Liquidity commonality and high frequency trading:

Evidence from the French stock market

Panagiotis Anagnostidis, [1] Patrice Fontaine [2]

[1] *Institut Europlace de Finance (IEF) and European Financial Data Institute (EUROFIDAI)*

[2] *CNRS, European Financial Data Institute (EUROFIDAI) and Léonard de Vinci Pôle Universitaire, Research Center*

Abstract

High frequency trading (HFT) depends on sophisticated algorithms to closely monitor price changes across securities. Theory predicts this technological advantage should translate into market-wide liquidity co-variation, by transmitting information-based liquidity shocks. Using a dataset of orders and trades from the French stock market, we investigate whether HTF algorithms constitute a source of systematic liquidity risk. We demonstrate that, across securities, the liquidity offered by high frequency traders is significantly less diverse than that of traditional traders; this finding is in line with the cross-asset learning hypothesis. The excessive co-movement in liquidity is also partly explained by common market making rules. In periods of increased market stress, we find HFT, designated market making, and order size to be important sources of liquidity commonality. Our results have policy implications for market regulators in Paris, suggesting the inclusion of maximum spread-limit rules in market making contracts will reduce the possibility of liquidity drying up when markets are in turmoil.

Key words: Liquidity, Liquidity commonality, High-Frequency Trading, Euronext Paris

JEL codes: G11, G12, G15

Acknowledgement
The authors acknowledge support support from the framework of the Trans-Atlantis Platform ANR-16-DATA-002-04. We thank Yacine Ait-Sahalia, Hendrik Bessembinder, Carole Metais, Terrence Hendershott, Loriana Pelizzon, Satchit Sagade, Mark Seasholes and Jean-Pierre Zigrand for valuable comments on previous versions of this paper, as well as the seminar participants at Arizona State University (2017), Princeton University (2017), SAFE school of Finance (2018), AFFI (2018), AMEF (2018), and the 2nd Trans-Atlantis workshop (2019).

Panagiotis Anagnostidis. *Email*: panagiotis.anagnostidis@eurofidai.org
Patrice Fontaine. *Email*: patrice.fontaine@eurofidai.org

1. Introduction

A security is considered to be liquid when investors are able to acquire the desired number of shares at the minimum cost as fast as possible, without severely affecting the continuity of prices. Commonality in liquidity occurs when firm-specific liquidity varies in tandem with that of the market as a whole. At such times, portfolio managers are more likely to be exposed to the risk of a systematic drying up of liquidity, facing transaction costs that are not diversifiable. The dangers of liquidity commonality rise when financial markets are in turmoil, as revealed by such events as the 2008 financial crisis (Aragon and Strahan, 2012; Nagel, 2012) and the May 6, 2010 E-mini S&P 500 Stock Index Futures flash crash of 2:45 (Kirilenko et al., 2017). These events reveal, as well, the need to better understand the effects of modern electronic trading platforms on liquidity.

Evidence shows that variations in cross-sectional liquidity are driven by a wide range of market parameters. Correlated trading strategies (Corwin and Lipson, 2010; Chaboud et al., 2014; Boehmer et al., 2018); specialists' and market-makers' inventory handling activities (Coughenour and Saad, 2004; Comerton-Forde et al., 2010; Anand and Venkataraman, 2016); market depth (Domowitz et al., 2005; Kempf and Mayston, 2008); volatility and market momentum (Chordia et al., 2000); and industrial, regional, and international cross-listings (Chordia et al., 2000; Brockman et al., 2009; Zhang et al., 2009; Karolyi et al., 2012; Dang et al., 2015a; Dang et al., 2015b; Moshirian et al., 2017) are all well-documented determinants of liquidity co-movement.[1] This paper investigates an alternative source of liquidity risk: the use of high frequency trading (HFT) algorithms.

