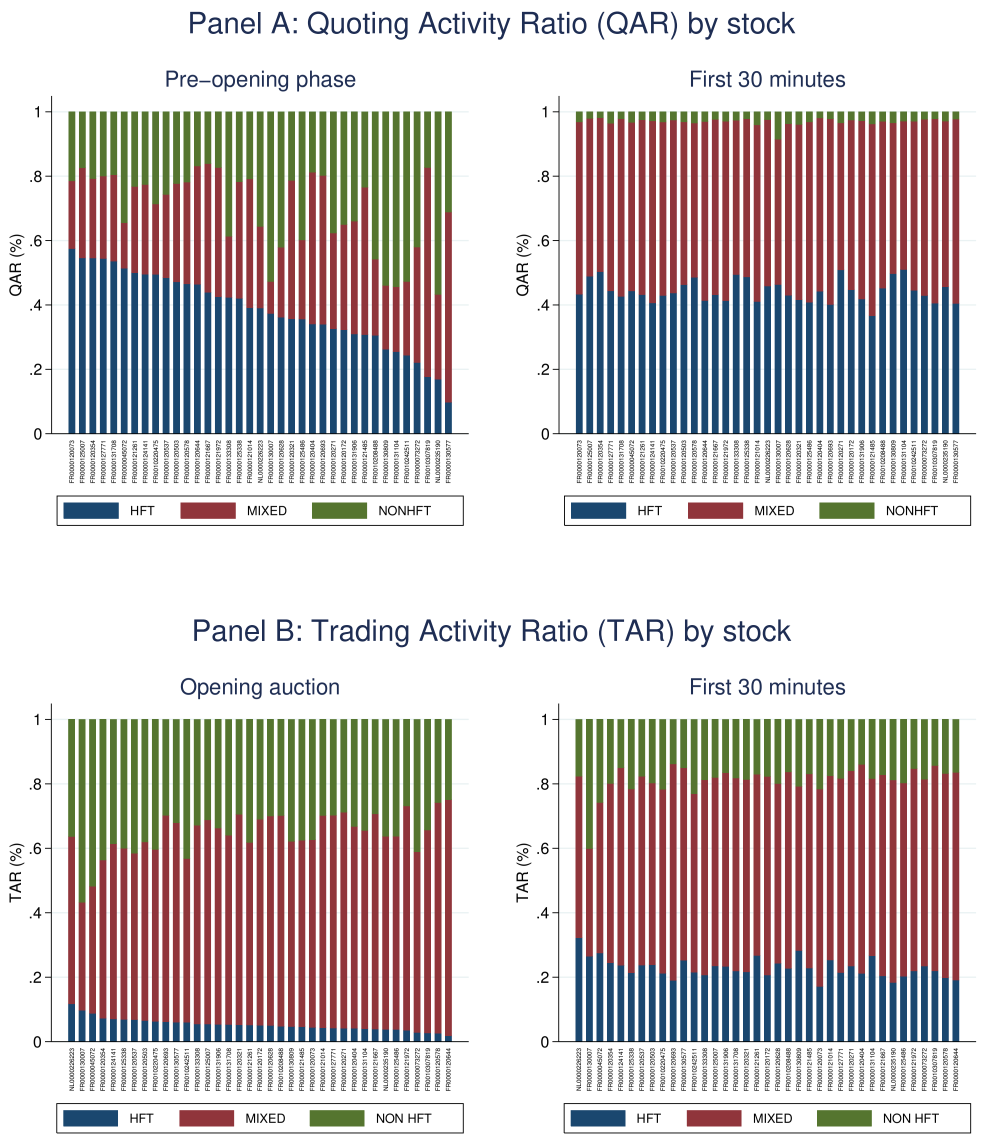
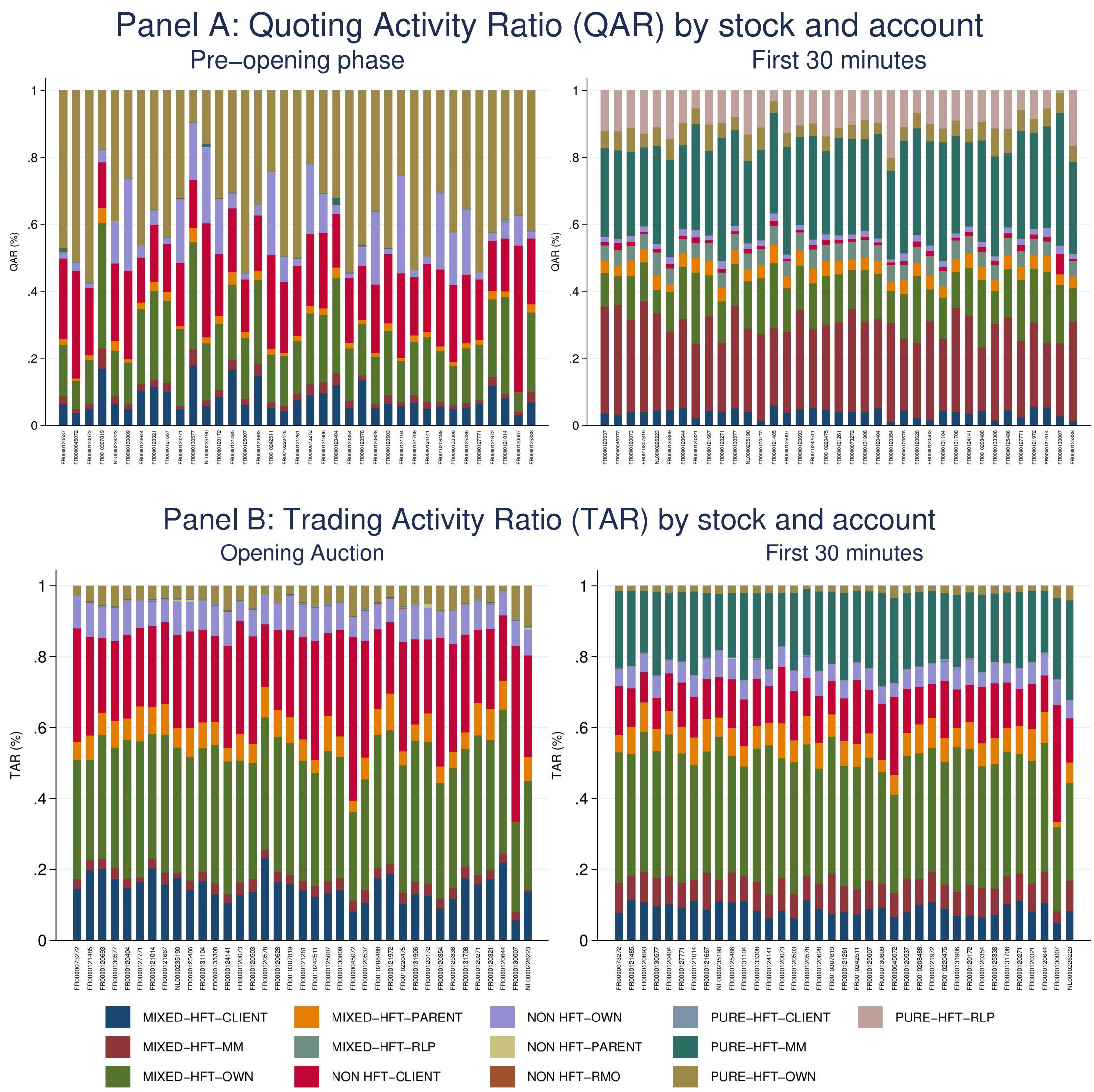


FIGURE A.3: **Quoting and Trading activity ratio by stock and accounts**

This figure shows the average quoting (Panel A) and trading (Panel B) activity ratios for each stock in our sample, for three trader groups (PURE-HFT, MIXED-HFT and NON-HFT), six account types (CLIENT, OWN, RLP, RMO, MM, PARENT), for the pre-opening phase, opening auction and the first 30-minutes of main trading phase. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.



A.3 Participation statistics for the pre-opening phase and opening auction

Table A.2 provides descriptive statistics for the participation of the various groups of traders in the pre-opening phase and opening auction. Most of the traders participate during the pre-opening with their OWN account, in all 37 stocks. The median number of days ranges from 237 to 248. On average, 98 trades for every stock-day are executed on behalf of their clients from the NON-HFT group. In our sample, MIXED-HFT-OWN traders represent the second largest trader group in the auction. Despite the intense quoting activity of PURE-HFT-OWN traders, the quantity traded is quite small, compared to the other categories.

TABLE A.2: **Participation**

This table shows the summary statistics for the pre-opening and auction participation by trader/account type. Data are presented for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT) and six account types. The orders/account can be flagged as own proprietary trading orders (OWN), orders on behalf of the client (CLIENT), submitted due to their market making affiliation (MM), parent company order (PARENT) or related to retail market organization (RMO) and retail liquidity provision (RLP) activities. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel C: traders' participation in the auction by account

		Median # of stocks per day	Median # days per stock	Average # of shares traded	Average gross capital for the auction (euro)	Average # of trades
PURE-HFT	Client	4	29	6'610.39	46'495.10	3.8
	Own	36	244	5'004.88	47'906.19	7.4
	MM	35	27	412.51	14'894.41	1.7
MIXED-HFT	Client	36	245	10'251.64	284'998.70	19.1
	Own	37	248	28'176.47	653'902.17	46.7
	MM	29	164	2'655.93	66'631.77	4.8
	Parent	35	220	3'230.69	102'289.09	7.0
NON-HFT	Client	37	248	34'413.05	455'046.93	98.1
	Own	35	237	7'755.94	154'910.48	11.2
	RMO	5	27	664.39	6'131.44	1.9
	Parent	1	2	32'833.33	141'488.33	4.3

A.4 Speed of the traders

We aim to investigate whether HFTs *always* use their speed capability equally, regardless of the period of the day and the account they are trading for, especially when the speed is more important, i.e. just before the opening auction. In order to address the speed capacity usage by different trader groups and account types, we first estimate the median of the speed distribution per stock-day-trader-account to use as a benchmark. Speed is defined as the time elapsed between order entry/modification and modification/cancellation of the same order. We test whether the speed capacity usage is the same for different trader/account types, and for different time intervals, by running the following panel regression separately for the pre-opening and first 30-minutes of the continuous trading phases:

$$Speed_{i,j,k,l} = a_{0,l} + \sum a_{k,l} * I_k + e_{i,j,k,l} \tag{A.1}$$

where $Speed_{i,j,k,l}$ is our measure of median speed for stock i, day j, trader/account k for the period l. The periods considered are the last minute, the last 15 seconds, the last 5 seconds and the very last second of the pre-opening phase. I_k is a dummy variable that equals 1 for trader/account k. We use the NONHFT-CLIENT accounts as a base category. Table 1.3 of the paper presents the summary statistics of the speed distribution of the different trader groups and account types, where we find that the 5th percentile of speed is extremely high (the time elapsed is less than 5 milliseconds) even for NONHFT account types.

We investigate whether one group of traders is faster compared to the others, by regressing the median (stock-day) realized speed over a set of dummies that identify each group as described in Equation A.1. We use, again as a base case, the NONHFT-CLIENT category. Table A.3 shows that during the pre-opening phase and in all intervals considered, PURE-HFT-OWN traders are the fastest market participants (the lower the coefficient, the lower is the elapsed time and the higher is the speed). The MIXED-HFT traders are, in general, very close to the PURE-HFTs, due to the fact that the investment banks and the big brokers are using the same technology and comparable strategies. In the first 30 minutes, the field is more leveled and almost all the HFTs and the MIXED-HFTs use a comparable speed. The analysis suggests that HFTs engage in strategies that essentially require high speed. This is consistent with the notion that HFTs use their superior speed capability for risk management, when they act as MMs (as in Aït-Sahalia and Sağlam (2014)).

