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

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ABSTRACT

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.

JEL classification: G12, G14.

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1 Introduction

Over the past decade, the evolution of the trading environment reshaped the market-making business, traditionally run by specialists but now firmly in the hands of High-Frequency Trading (HFT) firms, the "new players.'. Their prominence was acknowledged by regulators with the formal recognition of algorithmic trading strategies as official market makers, 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 HFTs' fundamental function of designated liquidity providers, and assess the risks they face. The provision of liquidity by algorithms is pivotal for the well functioning of the financial markets, given the forthcoming MiFID II regulation in Europe, which 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 avoid being adversely selected when providing liquidity to them. I show that HFT-MMs discriminate between traders, selectively providing liquidity to NON-HFTs. 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 adverse selection costs.

My first contribution is to show the dual role of HFTs. They can "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 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 by the Paris Bourse the same duties was carried out by the "animateurs".[1]

Technological innovation, faster computers with sophisticated execution algorithms, and new trading platforms completely changed the trading landscape. A new class of electronic liquidity providers emerges. The "old" class of specialists disappeared, leaving room for a "modern" version of designated market makers that make extensive use of co-location facilities, high-speed connections, and fast computers.

Exchanges impose various obligations but also grant advantages to their designated liquidity providers. The "old" specialists have 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. The advantages include fee reductions or privileges in the execution of particular orders.[2] Under the SLP program, the "modern" electronic market makers have to be present on 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

[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 in the Paris Bourse, also giving 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 was part of the benefits accredited for their services (Hasbrouck and Sofianos, 1993)

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 firms (e.g., Getco or Virtu); MIXED, when submitted by an investment bank with HFT activity (Goldman Sachs, JP Morgan); or as NONHFT, if submitted by any market participants that is 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 the market makers (high number of quotes, high cancellation ratios, very low inventories). HFT-MMs provide a considerable quantity 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 with the one of the HFT-MMs, their activity in terms of trading is less than half, contributing only for 5% of the gross liquidity provision, and quoting a higher spread. Looking at the flow of liquidity provision, I find that HFT-MM attempt to discriminate between traders. They are statistically 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 higher information advantage. The market makers will lose money providing

[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.

liquidity to better-informed trader, 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 are providing 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 are providing liquidity to other HFTs, and profit when providing liquidity to NONHFTs. Confirming the theoretical implications of Budish, Cramton, and Shim (2015) and Menkveld and Zoican (2017), I verify empirically that HFT-MMs play opportunistically 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 et al., 2015) or, when the speed of the exchange increase, 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 quantity they display at the best prices, but they 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 increase 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 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 dealers 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 makers 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, Kyle, Samadi, and Tuzun (2017), 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, Riordan, Shkilko, and Sokolov (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, Gomber, Lausen, and Panz (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, Saliba, Lehalle, and Rosenbaum (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.

[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.

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. 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

[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.

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 1. *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.

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.

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

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 2. *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

[8] See, among others, Menkveld (2013), Brogaard, Hendershott, and Riordan (2014), Malinova and Park (2016), and Gomber, Sagade, Theissen, Weber, and Westheide (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

the first day of the renewal, June 3 2013.[11]. A further source of competition comes from the basket composition. Before July 2013, 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 3. *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.

[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%.

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

3 Institutional structure and liquidity incentives

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, 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

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

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.

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

[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.

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 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).

[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 IA.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.

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.

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

[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).

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).

[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.*

5 Empirical Evidence

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 1 provides a comprehensive set of descriptive statistics for the traders' groups in the sample.

INSERT TABLE 1 HERE.

Table 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 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-days 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 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.

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

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 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:

$$\textit{liquidity provision}_k = \frac{\text{Number of shares traded}_k \mid \text{Trader } k \text{ provides liquidity}}{\text{Total traded volume}} \tag{1}$$

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 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:

$$NLP_k = \textit{liquidity provision}_k - \textit{liquidity comsumption}_k \tag{2}$$

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 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,

[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.

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 loose requirements for the SLP program, discussed in Section 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 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:

$$\textit{effective half spread}_{t,k} = \left| P_t - \left(\frac{Ask_t + Bid_t}{2} \right) \right| \tag{3}$$

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:

$$realized\ spread_{k,t} = \begin{cases} ln(P_t) - ln(P_{t+\delta}) & if\ liquidity\ provider\ sells \\ ln(P_{t+\delta}) - ln(P_t) & if\ liquidity\ provider\ buys \end{cases} \tag{4}$$

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 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 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

[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.