We rely on a dataset from the Euronext Paris Exchange for the CAC 40 Index securities, which attract both traditional non high frequency traders (NON HFTs) and modern high frequency traders (HFTs), the latter comprising designated market markers (DMMs) and other high frequency traders (OHFTs). We exploit the data's granularity to estimate trader-specific measures of supply-side liquidity, i.e., immediacy (measured by the number of passively traded

[1] Commonality in liquidity has been studied in a wide range of financial markets and asset classes. Chordia et al. (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), Coughenour and Saad (2004), Kamara et al. (2008), Corwin and Lipson (2010), and Comerton-Forde et al. (2010) examine the US stock markets (NYSE and AMEX). In the European domain, Foran et al. (2015) investigate the London Stock Exchange, Kempf and Mayston (2008) the Frankfurt Stock Exchange, and Anagnostidis et al. (2016) the Athens Stock Exchange. Brockman and Chung (2002) and Domowitz et al. (2005) analyze the Hong Kong Stock Exchange and the Australian Stock Exchange respectively, while Wang (2013) examines the Asian stock markets. Other empirical studies that report liquidity commonality concern the bond and CDS markets (Chordia et al., 2005; Pu, 2009; Gissler, 2017), the derivative markets (Cao and Wei, 2010), the foreign exchange markets (Mancini et al., 2013; Karnaukh et al., 2015), and the commodity markets (Marshall, 2013).

shares) and the *ex-ante* cost of trade (measured by the *ex-ante* price impact). We then use Principal Components Analysis (PCA) and the liquidity factor model of Chordia et al. (2000) to infer and, in turn, compare trader-specific liquidity co-movement over trading days and during a trading session.

The rapid advance of technology has caused a substantial increase in HFT over the past two decades, changing the way securities are traded. HFTs optimize their order placement strategies, finding the best prices across multiple venues, within milliseconds or microseconds. Extensive use of HFT has increased competition for liquidity among investors, significantly reducing the average cost of trade (e.g., Hendershott et al., 2011; Hendershott and Riordan, 2013; Carrion, 2013; Brogaard et al., 2014).

Despite this beneficial impact at the firm level, HFT may amplify systematic liquidity variations, increasing the possibility of liquidity dry-ups during turbulent market periods. On the demand side, Chaboud et al. (2014), Benos et al. (2017), and Boehmer et al. (2018) provide evidence that HFTs' trading strategies are highly correlated with each other, to a greater extent than those of NON HFTs.[2] Chaboud et al. (2014) attribute this feature to the fact that HFT algorithms are similarly designed, taking the same actions at the same time and using the same sets of information, causing common sharp price adjustments. Using both demand- and supply-side measures of liquidity, Malceniece et al. (2019) and Klein and Song (2018) demonstrate that the staggered entry of Chi-X in twelve European markets has increased HFT activity, leading to an increase in systematic liquidity variation. Both studies conclude that the ability of HFTs to better monitor price changes across securities, via fast and sophisticated algorithms, is likely the main driver of HFT's impact on liquidity co-movement.[3]

Motivated by these documented market-wide effects of HFT on liquidity, we provide new empirical evidence from the French market that confirms the impact of HFT on liquidity risk. We explore the prospect, however, that the effect of HFT on liquidity co-variation is not as severe as is expressed in the literature; rather, it may be partially (or largely) explained by the structure of the market. Finally, we document evidence of commonality in HFT liquidity with respect to time periods not investigated before, i.e., the time of day and upon announcement of European and US macro-economic news.

[2] Benos et al. (2017) examine the UK equity market, Chaboud et al. (2014) the foreign exchange market, and Boehmer et al. (2018) the Canadian equity market.
[3] Also, Jain et al. (2016) provide evidence that HFT increases the systematic risk of returns in the Japanese market.

Existing theories on liquidity co-movement guide our framing of three hypotheses. Using the rational expectations framework, Cespa and Foucault (2014) demonstrate that cross-asset learning about prices leads to the transmission of information-based liquidity shocks across securities, generating liquidity commonality.[4] Accordingly, taking HFTs' increased information processing power into account, our first hypothesis can be stated as:

H1: *Across securities, HFTs' (DMMs and OHFTs) liquidity supply co-moves more than NON HFTs' liquidity supply.*

After controlling for well-known determinants of liquidity (volatility, market momentum, asynchronous trading, and order size), as well as for common components across HFTs' and NON HFTs' quotes, we find strong evidence supporting this hypothesis. Our analysis has similar implications to those of Malceniece et al. (2019) and Klein and Song (2018), suggesting that HFT constitutes an important source of systematic liquidity variation. Further, by testing the magnitude of HFT versus NON HFT liquidity co-movement on the supply side of the market, we complement the empirical findings of Chaboud et al. (2014), Benos et al. (2017), and Boehmer et al. (2018) on the demand side.