Table A.3: **Speed of the Traders Regression**

This table shows the regression coefficients of the speed capacity by three trader groups (PURE-HFT, MIXED-HFT, NON-HFT) and six account types (CLIENT, OWN, RLP, RMO, MM, PARENT) for different segments of the pre-opening phase and first 30-minutes of main trading phase. We refer to speed as the time elapsed between order entry/modification and modification/cancellation of the same order. We present the coefficients of the regressions described in Section A.4, by group, where ***, **, * correspond to 1%, 5%, and 10% significance levels. Statistics and regression estimates are presented for 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Speed regression by stock-date						
		Pre-Opening Phase				**First 30 minutes**
		Last minute	Last 15 seconds	Last 5 seconds	Last second	Median Speed
PURE-HFT	Client					671.5***
	MM					-180.6***
	Own	-21.13***	-4.003***	-0.596***	-0.244***	-173.9***
	RLP					-182.6***
MIXED-HFT	Client	-11.82***	-0.833**	0.657***	0.0751***	-158.3***
	MM	-17.89***	-1.791***	0.335***	0.0620***	-177.3***
	Own	-18.58***	-1.533***	0.563***	-0.0126	-176.8***
	Parent	1.877*	0.758**	1.482***		-169.4***
	RLP					-175.2***
NON HFT	Own	-19.15***	-2.704***	0.348***	0.0492*	-164.6***
	Parent					
	Client	base	base	base	base	base
	Constant	23.08***	4.686***	1.148***	0.475***	183.8***
	# obs	36,902	30,170	24,582	8,402	95,037
	Adj R^2	0.341	0.131	0.105	0.164	0.225
	Clustered St. Err	by stock	by stock	by stock	by stock	by stock

Test of equality of coefficients - Fstat (Pvalue)					
$beta_{PURE-HFT-OWN}$=$beta_{MIXED-HFT-MM}$	107.09 (0.00)	641.5 (0.00)	344.8 (0.00)	720.5 (0.00)	5.29 (0.027)
$beta_{PURE-HFT-OWN}$=$beta_{MIXED-HFT-OWN}$	63.51 (0.00)	778.3 (0.00)	758.4 (0.00)	356.2 (0.00)	3.52(0.068)
$beta_{MIXED-HFT-OWN}$=$beta_{MIXED-HFT-MM}$	8.75 (0.01)	6.9 (0.01)	29.9 (0.00)	47.3 (0.00)	0.83 (0.3670)

A.5 Order submission in the last second of the pre-opening phase

Figure A.4 and A.5 show the total number of new orders and cancellations in the last second of the pre-opening phase, for the most relevant traders and for each stock. Each column represents the total number of new order (or cancellations) submitted during the ten-millisecond window interval. Both MIXED-HFT-OWNs and NON-HFT-OWNs submit a relevant number of new orders within the last 100 milliseconds of the pre-opening phase. However, almost all trader groups are able to submit and cancel orders few milliseconds before the opening auction. This opportunity can easily be exploited, since the auction time is fixed and every trader can measure the latency between their device and the exchange matching engine in normal times. The speed and the capacity (number of messages sent) can be fully exploited only in case of co-location of the servers, a typical setup for HFTs.

FIGURE A.4: **New Order and modification submission across stocks during the last second of the Pre-Opening Phase**

This figure shows the total number of new order submissions for the most relevant trader/account categories. Each column represents the total number of new orders submitted during the last second, for each stock, summed across days. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

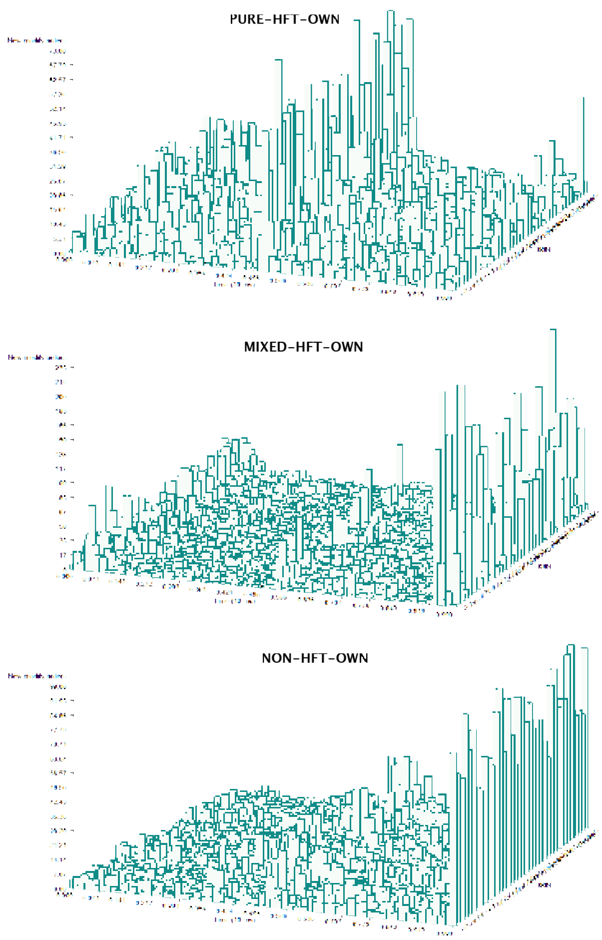
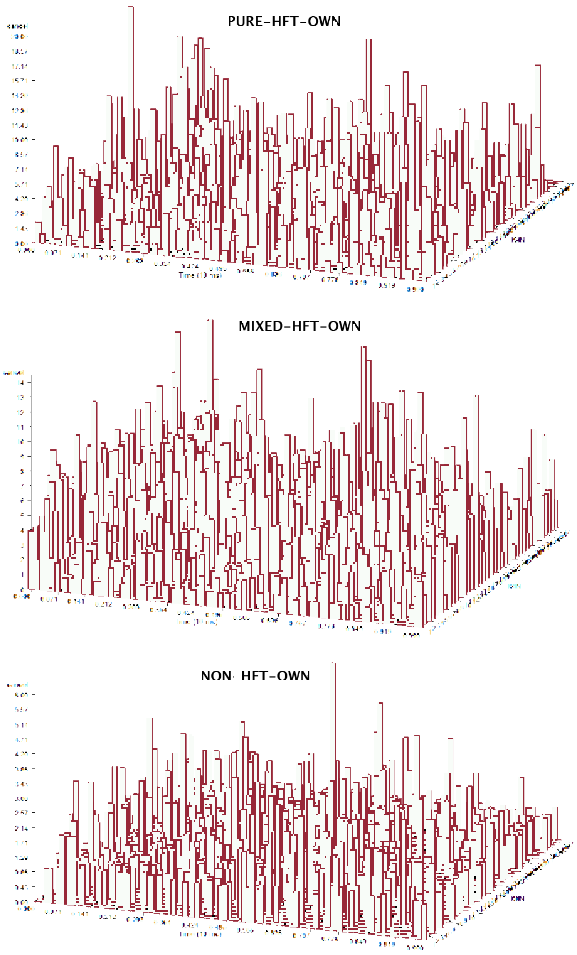


FIGURE A.5: **Cancellations across stocks during the last second of the Pre-Opening Phase**

This figure shows the total number of cancellations for the most relevant trader/account categories. Each column represents the total number of cancellations submitted during the last second, for each stock, summed across days. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.



A.6 Weighted Price Discovery order by order

The contribution to price discovery, as described in the Section 1.5.3 of the paper, is measured using the Weighted Price Discovery Contribution (WPDC). We define the WPDC order by order: this estimation helps us to exploit the overall contribution of each group of traders by different order type. We can also gain some insights about the different submission strategies that the traders follow during the pre-opening phase, using limit orders, limit orders with iceberg quantities, market orders or very aggressive orders.

The distinct feature of our measure of price discovery is that it sums up to -100%, in a way that a negative value reduces the deviation and moves the price close to the opening price. A positive WPDC is viewed as a deterioration of price discovery (the theoretical opening price is pushed away from the future opening price), while a negative WPDC represents an improvements in price discovery. Each panel of Table A.4 and A.5 represents the price discovery that occurs during the specific time period until the end of the pre-opening phase (Panel B of Table A.4, the WPDC is calculated from 8.10 a.m. until the auction, thus excluding the period from 7.15 a.m. to 8.09 a.m.). The *Total* columns represent the total WPDC as reported in Table 1.7 of the paper. In the top-left corner of the intermediate tables, the WPDC for each interval is reported. If the value is below -100%, it means that the price has moved away from the direction of the final auction price. The value of -48.77%, reported in Panel A of Table A.5, indicates that 48.77% of the price discovery will occur in the last minute of the pre-opening phase.

The overall assessment of the total price discovery is provided in Panel A of Table A.4. New limit orders and cancellations of market orders drive the price discovery process, while the submission of new market orders, especially from NON HFT-Client, deteriorate the WPDC. In general, the cancellation of limit orders deteriorate the price discovery, most likely because there is no intention to execute the order at the theoretical opening price. However, if the trader is not willing to participate at the auction, the cancellation of the order will occur before the very last moments of the pre-opening phase. In fact, Panel B and C of Table A.5 show that the cancellation of both limit and market orders do provide price discovery, with the exception of MIXED-HFT-Client and NON HFT. Further, in the very last second and last 100 milliseconds, cancellation does not move the price significantly, which indicates that the orders accumulated are large enough to absorb the impact of a cancellation, making it difficult to manipulate the opening price.

The behavior of the PURE-HFT traders is mainly driven by the fact that most of them start submitting their orders after 8.30. The speed advantage is exploited in the last part of the pre-opening phase. During the last minute (Table A.5, Panel A), the price discovery of PURE-HFT-OWN traders is provided by modification of existing limit orders, since the WPDC of new orders and deleted limit orders cancel out. In the last second and last 100 milliseconds, their intention to execute is signaled by the submission of new limit orders that contribute to the price discovery. The majority of price discovery, in all intervals considered, is provided by the MIXED-HFT-OWN.

Since the theoretical opening price includes also the iceberg quantities, we analyze if the submission of orders with hidden quantities do contribute or deteriorate price discovery. In general, new limit orders with iceberg quantity do not harm price discovery and follow the regular limit orders and the market orders in the price discovery process. Finally, we also document the usage of very aggressive limit orders (orders that are over the 6% change from the yesterday closing price), and flash-crash orders. Aggressive limit orders marginally provide price discovery, especially in the last portion of the pre-opening phase. Flash crash orders have a very small impact on the determination of the opening price, since their purpose is to exploit temporary and unexpected price movements.