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 1.

INSERT FIGURE 1 HERE.

Figure 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.

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 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 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 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%.

INSERT FIGURE 2 HERE.

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

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 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-MMss 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%.

INSERT FIGURE 3 HERE.

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 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%.

INSERT FIGURE 4 HERE.

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

[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.

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 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?

INSERT FIGURE 5 HERE

Figure 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 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?

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

The matrices reported in Table 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 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]

INSERT TABLE 2 HERE.

To verify if the average numbers reported in Table 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:

$$LP_{i,j,k,m} = \frac{\text{Number of shares traded}_{i,j,k,m} \mid \text{Trader/Account } k \text{ provides liqudity to } \ m}{\text{Total traded volume in the main tradin phase}_{i,j}} \quad (5)$$

and run the following regression:

$$LP_{i,j,k,m} = a_0 + \sum a_{MM,m} * I_{MM,m} + Controls_{i,j} + e_{i,j,k,m} \quad (6)$$

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 3.

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

[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 3.

INSERT TABLE 3 HERE.

Table 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. 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 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.

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 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 4 reports the average realized spread, calculated as presented in Section 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".

INSERT TABLE 4 HERE.

Panel A of Table 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.

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 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 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 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 6 the histogram of the frequencies.

INSERT FIGURE 6 HERE.

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 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:

$$\textit{realized spread}_{i,j,k,m}(\delta) = \alpha_0 + \beta_1 * I_{MM,m} + e_{i,j,k,m} \tag{7}$$

where $\textit{realized spread}_{i,j,k,m}$ 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 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 4, panel A.

INSERT TABLE 5 HERE.

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 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 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 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 6 almost mirror the sign and significance of the trade-by-trade analysis of Table 5: HFT-MMs are picked-off by other HFT-MMs and realized a positive profit when they provide liquidity to NONHFTs.

INSERT TABLE 6 HERE.

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.

5.5 Market Making agreements and Competition

Hypothesis 3. *Increasing competition among market makers:*

[28] Detailed results of the regression are reported in Internet Appendix, Section D

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 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 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

[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 3 for the MIXED-MMs is due to the testing of the new channels.

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 7 provides the mean and the standard deviation across stocks and days of both traders' characteristics and order book measures presented in Table 1, for the two subsamples.

INSERT TABLE 7 HERE.

Table 7 shows that there are some remarkable differences in the two-month period. Regarding HFT-MMs (Table 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 (Table7 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:

$$y_{i,j,k} = \alpha_i, j + \beta_1 SLP_{i,j,k} + \beta_2 VCAC_k + \epsilon_{i,j,k} \tag{8}$$

where y is one of the variables defined in Section 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), 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 8.

INSERT TABLE 8 HERE.

Table 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 9 for each basket for the two groups of market makers.

INSERT TABLE 9 HERE.

Table 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 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 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 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 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.

INSERT FIGURE 7 HERE.

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 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 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.

INSERT FIGURE 8 HERE.

I formally test the changes in the liquidity-provision behavior, estimating equation 6 for the two subsamples (two months before and two months after the kick-off date of the new SLP program) and for the two groups of market makers. The results are presented in Table 10.

INSERT TABLE 10 HERE.

Table 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 7 two months before and two months after the introduction of the program. Table 11 show the results for three representative time intervals (10 seconds, 1 minute, and 5 minutes).

INSERT TABLE 11 HERE.

The greater provision of liquidity to other HFT-MMs does not translate into a 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 decreases, and the adverse selection costs for the slow traders mildly decrease.

6 Conclusion

In this paper, I provide empirical evidence on the behavior of HFT-MMs in view of three recent theoretical contributions on the new market microstructure models by Budish et al. (2015), Menkveld and Zoican (2017), and Aït-Sahalia and Sağlam (2017a). I do find that HFT-MMs are consistently but selectively providing liquidity to the market. Their algorithms are very efficient to intercept the order flow of slow traders and to avoid 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 granted 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 against a carrot and could assume both the role of MM or 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 allows us 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 and reduce drastically their displayed quantity at the best prices. Further, I do 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 is expecting from an electronic liquidity provider, the latter are trading 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, introduced by NYSE Euronext and similar to a DMM 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 competition.