Previous studies indicate that designated market makers (DMMs) generate liquidity co-variation through handling multiple securities, employing shared capital and information (e.g., Coughenour and Saad, 2004). In line with this idea, our second hypothesis states:

H2. *Across securities, DMMs employing HFT algorithms are less diverse in their liquidity supply, as compared to other HFTs (OHFTs)*.

In Euronext Paris, DMMs handling common baskets of securities (including the CAC 40 Index constituents) must comply with common rules of passive trading (e.g., to be present at the best quotes for a certain fraction of the day). An initial order flow analysis reveals that DMM liquidity provisions, which account for more than 70% of market liquidity, are exclusively based on HFT algorithms. In line with this hypothesis, we find that commonality in DMM liquidity has a magnitude twice that of commonality in OHFT liquidity. Our results do imply the existence of common components between DMM and OHFT liquidity; however, these components are significantly weak. We conclude that the Paris trading framework induces significant cross-sectional co-variation in HFT liquidity (via the DMM programs) that is not likely due to the HFT algorithms alone. Overall, our evidence highlights the importance of considering designated

[4] Similarly, in Watanabe (2014), liquidity commonality arises due to the transmission of information-based liquidity shocks among assets through increases in the volatility of returns. Also, in Fernando (2003), liquidity commonality is linked to the reactions of investors to liquidity shocks which have both systematic (information based) and idiosyncratic (non-information based) components.

market making when analyzing the impact of HFT on market-wide liquidity, rather than solely relying on HFT proxies based on the aggregate message traffic (e.g., Malceniece et al., 2019; Klein and Song, 2018).

Because liquidity commonality varies over time (e.g., Kempf and Mayston, 2008), we analyze different market periods. In times of higher price uncertainty, stricter capital requirements by lenders and an increased level of information asymmetry make it hard for investors and market makers to handle their trading costs. Such conditions, in theory, lead to systematic adjustments in liquidity (Gromb and Vayanos, 2002; Garleanu and Pedersen, 2007; Brunnermeier and Pedersen, 2009; Gorton and Metrick, 2010; Cespa and Foucault, 2014; Ait-Sahalia and Saglam, 2017a, 2017b).[5] Accordingly, our third hypothesis states:

H3: *Cross-sectional co-movement in DMM, OHFT, and NON HFT liquidity increases with market stress*.

To conduct our tests, we follow Anand and Venkataraman (2016) and utilize the daily Chicago Board Options Exchange Volatility Index (US CBOE VIX) as an instrument for exogenous market volatility. In line with this hypothesis, our results show that on days of high volatility, co-movement in liquidity supply is higher for all market participants. Co-movement is more pronounced in HFT liquidity, especially in DMM liquidity, on days of both high and low volatility, further confirming our results regarding our first and second hypotheses (H1 and H2).

In the last part of our analysis, we examine liquidity co-movement within the trading day. While previous studies focus on interday analyses (e.g., Malceniece et al., 2019), there is a remarkable dearth of evidence on the co-movement of HFT liquidity during the day. This question, however, is vital to portfolio managers with daily (or shorter) investment horizons. We first examine the intraday patterns of liquidity co-movement for each trader type. We find that intraday commonality in the cost of trade imposed by HFTs (whether DMMs or OHFTs) follows a U shape, similar to volatility, whereas co-movement in HFTs' provision of immediacy exhibits an inverted U shape. We report similar patterns for NON HFTs. In line with our third hypothesis (H3), the systematic risk of execution cost is higher during the more volatile periods of the day (post-opening and pre-closing). Conversely, the systematic risk of immediacy is of more concern during the middle of the trading day.

[5] Empirical evidence supporting the increase of liquidity co-movement during turbulent market periods is provided in Longstaff (2004), Boyson et al. (2010), Hameed et al. (2010), Næs et al. (2011), Cao and Petrasek (2014), Rösch and Kaserer (2013), and Qian et al. (2014).

Overall, our intraday findings support our first and second hypotheses (H1 and H2). Commonality in DMM liquidity is consistently higher than commonality in OHFT liquidity throughout the trading day, while HFT (both DMM and OHFT) liquidity co-moves more than NON HFT liquidity. Before the announcement of EU and US macro-economic news at 14:30 CET and 16:00 CET, HFT algorithms (particularly those implemented by DMMs) are programmed to reduce the aggressiveness in their liquidity supply by widening their quoted spreads; this behavior contributes to the increase of systematic liquidity risk. By contrast, NON HFTs are less consistent in this behavior.