TABLE A.4: **Weighted Price Discovery Contribution (WPDC) by type of order**

This table shows the Weighted Price Discovery Contribution, defined in Section 1.5.3 of the paper, for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT) and six account types (CLIENT, OWN, RLP, RMO, MM, PARENT) during the pre-opening phase. All numbers in each panel sum to 100%. Data are for 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

			Limit Orders			Market Orders			Limit w. Iceberg			Flash Crash Limit			Flash Crash Limit w. Iceberg			Aggressive Limit			Aggressive Limit w. Iceberg		
		TOTAL	**New**	**Modify**	**Cancel**	**New**	**Modify**	**Cancel**	**New**	**Modify**	**Cancel**	**New**	**Modify**	**Cancel**	**New**	**Modify**	**Cancel**	**New**	**Modify**	**Cancel**	**New**	**Modify**	**Cancel**
Panel A: WPDC by type of order during the entire pre-opening phase																							
PURE-HFT	Client	0.32%	-0.49%		0.03%	0.87%		-0.05%	-0.07%		0.04%							0.02%		-0.03%			
	Own	-11.75%	-16.79%	-2.22%	6.20%	1.01%		0.04%	0.00%	0.00%		0.00%		0.00%				0.02%		-0.02%			
	MM	-0.03%	0.00%			0.00%												-0.02%					
MIXED-HFT	Client	-8.75%	-32.09%	-3.12%	16.71%	12.00%	-0.44%	-0.79%	-4.60%	1.30%	0.68%	-0.04%	0.00%	0.00%	-0.03%	-0.01%	0.01%	1.62%	0.01%	0.04%	-0.03%	0.01%	0.02%
	Own	-47.47%	-56.27%	-4.57%	4.13%	35.23%	-3.05%	-20.23%	-2.87%	-0.03%	0.16%	-0.06%	0.00%	0.00%				0.02%	-0.05%	0.12%	0.03%		-0.04%
	MM	-6.03%	-6.21%	-0.16%	0.33%							0.00%	0.00%					0.00%					
	Parent	-12.71%	-7.94%	0.04%	-0.47%	-3.50%		-0.81%	-0.02%	0.01%	0.00%				0.00%			-0.01%					
NON HFT	Client	3.09%	-69.57%	-0.34%	6.82%	119.66%	0.06%	-46.45%	-8.48%	-0.30%	0.48%	0.07%	0.01%	0.02%	0.00%	0.00%		1.07%	0.01%	-0.05%	0.10%		-0.01%
	Own	-16.96%	-18.32%	-0.61%	2.27%	0.52%	-0.10%	0.15%	-1.38%	0.46%	0.14%	-0.07%	-0.05%	0.00%		0.03%		0.07%	0.01%	-0.06%	-0.01%	0.02%	-0.01%
	RMO	0.05%	-0.18%	-0.01%	0.01%	0.22%		0.01%										0.01%					
	Parent	0.24%	-0.14%	0.09%	0.03%	0.25%		0.03%										-0.02%	0.00%				
WPDC LEFT:	**-122.83%**	**Panel B: WPDC by type of order in the pre-opening phase: from 8:10 AM**																					
PURE-HFT	Client	-0.09%	-0.36%		0.03%	0.29%		-0.03%	-0.05%		0.03%							0.00%		0.00%			
	Own	-9.07%	-12.76%	-1.85%	5.26%	0.26%		0.03%	0.00%	0.00%		-0.01%		0.00%				0.00%		-0.01%			
	MM	-0.02%	0.00%			0.00%												-0.02%					
MIXED-HFT	Client	-7.86%	-25.55%	-2.47%	13.81%	8.21%	-0.25%	-0.56%	-3.58%	1.09%	0.61%	-0.03%	0.00%	0.00%	-0.04%	0.00%	0.01%	0.84%	0.01%	0.05%	-0.02%	0.01%	0.01%
	Own	-37.35%	-46.63%	-3.77%	3.60%	32.78%	-2.63%	-18.52%	-2.30%	-0.03%	0.14%	-0.06%	0.00%	0.00%				0.00%	-0.02%	0.09%	-0.01%		
	MM	-5.07%	-5.09%	-0.29%	0.31%							0.00%	0.00%					0.00%					
	Parent	-10.47%	-6.48%	0.05%	-0.55%	-2.26%		-1.19%	-0.02%	0.01%	0.00%				0.00%			-0.02%					
NON HFT	Client	-16.48%	-21.70%	-0.29%	4.14%	11.16%	-0.08%	-3.56%	-6.75%	-0.24%	0.42%	0.00%		0.00%	-0.01%	0.00%		0.35%	0.01%	-0.05%	0.16%		-0.04%
	Own	-13.74%	-14.73%	-0.51%	1.82%	1.02%	-0.09%	-0.51%	-1.07%	0.36%	0.07%	-0.06%	-0.04%	0.00%		0.03%		0.05%	0.00%	-0.05%	0.01%	-0.01%	0.00%
	RMO	-0.08%	-0.04%	-0.01%	0.00%	-0.04%		0.01%															
	Parent	0.24%	-0.09%	0.07%	0.02%	0.21%		0.04%										-0.02%	0.00%				
-																							
WPDC LEFT:	**-121.78%**	**Panel C: WPDC by type of order in the pre-opening phase: from 8:30 AM**																					
PURE-HFT	Client	-0.12%	-0.33%		0.05%	0.23%		-0.04%	-0.06%		0.04%							0.00%		0.00%			
	Own	-8.86%	-12.31%	-1.89%	5.20%	0.14%		0.00%	0.00%	0.00%		-0.01%		0.00%				0.00%		-0.01%			
	MM	-0.02%	0.00%			0.00%												-0.02%					
MIXED-HFT	Client	-8.90%	-24.81%	-2.41%	13.98%	4.76%	-0.20%	-0.01%	-2.68%	1.11%	0.52%	-0.03%	0.00%		-0.04%	-0.01%	0.01%	0.78%	0.01%	0.10%	-0.01%	0.01%	0.01%
	Own	-40.74%	-46.00%	-3.85%	3.41%	28.10%	-2.68%	-17.97%	-1.94%	-0.03%	0.15%	-0.05%	0.00%	0.00%				0.06%	-0.04%	0.10%	-0.01%		
	MM	-5.06%	-5.16%	-0.24%	0.34%							0.00%	0.00%					0.00%					
	Parent	-10.03%	-6.77%	0.05%	-0.32%	-1.85%		-1.12%	-0.02%	0.01%	0.00%				0.00%			-0.02%					
NON HFT	Client	-13.27%	-17.95%	-0.29%	3.67%	9.55%	-0.13%	-2.49%	-6.04%	-0.20%	0.39%	-0.02%		0.00%	-0.01%	0.00%		0.24%	0.01%	-0.02%	0.03%		-0.03%
	Own	-13.16%	-14.26%	-0.49%	1.76%	1.46%	-0.08%	-0.90%	-1.02%	0.38%	0.04%	-0.06%	-0.04%	0.00%		0.03%		0.04%	0.01%	-0.02%		-0.01%	0.01%
	RMO	-0.07%	-0.04%	-0.01%	0.00%	-0.04%		0.01%															
	Parent	0.25%	-0.08%	0.07%	0.02%	0.27%		-0.01%										-0.02%	0.00%				
-																							

TABLE A.5: **Weighted Price Discovery Contribution (WPDC) by type of order from 8:59 AM**

This table shows the Weighted Price Discovery Contribution, defined in Section 1.5.3, for three trader groups (PURE-HFT, MIXED-HFT, NON-HFT) and six account types (CLIENT, OWN, RLP, RMO, MM, PARENT) during the last second of the pre-opening phase. Compared to Table 1.8, we exclude the order type that does not contribute to the price discovery in the very last second. Data are for 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A: WPDC by type of order during the last minute of the pre-opening phase (WPDC LEFT: -48.77%)

		TOTAL	Limit Orders			Market Orders			Limit w. Iceberg			Flash Crash Limit			Flash Crash Limit w. Iceberg			Aggressive Limit			Aggressive Limit w. Iceberg		
			New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel
PURE-HFT	Client	-0.14%	-0.07%		-0.01%	-0.06%		0.01%			-0.02%												
	Own	-1.97%	-5.47%	-2.75%	5.92%	0.32%		0.00%										0.01%					
	MM	-0.06%	0.00%			0.00%												-0.05%					
MIXED-HFT	Client	-2.89%	-9.84%	-1.60%	7.51%	-0.26%	0.14%	-0.02%	-0.53%	1.70%	0.09%	0.00%				0.00%		-0.04%	0.00%	-0.04%		0.01%	
	Own	-51.92%	-49.26%	-2.05%	1.62%	1.99%	-1.21%	-2.57%	-0.33%	0.00%	0.00%	-0.04%	0.00%					0.01%	-0.05%	-0.01%			
	MM	-10.54%	-10.75%	-0.21%	0.41%							-0.01%	0.00%					0.01%					
	Parent	-14.49%	-13.64%	-0.01%	-0.60%	0.23%		-0.44%	-0.02%	0.00%	0.00%				0.00%			-0.01%					
NON HFT	Client	-4.31%	-6.11%	-0.11%	3.01%	0.00%	0.02%	-0.46%	-0.56%	-0.10%	0.08%			0.00%				-0.02%	0.00%	-0.05%			
	Own	-13.78%	-15.12%	-1.39%	3.28%	-0.44%	-0.03%	-0.05%	-0.20%	0.14%	-0.01%	0.01%	0.01%	0.00%				0.04%		-0.01%			0.00%
	RMO	0.00%	0.00%			0.00%																	
	Parent	0.11%	-0.05%	0.15%	0.05%	0.01%												-0.05%	0.00%				

-

Panel B: WPDC by type of order during the last second of the pre-opening phase (WPDC LEFT: -10.60%)

		TOTAL	Limit Orders			Market Orders			Limit w. Iceberg			Flash Crash Limit			Flash Crash Limit w. Iceberg			Aggressive Limit			Aggressive Limit w. Iceberg		
			New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel
PURE-HFT	Client	-0.03%	-0.03%																				
	Own	-13.61%	-13.15%	-0.47%	0.01%	0.00%																	
	MM	-0.49%																-0.49%					
MIXED-HFT	Client	-2.30%	-1.64%	-0.49%	0.57%	-0.21%	-0.02%	0.18%	-0.02%	-0.58%								-0.11%	0.00%				
	Own	-54.61%	-49.84%	-1.15%	-0.60%	-2.03%	-0.03%	-0.83%	-0.01%									-0.09%		-0.03%			
	MM	-2.79%	-2.45%	-0.26%	-0.08%																		
	Parent	-0.91%	-0.23%		-0.57%	-0.06%		-0.04%															
NON HFT	Client	-0.82%	-0.24%	-0.04%	0.03%	-0.18%	-0.04%	-0.25%	-0.05%	-0.05%													
	Own	-24.39%	-23.16%	-1.64%	0.47%	0.00%		0.00%		-0.04%	-0.01%							0.00%					
	RMO	0.00%	0.00%																				
	Parent	-0.04%	0.01%	-0.04%	-0.01%																		

-

Panel C: WPDC by type of order during the last 100 milliseconds of the pre-opening phase (WPDC LEFT: -1.71%)

		TOTAL	Limit Orders			Market Orders			Limit w. Iceberg			Flash Crash Limit			Flash Crash Limit w. Iceberg			Aggressive Limit			Aggressive Limit w. Iceberg		
			New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel	New	Modify	Cancel
PURE-HFT	Client																						
	Own	-8.75%	-8.08%	-0.18%	-0.49%																		
	MM																						
MIXED-HFT	Client	-1.66%	-0.49%	-1.15%	-0.22%	-0.11%	-0.01%	0.37%		-0.04%													
	Own	-81.83%	-76.66%	-0.37%	-1.63%	-2.31%	-0.03%	-0.82%															
	MM	-0.75%	-0.67%	-0.08%																			
	Parent	-0.52%	-0.37%			-0.15%																	
NON HFT	Client	-1.42%	-0.96%	-0.11%	-0.07%	-0.18%	-0.06%			-0.04%													
	Own	-4.27%	-2.66%	-1.18%	-0.36%						-0.08%												
	RMO																						
	Parent	0.01%		0.01%																			

-

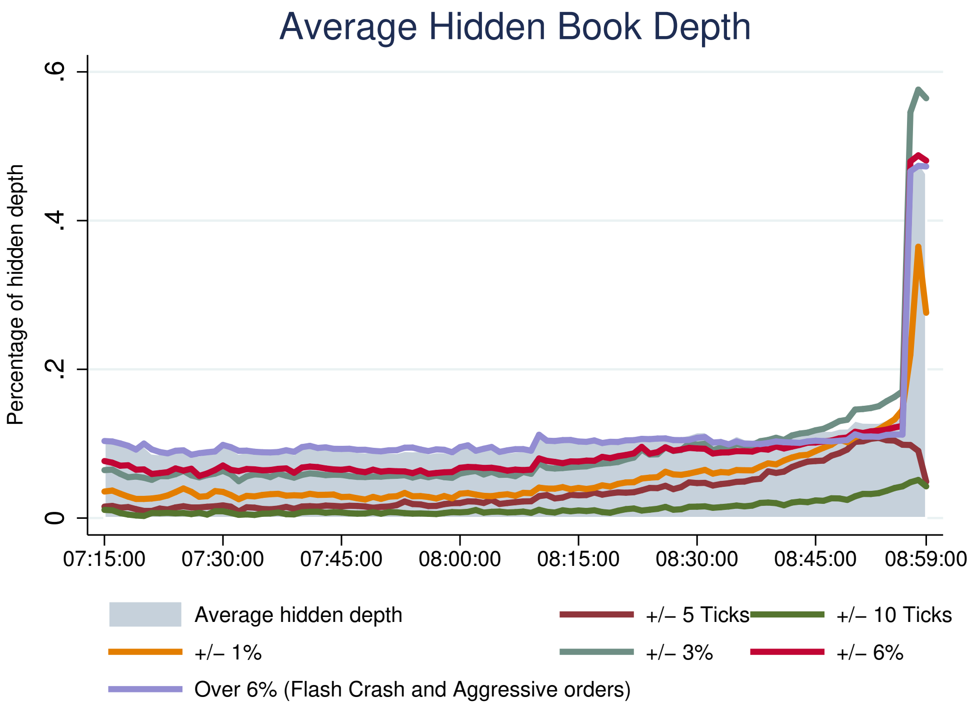
A.7 Iceberg orders usage

According to the Euronext Trading Manual for the Universal Trading Platform (Euronext (2016)), when an order is entered, the trader has to specify the total volume and the peak volume. The latter will be disclosed to the central order book, while the total quantity will be hidden to the other market participants. In our database, we can observe both quantities. An iceberg order can be submitted both during the pre-opening phase and the main trading phase. There are several papers that investigate the presence and the usage of the iceberg orders, especially on the Euronext market. Remarkable examples are De Winne and D'hondt (2007) and Bessembinder, Panayides, and Venkataraman (2009), who also provide the rationale behind the usage of the iceberg orders. We only document empirically what happens to the visible (and invisible) part of the order book during the pre-opening phase.