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Table 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 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 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%	

Table 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						

Table 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						

Table 4 Realized spread statistics

This table shows the average realized spread as defined in Equation 4 of Section 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 4 Realized spread statistics (cont.)

HFT-MM		**Panel C: number of trades**				
provide liquidity:		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		**Panel D: coverage**				
provide liquidity:		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%

Table 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 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				

Table 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 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 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*** (0.0638)	-1.560*** (0.205)	-2.211*** (0.246)	-2.009*** (0.236)	-2.084*** (0.319)
To MIXED-MM	-0.0333 (0.0316)	-0.165* (0.0911)	-0.306*** (0.0933)	0.220* (0.125)	1.204*** (0.458)
To MIXED-Others	0.0738 (0.0454)	0.394** (0.170)	0.867*** (0.300)	0.410 (0.332)	0.339 (0.639)
To NON HFT	0.429*** (0.0849)	1.934*** (0.381)	4.509*** (0.702)	5.769*** (0.870)	5.358*** (0.908)
Constant	0.000686 (0.00778)	-0.00560 (0.0149)	0.0157 (0.0265)	-0.00240 (0.0383)	-0.0544 (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				

Table 7 Summary Statistics on the reduced sample

This table presents the average values of the variables included in the analysis presented in Section ??, 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 Before	Averages After	Diff. (SD)	Averages Before	Averages After	Diff. (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 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)

Table 8 Regression on the introduction of the new SLP program

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

$$y_{i,j,k} = \alpha_i, j + \beta_1 SLP_{i,j,k} + \beta_2 VCAC_k + \epsilon_{i,j,k} \tag{9}$$

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 9 Regression on Baskets of stocks

This table shows the estimation of regression 9 for the HFT-MM (Panel A) and the MIXED-MM (Panel B). The description of the variables is presented in Section 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 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 10 Liquidity Provision and SLP

This table shows the estimation of regression 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			

Table 11 Realized spread regression and SLP

This table shows the estimation of regression 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					

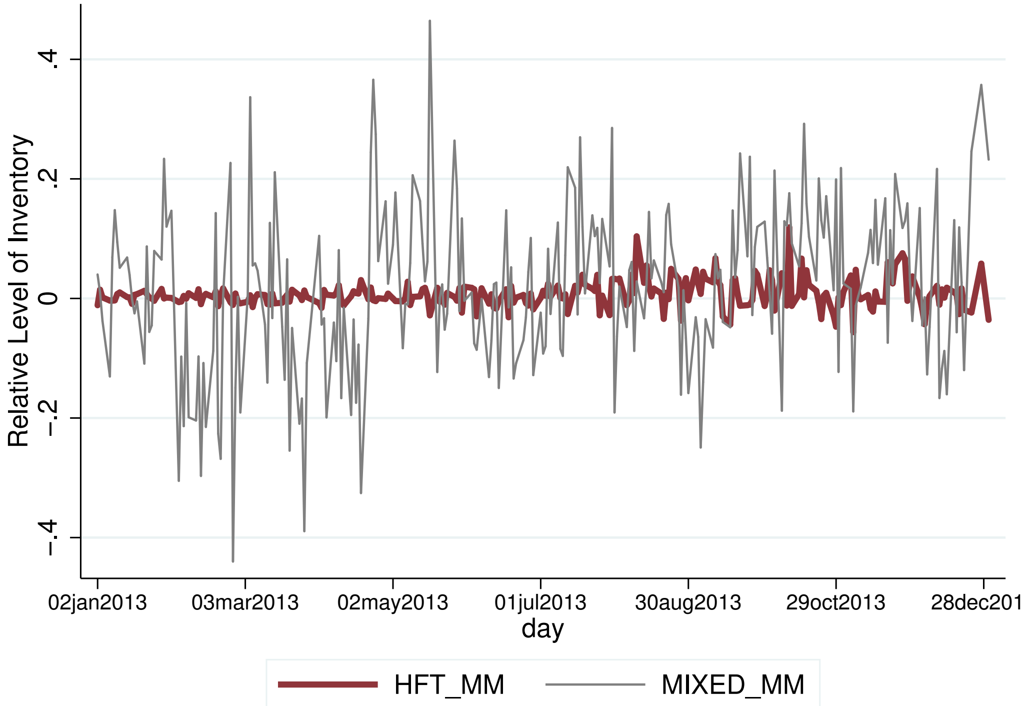

Figure 1. End of day net position

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.