Although peripheral to our main research question, our analysis points out a critical issue concerning the role of DMMs in automated trading. Bessembinder et al. (2015) show how imposing a maximum (quoted) spread limit on DMMs may improve market welfare, reducing the possibility of liquidity dry-ups. At the empirical level, Anand and Venkataraman (2016) and Clark-Joseph et al. (2017), for the Toronto Stock Exchange and the US Exchanges, respectively, empirically demonstrate the importance of DMMs in mitigating liquidity evaporation during stressful periods. By contrast, our results suggest that during the more volatile periods, although DMMs provide investors with immediacy, they systematically widen their spreads, leading to an increase in liquidity risk. This finding is of particular importance for policy makers. While the Euronext Paris DMM program does not include maximum spread limits, the TSE and the NYSE programs do.

2. Institutional details and data

2.1 Organization of trading

Stocks traded on the NYSE Euronext Paris platform follow two main market models: order driven and quote driven. The order driven system, examined here, operates as an automated continuous double auction, where liquidity is supplied by brokers and DMMs. DMMs are obliged to maintain pairs of bid-ask quotes for 95% of the organized trading session and for pre-specified baskets of securities, but there are no maximum spread restrictions. As a compensation for providing the market with immediacy, DMMs receive transaction rebates.[6] The time schedule of the continuous market is:

[6] DMM contracts may include maximum spread limits under certain circumstances. In the sample utilized in the present study, this is not the case. In an Appendix, we provide a detailed description of the DMM programs in Euronext Paris. More information on the Euronext Paris trading platforms and rules can be found at https://www.euronext.com/en/regulation/organization-of-trading

1) 07:15 to 09:00 Preopening phase - Order accumulation period
2) 09:00 Opening call auction (random time after August 2015)
3) 09:00 to 17:30 Main trading session: Continuous session
4) 17:30 to 17:35 Pre-closing phase - Order accumulation period
5) 17:35 Closing auction
6) 17:35 to 17:40 Trading at the last phase (at the close)
7) 17:40 to 07:15 After hours trading

Each trading day starts with an extended pre-opening order accumulation period, followed by an opening call auction to determine the opening prices. An auction is conducted for each listed security until all securities are open; the main continuous session follows. The trading day closes with a call auction that determines the closing price for each security. Trading after hours falls out of the scope of the current study.

During continuous trading, investors are allowed to submit, modify, or cancel their orders. The main orders allowed are: a) market orders, which have no price preference and are matched with the queuing orders at the prevailing quotes on the spot; b) limit orders, which have price preference and are stored in the limit order book (LOB) with price-time priority; c) stop market and stop limit orders, which are transformed into market and limit orders, respectively, when the trade price of the security reaches the threshold defined by the broker who submitted the order; d) pegged orders, which follow the best quotes; and e) market to limit orders, which are market orders that can be partially executed, with the remaining part stored in the LOB as a new limit order at the price of the partial execution. Limit orders can be marketable, depending on the limit price and the best quotes at the time of submission. For example, a sell (buy) limit order with a limit price smaller (greater) than the prevailing bid (ask) is an aggressive order, executed instantly. Thus, not only are market orders marketable, but aggressive limit orders are as well.

2.2 The data sample

We use an intraday dataset for stocks in the CAC 40 Index, retrieved from the *Autorité des Marchés Financiers* (AMF) BEDOFIH European high frequency database.[7] This dataset includes details for all order and trade messages for the year 2015 (256 trading days in total). We have

[7] More information on the BEDOFIH European High-Frequency financial database can be found at https://www.eurofidai.org/en/bedofih-database

excluded three trading days from our sample: 29/04/2015, because of a temporary halt of trading for several securities, and 24/12/2015 (Christmas Eve) and 31/12/2015 (New Year's Eve), which correspond to half-day trading. From the CAC 40 securities we have excluded seven stocks, either because they are not negotiated directly on the Euronext Paris platform (hence order data are not available), or because of missing data on specific days (for example, stocks that enter/exit the CAC 40 during 2015). Our final sample consists of 33 stocks for which orders and transactions are available for 253 trading days. Appendix Table A1 provides information on the companies in our stock sample, as well as on those excluded from our analysis.[8]

Each message (order or trade) in the dataset bears an HFT flag. The HFT classification, provided by AMF, is based on two criteria: a) a trader is classified as a pure high frequence trader if the average lifetime of her cancelled orders is less than the average lifetime of all orders in the book, and if she has cancelled at least 100,000 orders during the year; and b) the trader must have cancelled at least 500,000 orders with a lifetime of less than 0.1 second, with the top percentile of the lifetime of her cancelled orders being less than 500 microseconds. Once a trader is classified, the flag is immutable. Note, though, that traders' IDs are not directly available in our database. The AMF definition of HFT is in line with the Securities and Exchange Commission's (SEC, 2010) classification of HFTs as traders who frequently implement submit-cancel order placement strategies within very short time intervals. Using the HFT flag in the order record file, we can divide the LOB into HFT and NON HFT shares and directly test our first hypothesis (H1).