Figure A.6 shows the average hidden quantity for the entire pre-opening phase. For most of the time, the hidden quantity is around 10% of the total depth (visible plus hidden), and mainly driven by flash-crash and very aggressive orders. An interesting pattern arises in the last three minutes of the pre-opening phase: the hidden quantities skyrocket up to 50% on average. As we documented before, this increase in the hidden quantity does not have a remarkable impact on the price discovery process.

FIGURE A.6: **Iceberg orders during the Pre-Opening Phase**

This figure shows the average hidden quantity per minute, across stock-days,for different positions of the limit order book with respect to the calculated theoretical opening price. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

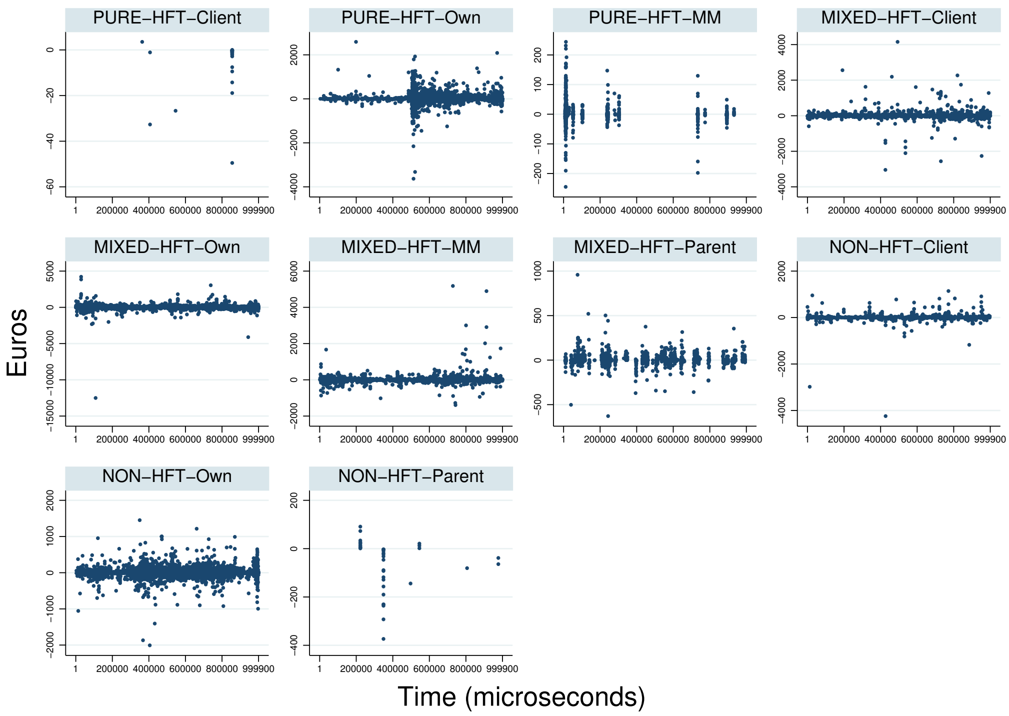


A.8 Profit by order

Figure A.7 plots the potential profits by order across all stock-days made on orders submitted during the last second of the pre-opening phase, assuming that the position taken in the auction is reverted one-minute after the auction at the market price, i.e., it is evaluated at the mark-to-market price one minute after the opening auction. We observe that PURE-HFT-OWN traders are the only ones for whom most of the executed orders were submitted in the last 500 milliseconds, while executed orders of all other trader/account types are spread evenly throughout the last second.

FIGURE A.7: **Time of submission and return in the last second**

The figure shows, for each trader/account, the return on individual orders executed at the auction and the time where the executed order has been submitted for the last second of the pre-opening phase. We assume that position taken in the auction is liquidated one minute after the auction at the market price. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belongs to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.



A.9 Shape of the order book during the Pre-Opening Phase

As explained in Section A.1 of this Appendix, the order book during the pre-opening phase looks quite different compared to the book during the main trading phase. This section describes the main differences and provides some insights about the shape of the order book, and how the traders behave during the pre-opening phase. First of all, in order to calculate the theoretical opening price order by order, it is necessary to rebuild the entire order book, which also includes the "left-over" orders from the previous days.A best-bid and best-ask price, at the top of the book, is not available given that the book is crossed. Further, the presence of the market orders (which are usually executed immediately in the main trading phase) requires a different set of metrics to establish if an order is executable or not. We define three price intervals: plus/minus 5 ticks, plus/minus 10 ticks (interval between 5 ticks and 10 ticks) and up to plus/minus 1% of the theoretical opening price. Orders inside the 10 tick interval are very likely to be executed at the opening auction. The tick size depends on the level of the stock price and varies between 0.001 euro (when the stock price is between 0 and 10 euro) and 0.05 euro (when the stock price is larger than 100 euro). Going down on the price grid, the probability of execution of an order decreases. We sample the presence of these three parts of the order book for every minute, and for every second, in the last minute of the pre-opening phase, and then draw a box plot that indicates the presence (in minutes or seconds) for the most relevant group of traders. As shown in Figure A.8, for entire pre-opening phase, PURE-HFT-OWN (MIXED-HFT- OWN) traders are present in the limit order book within +/- 5 ticks around the theoretical opening price for a median time of 15 (5) minutes, while NON-HFT-CLIENT traders are there for almost 90 minutes out of 105 minutes in total. If we focus on the period after 08:30 a.m. (Figure A.9), then PURE-HFT-OWN (MIXED-HFT-OWN) are present in the limit order book within +/- 5 ticks around the theoretical opening price for a median time of 15 (10) minutes out of 30 minutes remaining from the pre-opening phase. In the last one minute (Figure A.10), PURE-HFT- OWN (MIXED-HFT-OWN) are present in the top of the book for a median time of 45 (55) seconds, while MIXED-HFT-MM are there for only around 5 seconds.

FIGURE A.8: **Shape of the order book during the Pre-Opening Phase**

The box plots show the average presence time (in minutes) during the entire pre-opening phase. The presence is sampled at the end of every minutes from the rebuilt order book. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

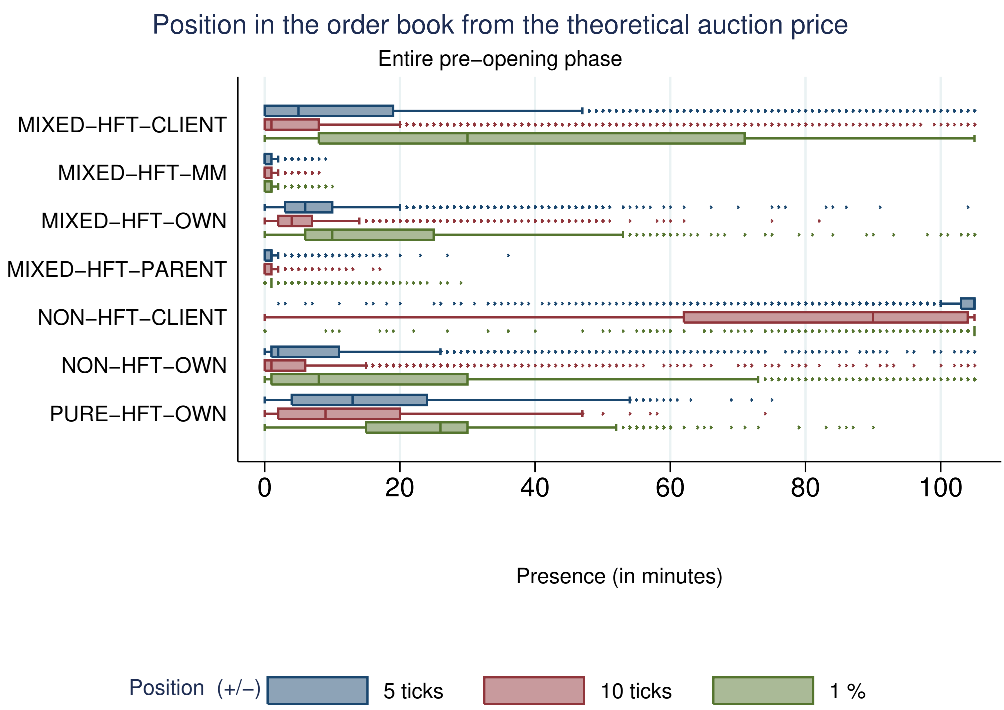


FIGURE A.9: **Shape of the order book during the Pre-Opening Phase: from 8:30 AM**

The box plots show the average presence time (in minutes) during the last 30 minutes of the pre-opening phase. The presence is sampled at the end of every minutes from the rebuilt order book, after 8:30 AM. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.