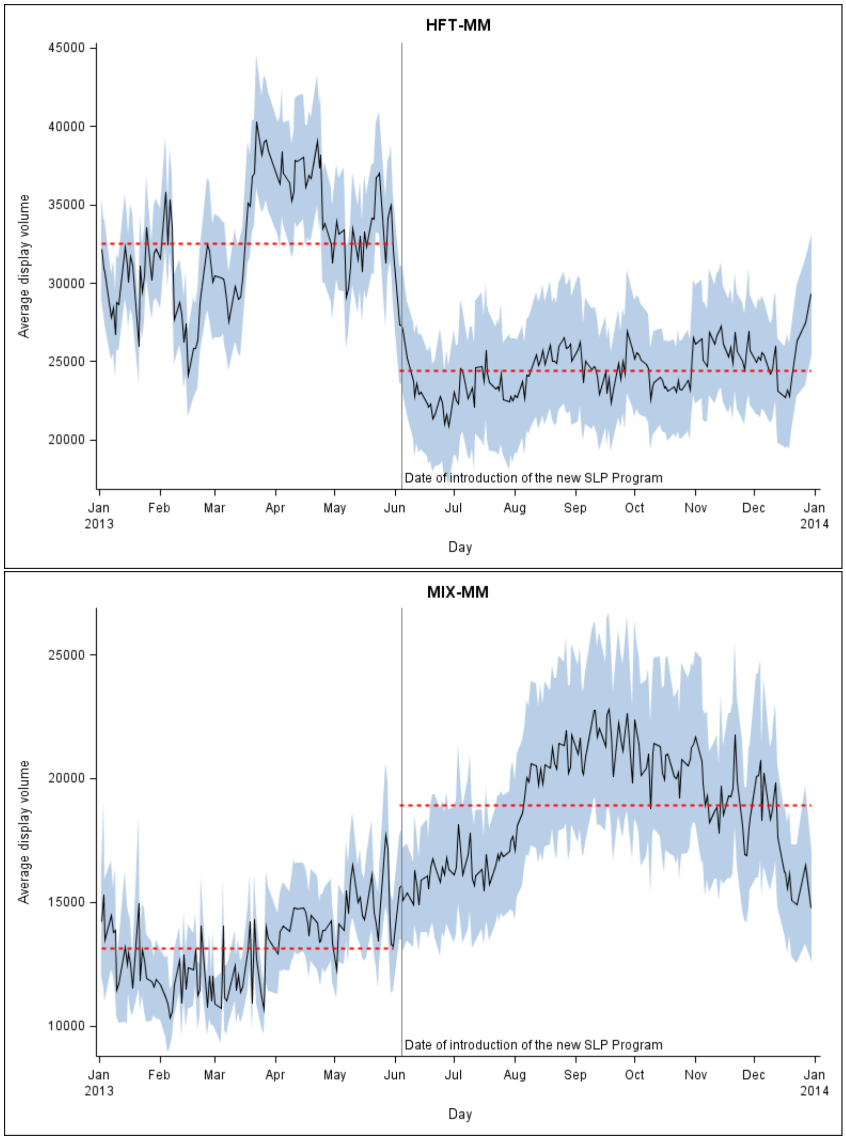

Figure 2. Average displayed order value for HFT-MM and MIXED-MM

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.