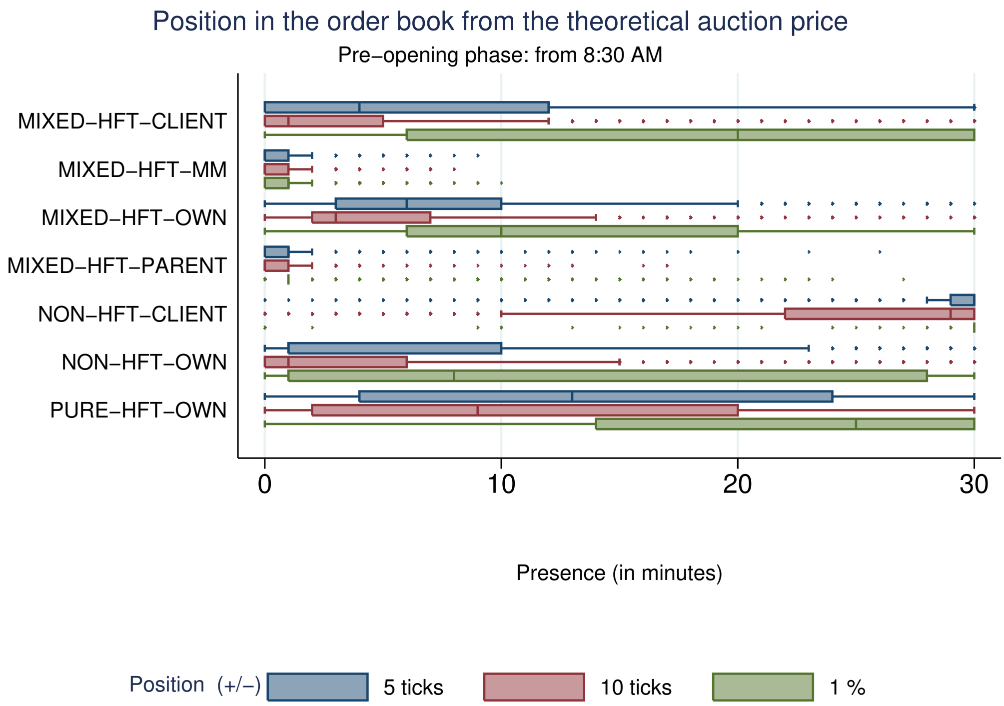
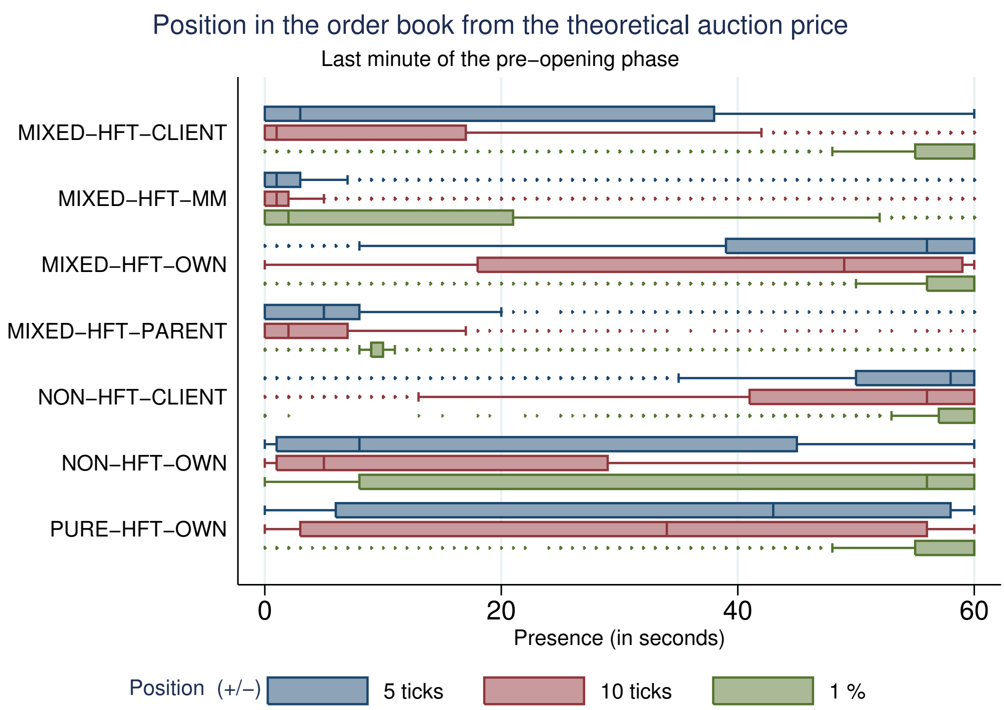


FIGURE A.10: **Shape of the order book during the Pre-Opening Phase: last minute**

The box plots show the average presence time (in seconds) during the last minute of the pre-opening phase. The presence is sampled at the end of every second from the rebuilt order book, after 8:59:00 AM. The sample is composed of 37 stocks traded on NYSE Euronext Paris that belong to the CAC40 index, for the year 2013. Order flow data, with trader group and account flags are from BEDOFIH.



Appendix B

Internet Appendix for "High-Frequency Market Making: Liquidity Provision, Adverse Selection, and Competition"

B.1 Sample Composition

This table shows the components of the sample that we consider for the empirical analysis. On the forty components of the CAC40 Index, three are not included since their main trading venues are Amsterdam (for Arcelor Mittal and Gemalto) and Bruxelles (Solvay). We also include the SLP basket belongings until end of May 2013. The market capitalization refers to the stocks traded only on Euronext Paris, excluding other venues. Data are from Bloomberg, as of January 3, 2013, in millions of euros (MEuro). Values range from 5'000 MEuro for Vallourec, to 146'000 millions of Euros for Total. The average number of trades and the average trading volume reflects the size of the stock in terms of market capitalization. The basket number one is characterized by the presence of three big companies (Total, Sanofi and BNP Paribas) that displays the highest average daily trading volume.

TABLE B.1: **Sample Composition**

Ticker	ISIN	Company Name	Sector	Market Cap (M Euro)	Average daily trading (N. trades)	Average daily volume (M Euro)	Basket
FP	FR0000120271	Total	Energy	145'995	26'025	348	1
AC	FR0000120404	Accor	Consumer Discr.	7'822	7'872	49	1
SAN	FR0000120578	Sanofi	Health Care	101'851	27'238	400	1
ML	FR0000121261	Michelin	Consumer Discr.	14'350	12'618	99	1
SU	FR0000121972	Schneider	Industrials	35'628	16'767	164	1
SGO	FR0000125007	Saint-Gobain	Industrials	22'193	13'639	116	1
BNP	FR0000131104	BNP	Financials	70'354	33'015	364	1
STM	NL0000226223	STMicroelectronics	Information Tech.	7'098	8'668	44	1
ACA	FR0000045072	Credit Agricole	Financials	23'221	12'774	88	2
SAF	FR0000073272	Safran	Industrials	21'064	8'569	60	2
AI	FR0000120073	Air Liquide	Materials	32'047	12'821	128	2
LG	FR0000120537	Lafarge	Materials	15'652	11'512	76	2
BN	FR0000120644	Danone	Consumer Staples	30'688	14'526	176	2
RI	FR0000120693	Pernod Ricard	Consumer Staples	21'799	10'385	96	2
VIE	FR0000124141	Veolia Environ.	Utilities	6'338	10'989	68	2
PUB	FR0000130577	Publicis Groupe SA	Consumer Discr.	13'740	9'466	75	2
TEC	FR0000131708	Technip	Energy	7'942	10'665	75	2
EDF	FR0010242511	EDF	Utilities	47'729	9'368	64	2
LR	FR0010307819	Legrand	Industrials	10'633	6'387	45	2
MC	FR0000121014	Lvmh Moet Henessy	Consumer Discr.	66'353	13'133	200	3
KER	FR0000121485	Kering	Consumer Discr.	19'395	6'899	83	3
EI	FR0000121667	Essilor International	Health Care	16'592	10'950	86	3
DG	FR0000125486	Vinci	Industrials	28'713	14'361	124	3
GLE	FR0000130809	Societe Generale	Financials	33'722	32'204	317	3
RNO	FR0000131906	Renault	Consumer Discr.	17'064	14'722	118	3
ENGI	FR0010208488	ENGIE	Utilities	40'349	13'831	148	3
ALO	FR0010220475	Alstom	Industrials	8'126	11'838	81	3
AIR	NL0000235190	EADS	Industrials	43'550	20'886	212	3
CA	FR0000120172	Carrefour	Consumer Staples	20'858	13'152	116	4
OR	FR0000120321	L'Oreal	Consumer Staples	76'594	10'612	139	4
VK	FR0000120354	Vallourec	Energy	5'035	9'902	51	4
EN	FR0000120503	Bouygues	Industrials	8'754	8'858	57	4
CS	FR0000120628	Axa	Financials	48'784	19'042	200	4
CAP	FR0000125338	Cap Gemini	Information Tech.	7'876	9'677	61	4
VIV	FR0000127771	Vivendi Universal	Consumer Discr.	25'660	13'320	143	4
ALU	FR0000130007	Alcatel	Information Tech.	8'981	18'282	131	4
ORA	FR0000133308	Orange	Telecommunication	23'630	21'114	167	4

B.2 Liquidity Provision Statistics

We provide in this section some additional statistics on the NLP (Table B.2 and on the average liquidity provision (B.3). Table B.2 reports the distribution across stock, day and group of traders (Panel A). We rank the NLP for each stock and we select the two most liquid and the two less liquid stocks according to the average value. Panel B shows that the Top 2 stocks are Renault (FR0000131906) and Carrefour (CARREFOUR): for the former, the average NLP is about +9.86%. For the MIXED-MM (Panel C), quite surprisingly there are no stocks with average positive NLP. The top scorer is Sanofi (FR0000120578), followed by Total (FR0000120271). The stock comparison shows that, in this ranking, HFT-MMs perform worse for Total (n. 36 out of 37 stocks) with -1.32%, while similar figures for the same stock holds for MIXED-MM (-1.13%) but in this case, it is at the position n. 2.

TABLE B.2: **Net Liquidity Provision Statistics**

Trader/Account		Average	Std.Dev.	P5	P50	P95
Panel A: Net liquidity provision statistics across stock-date						
HFT	MM	3.60%	5.63%	-5.46%	3.49%	12.92%
	Other	0.26%	0.77%	-0.80%	0.20%	1.52%
MIXED	MM	-3.49%	2.93%	-7.95%	-3.68%	1.37%
	Other	1.33%	4.94%	-6.70%	1.25%	9.56%
NON HFT	Other	-1.69%	3.25%	-7.33%	-1.44%	3.05%

Ranking	ISIN	Average	Std. Dev.	P5	P50	P95
Panel B: Best and worst NLP by Stock for HFT-MM						
1	FR0000131906	9.86%	5.46%	-0.39%	10.72%	17.46%
2	FR0000120172	7.75%	4.55%	0.90%	7.58%	15.97%
36	FR0000120271	-1.32%	5.40%	-9.42%	0.21%	6.13%
37	FR0010208488	-2.25%	3.55%	-8.14%	-2.17%	3.37%
Panel C: Best and worst NLP by Stock for MIXED-MM						
1	FR0000120578	-0.93%	3.06%	-4.99%	-1.48%	3.36%
2	FR0000120271	-1.13%	3.41%	-5.46%	-1.46%	4.09%
36	FR0010307819	-5.52%	2.93%	-10.75%	-5.40%	-0.86%
37	FR0000120537	-5.66%	3.29%	-10.63%	-5.83%	-0.65%

Table B.3 shows the average liquidity provision in number of shares for three trader groups (HFT, MIXED, NONHFT) and two account type (MM and Others) during the main trading phase. The liquidity provider is defined as the trader that does not initiate the trade, and the liquidity demander the trader that initiate the trade. On average, HFT-MM provides most of the liquidity to MIXED-Other and to NONHFT.

TABLE B.3: **Average Liquidity Provision**

			Liquidity Takers					
			HFT		MIXED		NON HFT	
			MM	Other	MM	Other	Other	Avg
Liq. Providers	HFT	MM	4.73%	0.30%	3.95%	14.55%	5.39%	5.79%
		Other	0.41%	0.05%	0.23%	0.76%	0.33%	0.36%
	MIXED	MM	1.35%	0.10%	0.74%	2.97%	1.16%	1.26%
		Other	10.47%	0.59%	5.79%	21.70%	9.47%	9.60%
	NON HFT	Other	4.76%	0.25%	2.57%	5.37%	2.25%	3.04%
	Average		4.34%	0.26%	2.65%	9.07%	3.72%	

B.3 Inventories of the Groups of Traders

To gain some insights about the net position of the groups of traders, we calculate the daily inventories as (buy - sell) divided by (buy + sell), in a way that the inventory position goes from -1 to +1. Then, we aggregate across days and groups. The total capital aggregation is carried out considering the price paid (received) when the stock has been bought (sold). We also include the opening and the closing auction in the calculation. As we can see from the following table, if we consider the P5 and P95, HFT-MM ranges from -10.3% to +11.52%, the lowest values across the groups. HFT-Others as a group could assume a considerable directional position, and range from -56% to + 63%. All the other groups are in an intermediate position.

Table B.4: **Inventories of the Traders**

Trader/Account		Average	Std.Dev.	P5	P50	P95
Panel A: Inventories (n.shares)						
HFT	MM	0.37%	6.53%	-10.30%	0.18%	11.52%
	Other	3.00%	34.73%	-55.99%	2.76%	63.05%
MIXED	MM	1.91%	24.28%	-39.34%	1.70%	41.91%
	Other	0.02%	8.82%	-14.25%	0.09%	14.14%
NON HFT	Other	-2.09%	24.37%	-42.35%	-2.30%	38.61%
Panel B: Inventories (Total Capital Millions euro)						
HFT	MM	-2.6	18.5	-31.7	-2.9	26.8
	Other	-3.3	9.5	-21.5	-2.2	9.6
MIXED	MM	-11.6	88.5	-131.8	-12.3	107.4
	Other	2.7	81.8	-105.0	-4.0	120.5
NON HFT	Other	14.8	98.2	-150.6	24.1	157.4

B.4 Realized spread and volatility

As a robustness check for the realized spread regression for HFT-MM, we introduced in the analysis a proxy for the riskiness, the realized volatility introduced in Section 2.5.1 and estimated at stock-day level. To address the effect of the idiosyncratic volatility, we interact the dummies that identify the trader with the realized volatility. We expect that a rise in the volatility increases the risk and the severity of the adverse selection for HFT-MM a, but also the profits opportunities. Formally, we estimate the following model:

$$\textit{cumulative realized spread}_{i,j,m}(\delta) = \alpha_0 + \beta_1 * I_{MM,m} + \beta_2\sigma_{i,j} + \beta_3(I_{MM,m} * \sigma_{i,j}) + e_{i,j,m} \tag{B.1}$$

where *cumulative realized spread*$_{i,j,m}$ is the cumulative sum of the stock-day realized spread when the HFT-MM provide liquidity to the trader m for stock i on day j. $I_{MM,m}$ is a dummy variable that equals 1 when HFT-MM is not the initiator of the trade and provides liquidity to the trader m. The variable $\sigma_{i,j}$ represents the realized daily volatility for the stock i. The regression is estimated for five different time intervals δ, using as a base case the HFT-Others. Standard errors are double clustered on both stock and day.

The results are discussed using as a benchmark the regression presented in Table B.5 of the main paper. We discuss in the following table only the coefficient of the interaction terms, since the interpretation of the "main-effects" coefficients in the regression with interaction terms is not straightforward. Jaccard and Turrisi (2003) provides a detailed discussion of this issue. They also suggest to include the variables without interaction in the regression, as we do in the analysis.

As expected, the volatility exacerbates the difference between traders. When HFT-MM provide liquidity to other HFT-MM, and the volatility is high, the price could potentially move against them quickly, and it is no longer possible to revert the position without losing money. With higher time horizons, the effect is even more severe, and the effect almost doubles after 30 minutes. In periods of high volatility, the speed of reaction seems to be the most important asset, as confirmed by the coefficient after 1 second. However, volatility can also be beneficial for profits. In fact, up to five minutes, the coefficient for the interaction term of NONHFT with the volatility is always higher than the base case, and significant. However, after 30 minutes the coefficient of the realized spread is no longer significant, meaning that the volatility has no impact. Only short-term volatility seems to affect the realized spread, after that the price will revert.

Table B.5: **Regressions on daily cumulative realized spread**

This table shows the results of the regressions where the dependent variable is the cumulative realized spread, calculated aggregating the realized spreads across stock and days, and multiplied by 100, in order to have a percentage value. We consider five different time horizon to compute the realized spread, as explained in Section 2.5.4 of the paper. The realized spread is calculated only for HFT-MM, when they provide liquidity to HFT-MM, MIXED-MM, MIXED-Others or NONHFT. The base category is the HFT-Others. Standard errors are double clustered on both stock and day. ***, **, * correspond to 1%, 5%, and 10% significance levels. The sample period is the year 2013, for the 37 French stocks of the CAC40 index traded on NYSE Euronext Paris. Order flow data, with trader group and account flags are from BEDOFIH.

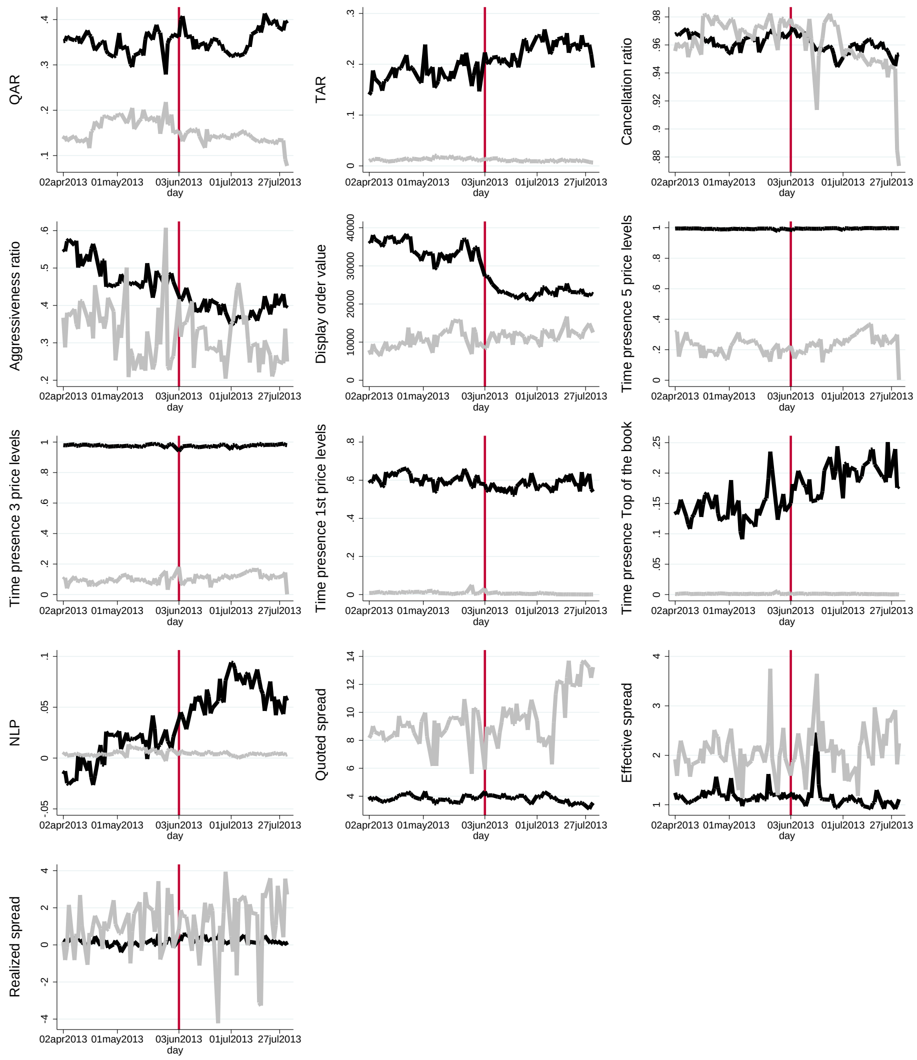
Panel B: realized spread and stock volatility					
	1 second	10 seconds	1 minute	5 minutes	30 minutes
HFT-MM * Volatility	-0.550***	-2.266***	-3.606***	-4.015***	-4.536***
	(0.200)	(0.683)	(0.946)	(0.829)	(1.217)
MIXED-MM * Volatility.	-0.0330	-0.172	-0.101	-0.455	-0.611
	(0.0371)	(0.127)	(0.158)	(0.322)	(0.708)
MIXED-Others * Volatility	-0.0305	-0.762**	-2.377***	-2.481***	-0.974
	(0.0623)	(0.338)	(0.619)	(0.628)	(1.552)
NONHFT * Volatility	1.210***	3.814***	5.932***	6.238***	1.611
	(0.345)	(1.064)	(1.476)	(1.502)	(1.093)
To HFT-MM	-0.233***	-0.800***	-1.006***	-0.680**	-0.550
	(0.0680)	(0.229)	(0.314)	(0.285)	(0.403)
To MIXED-MM	-0.0205	-0.110	-0.270***	0.373**	1.406***
	(0.0313)	(0.0871)	(0.0916)	(0.171)	(0.495)
To MIXED-Others	0.0821*	0.646***	1.648***	1.211***	0.564
	(0.0488)	(0.149)	(0.300)	(0.317)	(0.554)
To NON HFT	0.0146	0.631*	2.498***	3.656***	4.781***
	(0.105)	(0.334)	(0.624)	(0.715)	(0.888)
(Realized) Volatility	0.0366***	0.0513	0.0218	0.316	0.280
	(0.0117)	(0.0452)	(0.0734)	(0.370)	(0.543)
Constant	-0.0139*	-0.0258	0.00653	-0.110	-0.157
	(0.00753)	(0.0167)	(0.0295)	(0.144)	(0.196)
# obs	41,490	44,374	45,084	45,272	45,210
Adj R^2	0.0922	0.181	0.210	0.112	0.0156
Standard Errors	Clustered by stock and day				

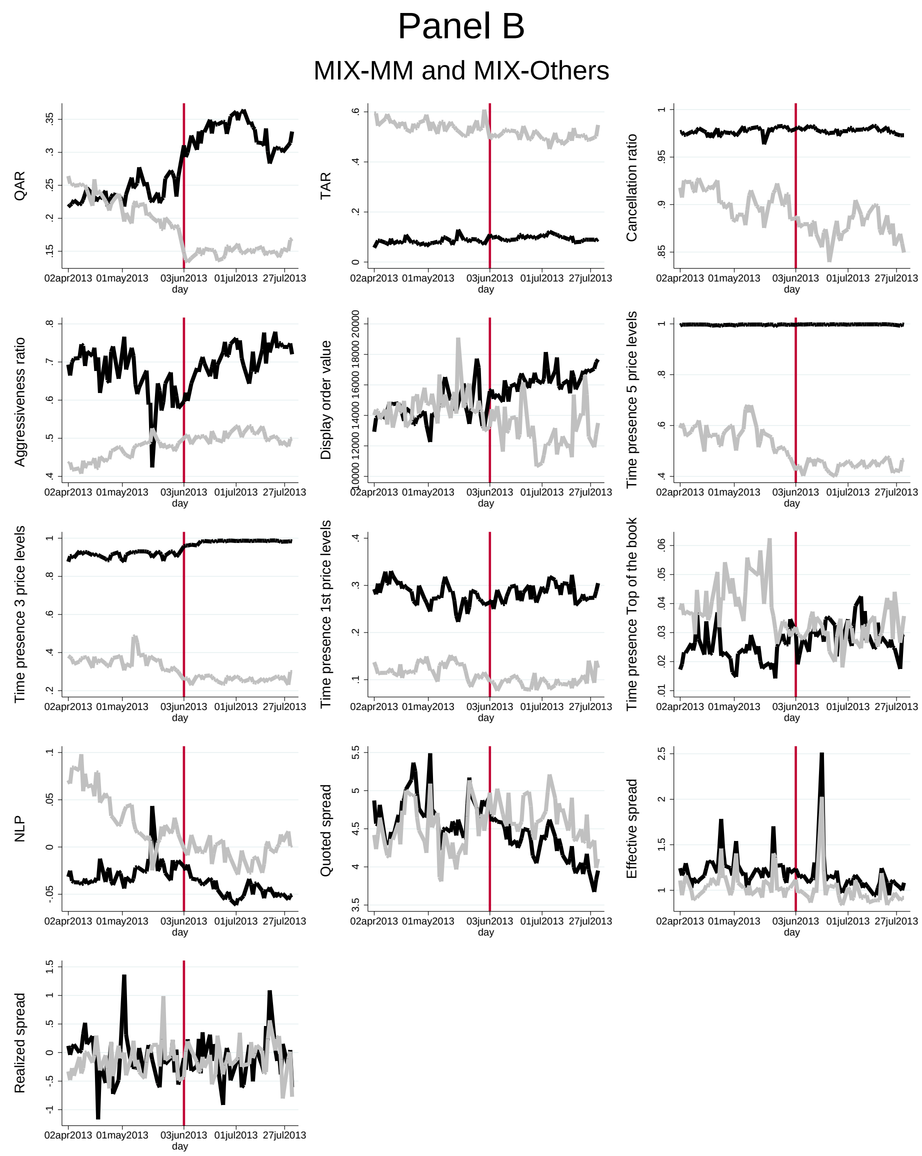
B.5 Time-series plots

These figures show the time series evolution of the 13 measures used for the analysis in Section 2.5.5, averaged across stocks. The black line represents the Market Makers (HFT for Panel A and MIXED for Panel B), while the grey line represents HFT-Others (Panel A) and MIX-Others (Panel B). The red vertical bar is in correspondence of the SLP renewal date (June 3rd, 2013). The sample is composed by 37 French stocks of the CAC40 index traded on NYSE Euronext Paris, for the sample period that goes from April 2nd to July 31st, 2013. Order flow data, with trader group and account flags are from BEDOFIH.