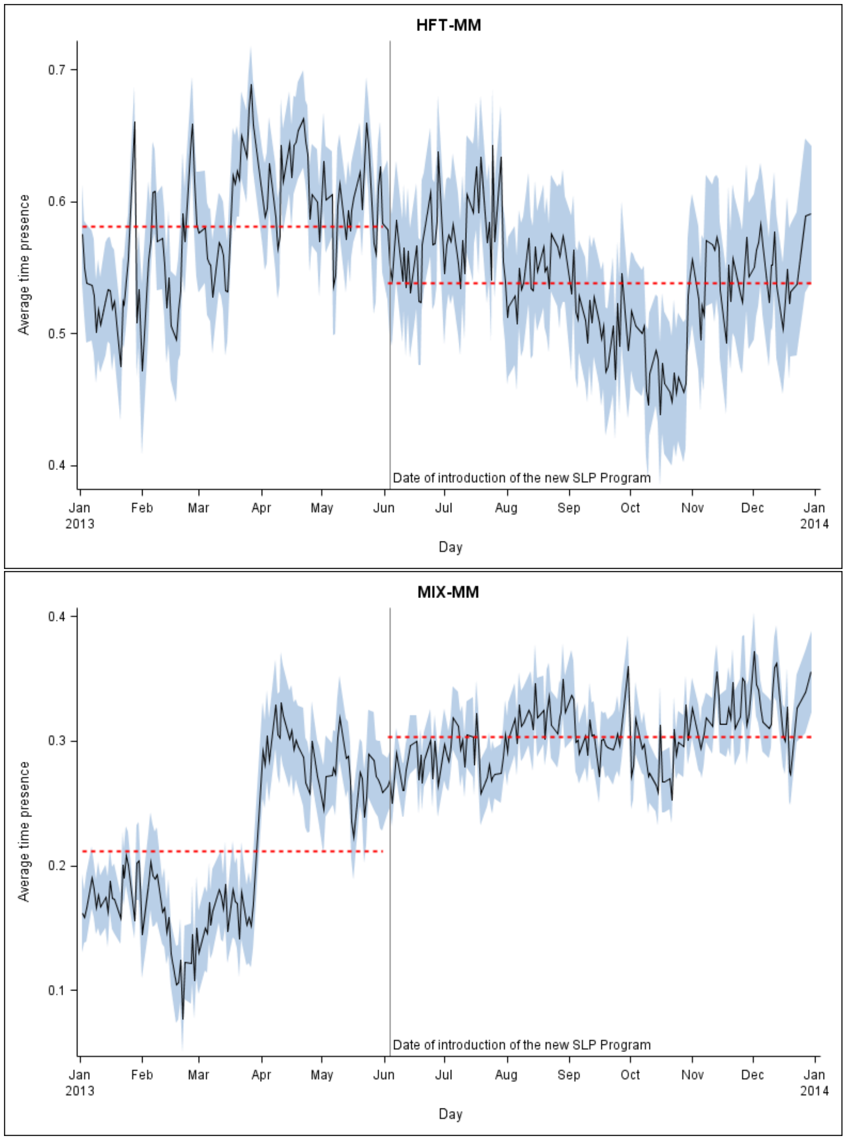

Figure 3. Average time presence at the best bid and ask price for HFT-MM and MIXED-MM

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.