Panel A

HFT-MM and HFT-Others




Panel B
MIX-MM and MIX-Others
QAR
TAR
Cancellation ratio
Aggressiveness ratio
Display order value
Time presence 5 price levels
Time presence 3 price levels
Time presence 1st price levels
Time presence Top of the book
NLP
Quoted spread
Effective spread
Realized spread
02apr2013 01may2013 03jun2013 01jul2013 27jul2013
day

Appendix C

Internet Appendix for "Intraday Pricing and Liquidity of Italian and German Treasury Auctions"

FIGURE C.1: **Yield difference for the Newly issued bonds**

This figure plot the average yield difference (top panel) and the total depth available in the market (bottom panel, in Millions of €), only for the new-issued bonds. The quotes are in the grey market before the issuance. The shaded area represents the 95% confidence interval around the sample mean, and the black dashed line represents the average yield difference on non-auction dates. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

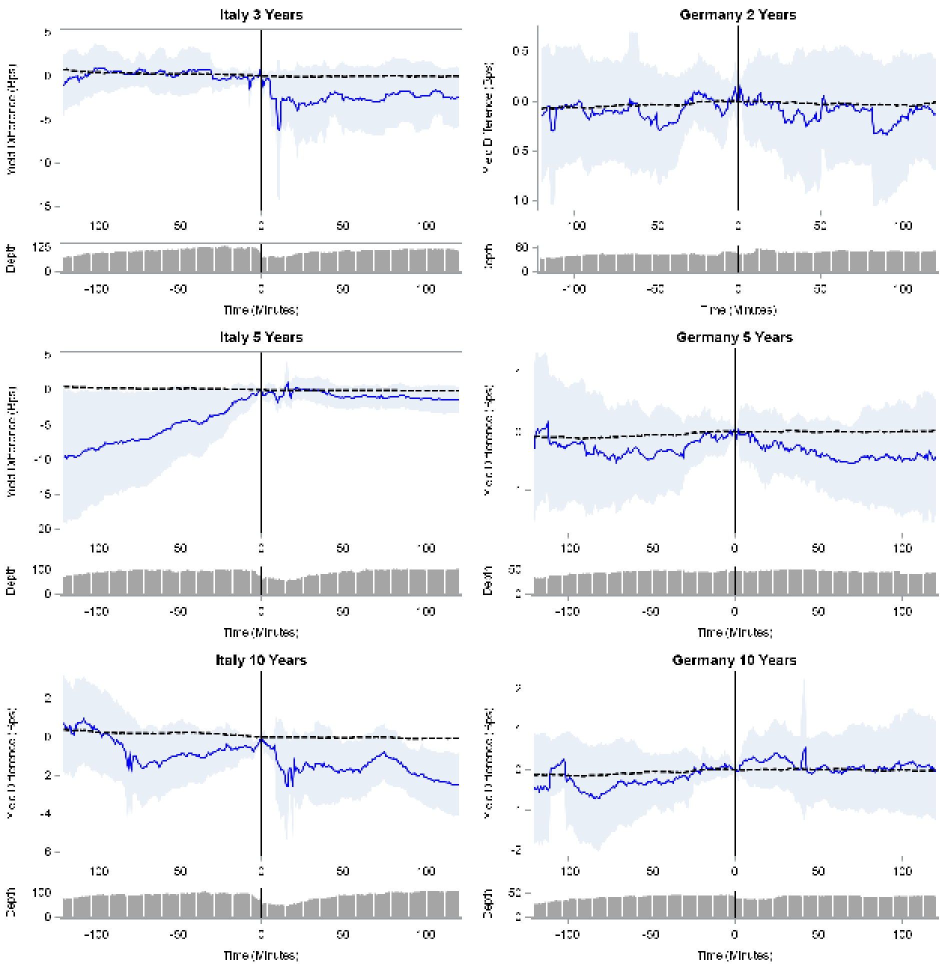


Table C.1: **Yield Difference for the Newly Issued Bonds**

This table shows the average yield difference, or the yield change from t minutes before the auction to the time of auction ($t = 0$), only for the newly issued bonds. The quotes are in the grey market before the issuance. The midpoint is converted into yields using the respective conventions. The number of observations corresponds to the number of auctions for each country and maturity (Panel A for Italy, and Panel B for Germany). *, **, and *** denote significance at the 10, 5, and 1% levels using a t-test to verify if the values are statistically different from zero. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

Panel A: Italy New Issues

	3Y		**5Y**		**10Y**	
t	Avg. Yield Diff.	Tstat	Avg. Yield Diff.	Tstat	Avg. Yield Diff.	Tstat
-120	-1.085	-0.647	-9.515*	-2.163	0.718	0.635
-100	0.821	0.634	-8.453**	-2.251	0.445	0.447
-80	0.357	0.455	-7.253**	-2.300	-0.945	-0.998
-60	0.55	0.458	-5.861*	-2.156	-1.218	-1.527
-30	0.228	0.323	-3.776*	-2.010	-0.854	-1.627
-20	-0.342	-0.689	-2.753*	-2.136	-0.472	-0.930
-10	-0.085	-0.237	-1.4	-1.556	-0.427	-1.482
10	-5.971	-1.648	-1.676**	-2.286	-1.354	-1.454
20	-3.092*	-1.789	1.065	1.437	-1.29	-1.630
30	-2.978	-1.685	-0.061	-0.075	-1.545*	-1.901
60	-2.407	-1.514	-0.976	-1.345	-1.845**	-2.571
80	-1.828	-0.949	-0.876	-1.063	-1.081	-1.658
100	-2.228	-1.239	-1.246	-1.505	-2.072**	-3.126
120	-2.357	-1.519	-1.446	-1.751	-2.463***	-3.390
Obs	14		13		11	

Panel B: Germany New Issues

	2Y		**5Y**		**10Y**	
t	Avg. Yield Diff.	Tstat	Avg. Yield Diff.	Tstat	Avg. Yield Diff.	Tstat
-120	-0.15	-0.468	-0.290	-0.476	-0.430	-0.684
-100	-0.027	-0.100	-0.218	-0.504	-0.253	-0.465
-80	-0.088	-0.356	-0.345	-0.798	-0.6	-1.003
-60	-0.129	-0.513	-0.272	-0.744	-0.261	-0.567
-30	0.026	0.166	-0.272	-1.342	-0.130	-0.427
-20	0.078	0.499	-0.1	-0.519	-0.023	-0.183
-10	-0.147	-0.884	-0.118	-0.860	0.030	0.304
10	0.022	0.108	-0.027	-0.124	0.276	0.833
20	-0.055	-0.248	-0.281	-0.987	0.269	0.809
30	-0.184	-0.703	-0.309	-1.417	0.338	0.838
60	-0.035	-0.126	-0.490	-1.563	-0.023	-0.056
80	-0.088	-0.339	-0.454	-1.119	-0.007	-0.015
100	-0.142	-0.449	-0.5	-1.154	0.123	0.230
120	-0.126	-0.473	-0.418	-0.973	-0.046	-0.080
Obs	20		13		13	

FIGURE C.2: **Cumulative Return for the Newly Issued bonds**

This figures plot the cumulative average Δ return, or the cumulative return before and after the auction as defined in Equation 3.2, during the auction dates only for the newly issued bonds. The quotes are in the grey market before the issuance. The shaded area represents the 95% confidence interval around the sample mean, and the black dashed line represents the average cumulative return on non-auction dates. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

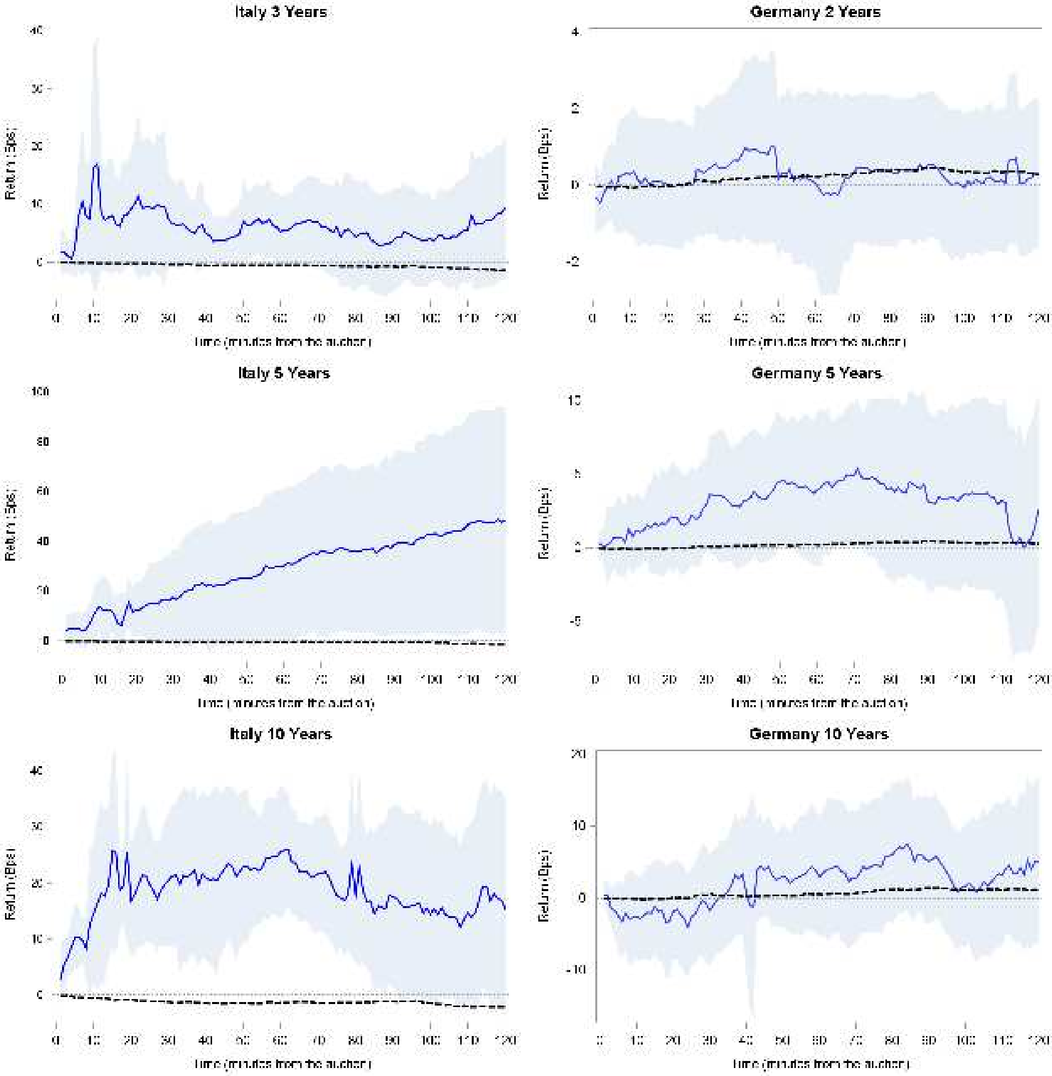


TABLE C.2: **Return for the Newly Issued Bonds**

This table shows the Average Δ Return, or the cumulative return before and after the auction as defined in Equation 3.2, during the auction dates during the auction dates only for the newly issued bonds. The quotes are in the grey market before the issuance. The number of observations corresponds to the number of auctions for each country and maturity (Panel A for Italy, and Panel B for Germany). *, **, and *** denote significance at the 10, 5, and 1% levels using a t-test to verify if the values are statistically different from zero. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)] and Germany [2 years Schatz, 5 years Bobl and 10 years Bund], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

Panel A: Italy New Issues bonds

	3Y		**5Y**		**10Y**	
t	Avg. ΔReturn	Tstat	Avg. ΔReturn	Tstat	Avg. ΔReturn	Tstat
10	16.157	1.647	13.853**	2.845	14.456**	2.585
20	9.194*	1.998	12.685**	2.544	16.897***	3.959
30	7.351*	1.913	17.497*	1.958	20.515***	3.898
60	5.234*	1.868	30.257*	2.147	25.550***	4.779
80	4.348	0.980	36.141**	2.400	17.768***	3.253
100	4.069	1.189	42.916**	2.330	14.449*	2.066
120	9.372	1.626	48.389**	2.297	15.497	1.753
Obs	14		13		11	

Panel B: Germany New Issues bonds

	2Y		**5Y**		**10Y**	
t	Avg. ΔReturn	Tstat	Avg. ΔReturn	Tstat	Avg. ΔReturn	Tstat
10	0.002	0.380	0.007	0.670	-0.025	-0.997
20	0.000	0.033	0.020	1.330	-0.019	-0.604
30	0.003	0.399	0.029*	2.079	-0.016	-0.473
60	0.000	0.055	0.039	1.684	0.028	0.741
80	0.003	0.380	0.040	1.471	0.060	1.338
100	-0.000	-0.064	0.036	1.341	0.016	0.418
120	0.003	0.329	0.026	0.754	0.049	0.936
Obs	20		13		13	

FIGURE C.3: **Yield Difference and Return for the off-the-run bonds**

This figure show the average yield difference (top panel), the total depth available in the market (bottom panel, in Millions of €), and the cumulative average Δ return (right side), only for the re-openings of off-the-run bonds. The shaded area represents the 95% confidence interval around the sample mean, and the black dashed line represents the average yield difference on non-auction dates. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 3, 5 and 10 years)], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

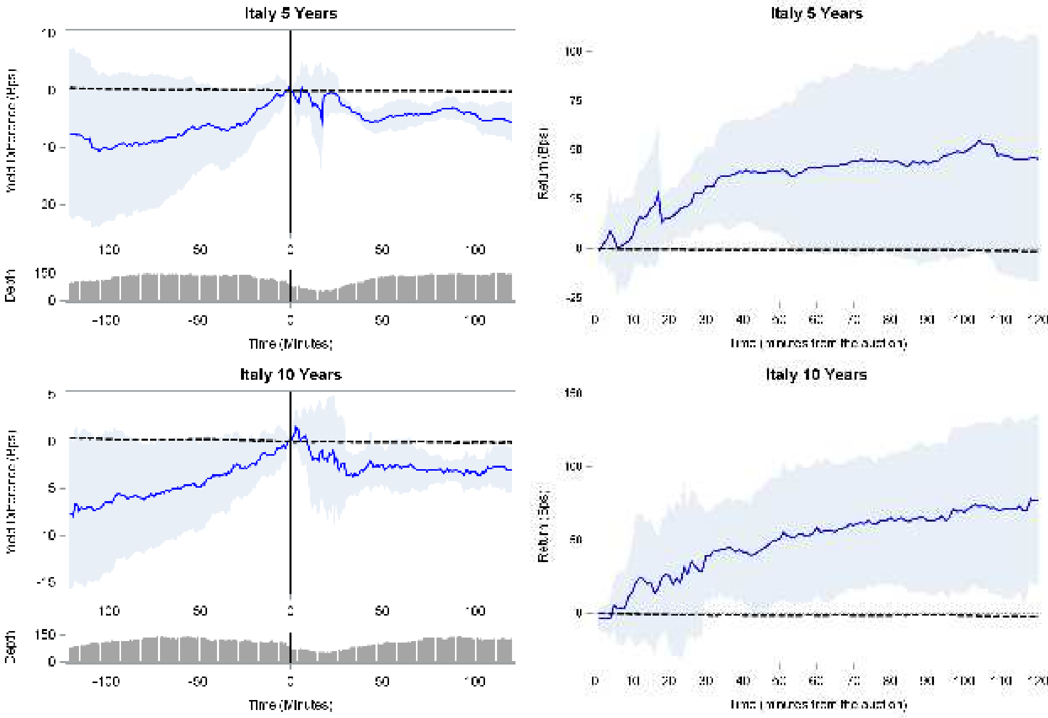


Table C.3: **Yield Difference and Return for the off-the-run bonds**

This table shows the average yield difference and the average Δ Return, during the auction datesonly for the re-openings of off-the-run bonds. The number of observations corresponds to the number of auctions for each country and maturity (Panel A for Italy, and Panel B for Germany). *, **, and *** denote significance at the 10, 5, and 1% levels using a t-test to verify if the values are statistically different from zero. The database is composed by fixed coupon sovereign bonds for Italy [Buoni del Tesoro Poliennali (BTP) with maturity of 5 and 10 years)], from June 2011 to December 2016. The source of data is the Mercato dei Titoli di Stato (MTS).

Panel A: Italy Yield change

	5Y		**10Y**	
t	Avg. Yield Diff.	Tstat	Avg. Yield Diff.	Tstat
-120	-7.416	-1.310	-7.712*	-2.262
-100	-10.066	-2.004	-6.362*	-1.964
-80	-9.2	-2.009	-6.2**	-2.507
-60	-7.783*	-2.066	-5.037*	-2.301
-30	-6.316**	-2.655	-2.6	-1.754
-20	-4.016*	-2.326	-2.225*	-1.992
-10	-1.566	-1.272	-1.425	-1.531
10	-0.6	-0.431	-0.662	-0.392
20	-0.5	-0.284	-2.000	-0.747
30	-2.966***	-6.033	-3.587**	-3.355
60	-4.216***	-4.104	-2.862*	-2.294
80	-3.516***	-5.446	-2.975***	-4.749
100	-4.066***	-5.322	-3.137***	-4.126
120	-5.5**	-4.018	-3.075**	-3.075
Obs	6		8	

Panel B: Italy Returns

	5Y		**10Y**	
t	Avg. ΔReturn	Tstat	Avg. ΔReturn	Tstat
10	6.664	0.882	15.144	1.052
20	15.541**	2.847	25.675	1.275
30	31.518***	4.034	39.362**	3.116
60	41.157*	2.455	58.245**	2.942
80	43.840*	2.395	65.395**	3.416
100	48.873*	2.320	68.970**	2.855
120	45.599	1.892	77.279**	3.155
Obs	6		8	

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Education

Goethe University, Frankfurt and Ca' Foscari University of Venice

Ph.D. and Doctorate candidate – Expected March 2018
Supervisors: Loriana Pelizzon (Goethe) and Monica Billio (Ca' Foscari)

Ca' Foscari University of Venice

Master of Science– International Master's in Economics & Finance (09/2008 – 06/2009)
Master of Science - Business administration and auditing (09/2006 – 03/2009)
Bachelor of Science – Business Administration (09/1998 – 03/2006)

Research Interests

Empirical finance (equity, fixed income and derivatives), market microstructure, high frequency trading.

References

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Job Market Paper

High-Frequency Market Making: Liquidity Provision, Adverse Selection, and Competition.

Using data from the NYSE Euronext Paris, with a specific identifier for electronic market- making activity, I examine the role of designated liquidity providers played by high-frequency traders (HFTs) as introduced by the forthcoming MiFID II regulation. I find that HFTs do provide liquidity to the market, but strategically so, to avoid being adversely selected by other fast traders when providing liquidity to them. Conversely, when they provide liquidity to slow traders, there is no evidence of adverse selection. I exploit a change in the liquidity provision agreement that introduces more competition among market makers. I show that higher competition is beneficial for the market. Liquidity provision increases and the quoted bid-ask spread decreases, as well as the adverse selection costs faced by all traders, especially for slow traders.

Presented at: Ca' Foscari University of Venice (2017) and Goethe University Frankfurt (2017).

Working Papers

Coming Early to the Party
(with Loriana Pelizzon, Marti G. Subrahmanyam, Jun Uno and Darya Yuferova)

Role of different types of High Frequency Traders (HFTs) during the pre-opening phase and the opening auction of Euronext Paris. This paper uses high frequency data provided by EUROFIDAI to our team of co-authors, which has been selected among 53 other projects proposed to them.

Best Paper on Equity Markets at the 25th Finance Forum, Pompeu Fabra University Barcelona (Jul 2017). *Presented at*: 24th Annual Meeting of the German Finance Association (DGF) Ulm (2017.)

Low-Latency Trading and Price Discovery without Trading: Evidence from the Tokyo Stock Exchange Pre-Opening Period
(with Loriana Pelizzon, Marti G. Subrahmanyam, Jun Uno and Darya Yuferova)

HFT presence in the Tokyo Stock Exchange (TSE) with unique identifiers based on server IDs, analyzing the presence of HFTs during the pre-opening period (where execution is not allowed), price discovery and liquidity provision during the opening auction and the first part of the continuous session.

Presented at: (* presented by co-author): XVIII Workshop on Quantitative Finance (Milan, 2017), FMA European conference (Venice, 2015)*, Bocconi University-CONSOB (Milan, 2016)*, Nippon Finance Association Meetings (Tokyo, 2016)*, Security and Exchange Commission (2016), Board of the Federal Reserve (2016), Cubist Systematic Strategies Annual Conference (New York, 2016)*

The Demand for Central Clearing: To Clear or not To Clear?
(with L. Pelizzon, T. Peltonen, and R. Panzica)

Drivers of the decision about centrally clearing of Sovereign Credit Default Swaps (CDS) contracts, using data available since the new EMIR regulations. This project is carried out under the auspices of a visiting research position at the European Systemic Risk Board (ESRB) in Frankfurt.

Teaching experience

Ca' Foscari University of Venice

- 2017 Economic Policy (TA-Bachelor's)
- 2014-2015-2016-2017 Foundations of Corporate Finance and Banking (International Master's in Economics and Finance)
- 2015 Economics and Econometrics of International Finance (Master's)
- 2013-2014 Pricing Derivatives using Bloomberg (International Master's in Economics and Finance)
- 2013-2014 Monetary and Financial Economics (Bachelor's)
- 2013 Economics of Financial Markets and Investments (Master's)
- 2012-2013-2014 Introduction to Financial Mathematics, Interest Rate and Risk Management for Regional and Local Governments (Master's in Public Administration)
- 2011-2012-2013 Economics and Econometrics of International Finance (TA-Master's) Practical Sessions
- 2010 Econometric Lab and Teaching Assistant, Introduction to Econometrics (Bachelor's)

Goethe University Frankfurt

- 2014: Money and Banking (TA-Bachelor's) Practical Sessions

Professional Experience

Research Visitor – ESRB Secretariat (Dec 2016-Jun 2017)
European Central Bank - Frankfurt am Main (DE)

Research and Teaching Assistant – Chair of Law and Finance (Oct 2013-)
Research Center SAFE House of Finance
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Consultant – Interest Rate Derivatives and Product Developer (Jun 2012-Sep 2013)
Pricing of structured products on interest rates through standard models and Monte Carlo simulation. Development and testing of web-based software that translates financial views into a multivariate scenario. GRETA Associati -Venezia

Research Officer (Mar 2010-May 2012)
Evaluation of firm internationalization in terms of performance and access to credit, using matching models and panel data regression. Credit risk and probability of rationing of firms included in supply network using Credit Scoring models. Risk evaluation in terms of profitability by accounting for geographical location and presence within the supply network.
Ca' Foscari University of Venice and ESF (European Social Fund)

Business Developer Risk Intelligence (Jun 2009-Feb 2010)
Development and implementation of solutions for Enterprise Risk Management in different areas (Finance and non-Finance). Design and Deployment of an IT platform in the field of Operational Risk, for Risk Self-Assessment, Loss data collection, aggregation of distributions and calculation of VaR.
SAS Institute - Milan

Founder, Partner, Executive Member and Technical Manager (Jan 2001-May 2009)
Television production and facilities for national and international broadcasters, outside broadcast production, live events and post-production.
Hot Spot srl, Scorzè (VE)

Skills

Languages:
Italian (native), English (fluent), French and Spanish (intermediate), German (Basic).
Programming:
Software: SAS, STATA, Matlab, R, EViews, Gretl, LateX, MySql. DB: MySql, PostgreSQL, Oracle.
Databases:
Bloomberg Professional, Datastream, WRDS, Markit, Eikon, Thomson Reuters Tick History.

Memberships

AFA – American Finance Association
EFA - European Finance Association