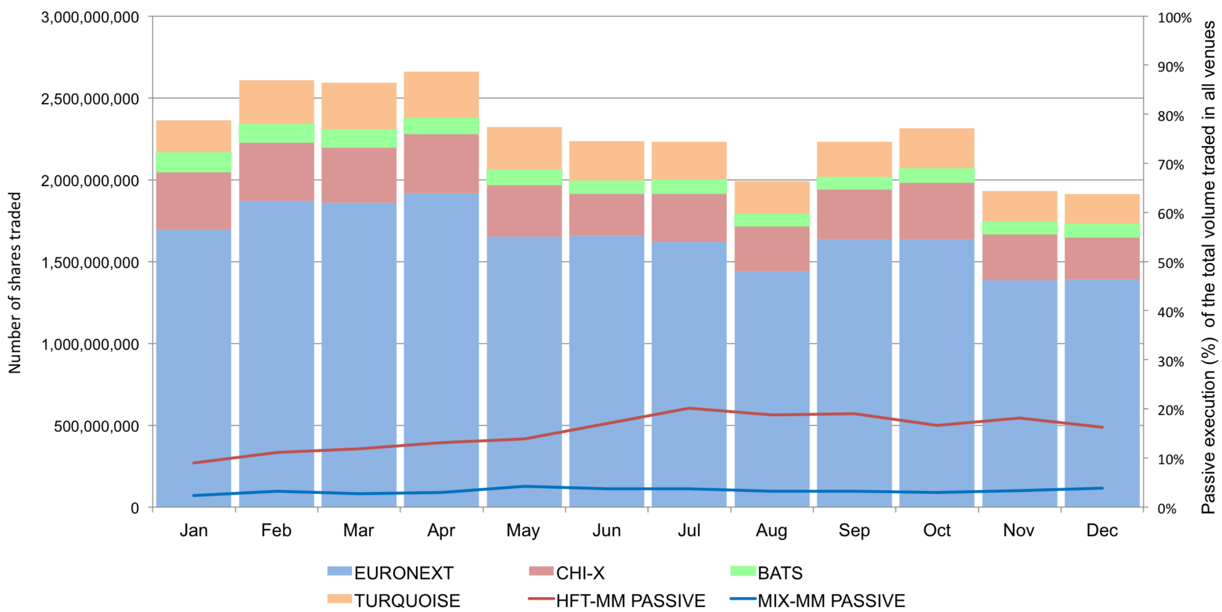

Figure 4. Total traded value in 2013 for Euronext, Bats Chi-X, and Turquoise

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.

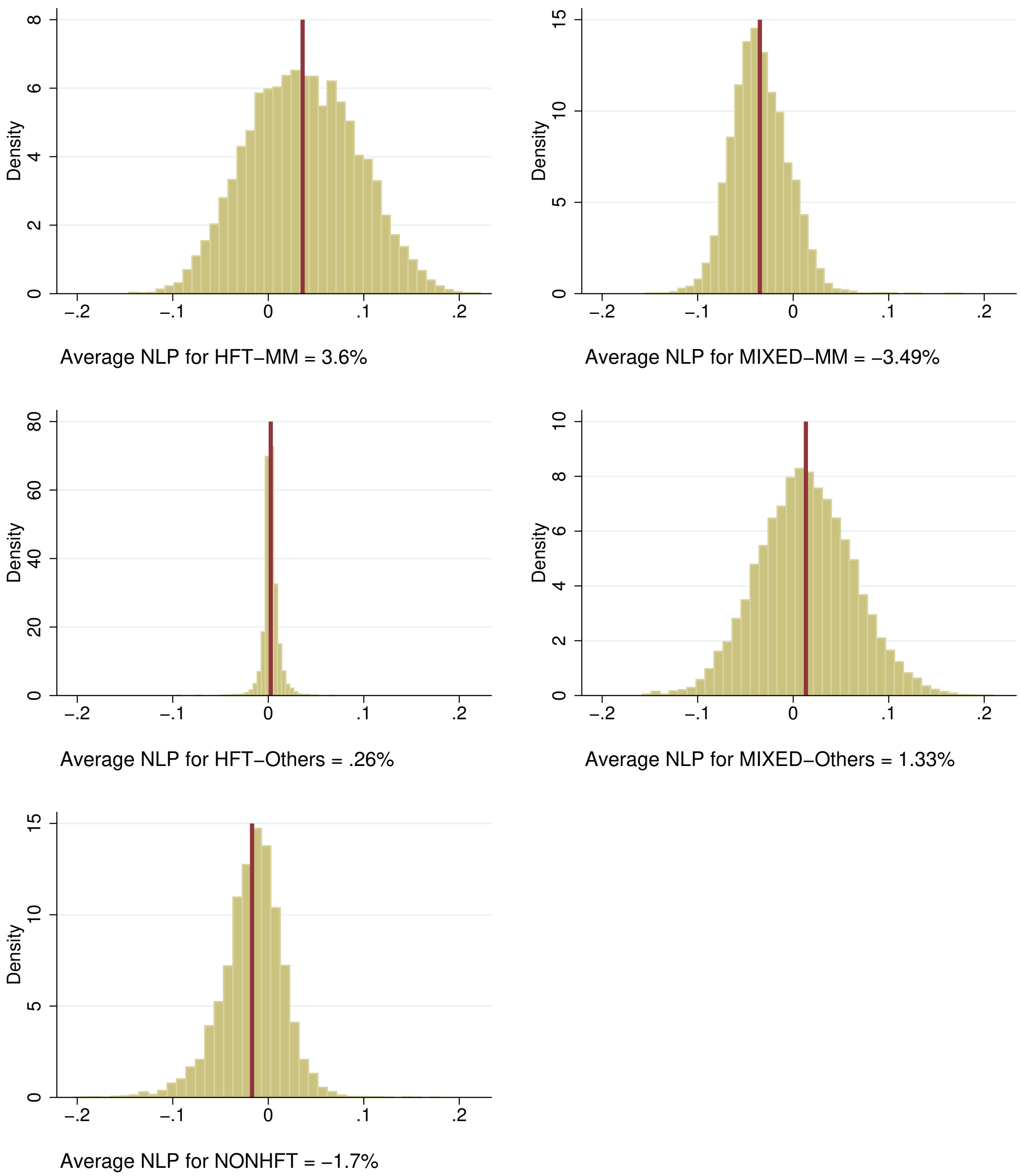

Figure 5. Distribution of Net Liquidity Provision in the full sample

This figure shows the density histogram of the net liquidity provision (NLP) as defined in Section 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.

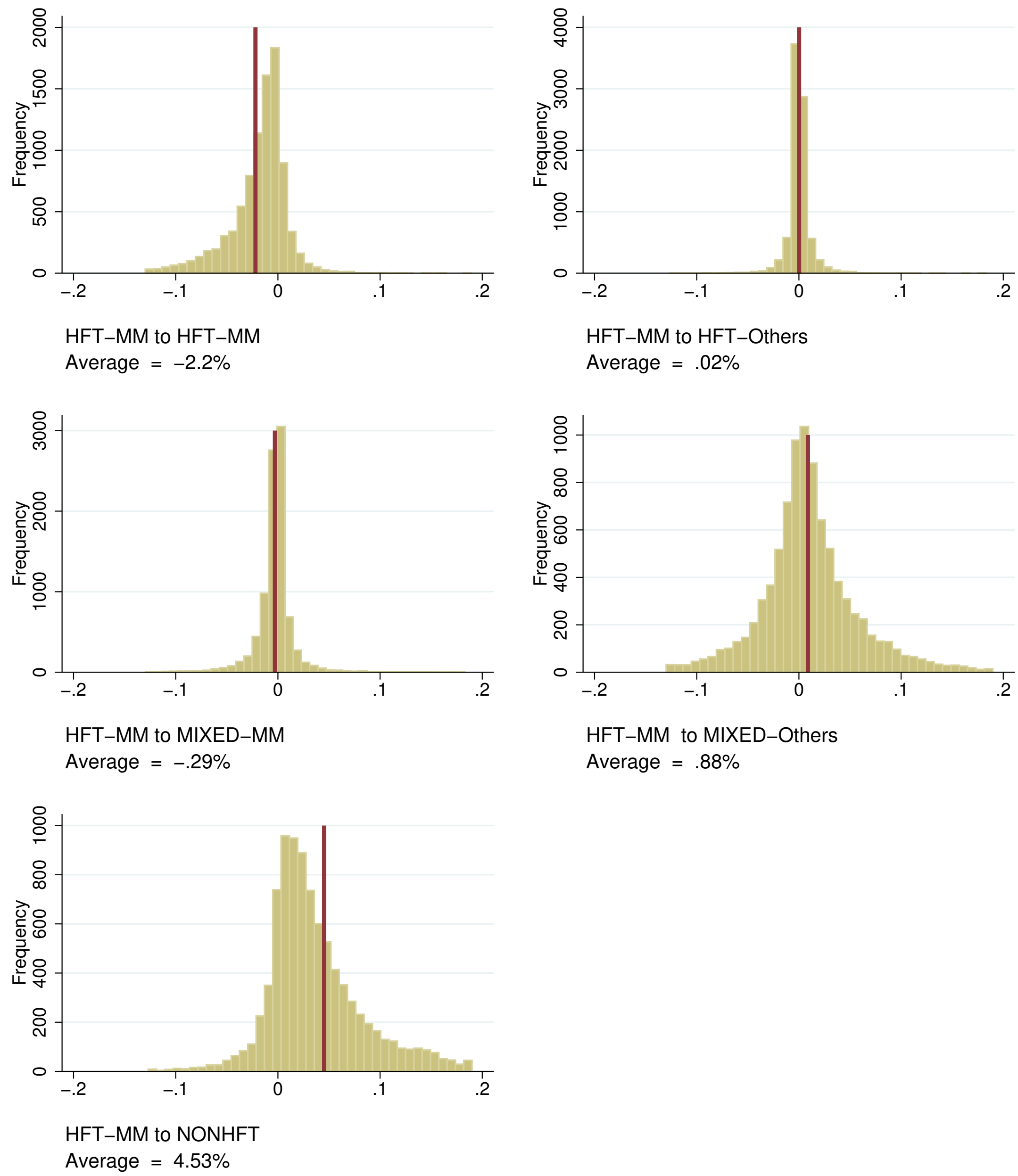

Figure 6. Realized spread distribution after 1 minute

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.

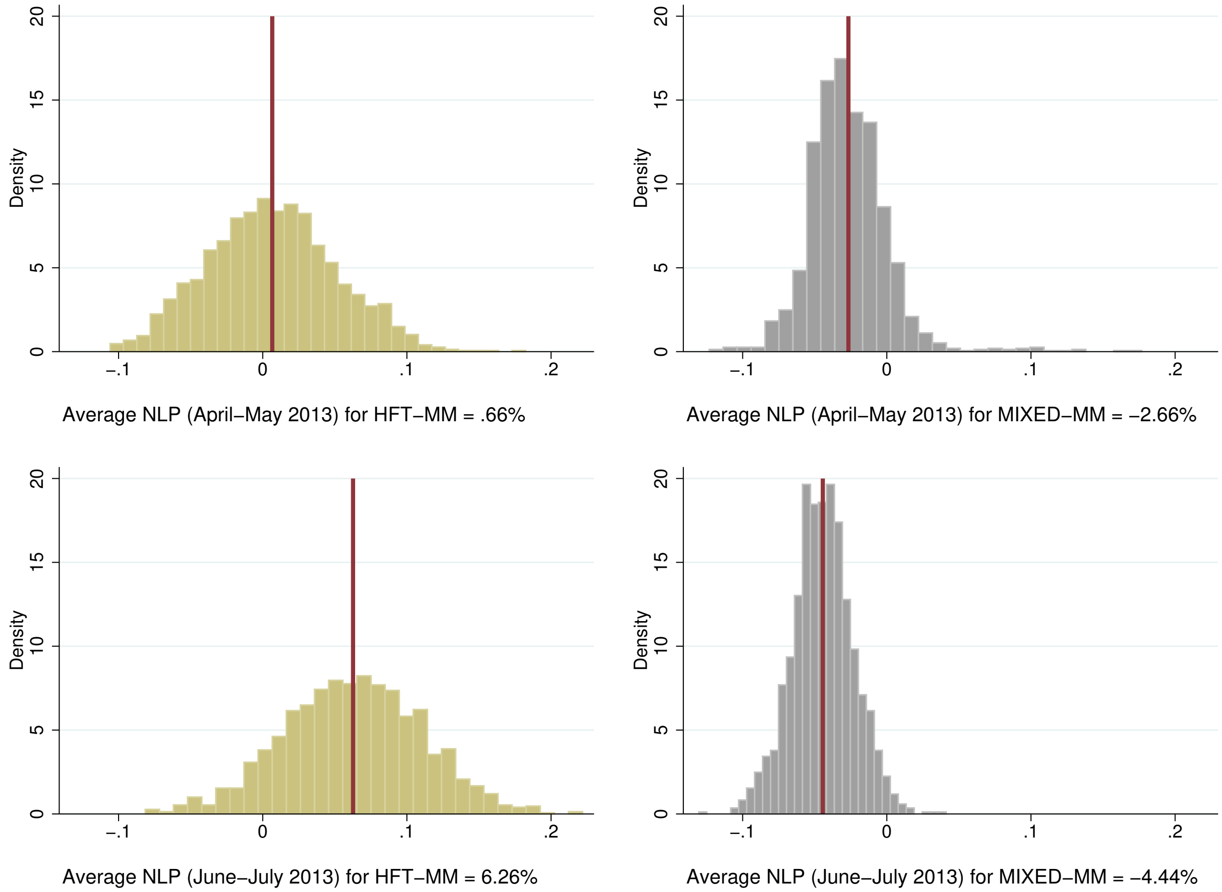

Figure 7. Distribution of Net Liquidity Provision Before and After the new SLP agreement

This figure shows the density histogram of the net liquidity provision (NLP) as defined in Section 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.

Figure 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 of Section 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.