A second variable in the dataset lets us distinguish between the trading activity of DMMs and that of voluntary liquidity providers. After filtering the data using the AMF market making flag together with the HFT identification, we find that all DMMs in our sample are HFTs.[9] This feature lets us test for differences between commonality in DMM liquidity (which is compulsory) and OHFT liquidity (which is voluntary), according to our second hypothesis (H2).

To summarize, using the HFT and DMM indicators, we obtain three groups of order and trade messages: a) DMM messages that are associated with designated market makers' HFT order placement activities, b) OHFT messages that are related to (non DMM) HFT order placement activities, and c) NON HFT messages stemming from (non-DMM) non-high frequency traders.[10]

---

[8] The daily data for the CAC 40 stock sample are retrieved from the EUROFIDAI database, at https://www.eurofidai.org/en/database/stocks-europe

[9] After discussions, this feature was also verified by the AMF (i.e., that market makers apply HFT algorithms to supply liquidity). Further, we have found a negligible percentage (<0.05%) of active orders on the LOB that pertain to NON HFT market making activity; we excluded these from our analysis.

[10] Appendix Figure A1 graphs the database structure.

3. Liquidity variables

3.1 Price impact and immediacy

As defined above, a market is considered to be liquid when investors are able to acquire the desired number of shares (depth) at the minimum cost (tightness) as fast as possible (immediacy), without severely affecting the continuity of prices (resiliency). This description implies several dimensions of market liquidity and, thus, several ways to quantify it.

We employ two proxies that together encapsulate all aspects of liquidity. The first, introduced in Domowitz et al. (2005), captures the *ex-ante* cost of trade against each investor type as follows:

$$CT_{i,d,n}^{j}(q) = \int_{0}^{q} [S_{i,d,n}^{j}(Q) - D_{i,d,n}^{j}(Q)]dQ\,, \qquad (1)$$

where $j = \{DMM, OHFT, NON\ HFT\}$ is the trader type, and $S_{i,d,n}^{j}(Q)$ and $D_{i,d,n}^{j}(Q)$ are, respectively, the submitted supply and demand schedules on the central LOB for stock i, on day d, and at the end of intraday interval n.[11] Equation (1) represents the area between the supply and demand schedules, as illustrated by Figure 1. Quantity $CT_{i,d,n}^{j}(q)$ is a function of $S_{i,d,n}^{j}(Q)$ and $D_{i,d,n}^{j}(Q)$; it corresponds to the total round-trip cost (i.e., price impact, or the inverse of liquidity) for a hypothetical trade of q shares. In other words, $CT_{i,d,n}^{j}(q)$ represents the cost that an impatient trader would have to pay for her order to be executed on the spot, against trader type j. Moreover, the greater (smaller) the distance between the supply and demand lines (i.e., market tightness), the greater (smaller) the trading cost; that is, the lower (higher) the liquidity of the stock.

Because the best quotes are typically contaminated with noise from the trading process, predicting commonality using the inside spread as a proxy of liquidity is problematic (Kempf and Mayston, 2008). Trading against large and potentially informed investors often involves increased adverse selection costs; these costs make it hard for market makers to handle their positions, particularly in periods of market instability. Naturally, these factors should translate to excessive co-movement in liquidity supply deeper in the LOB. For this reason, we investigate commonality in liquidity beyond the best limits. Our $CT_{i,d,n}^{j}(q)$ spans the entire LOB (i.e., market

[11] In a similar way, Subrahmanyam and Zheng (2016), in their investigation of the order placement strategies of HFTs on the NASDAQ market, extract the slope of the LOB for the sets of limit orders placed by HFTs and NON HFTs. Likewise, Næs and Skjeltorp (2006) compute slopes on the visible and the hidden order book for the Norwegian stock market.

depth), thus improving over spread-related proxies that are limited to the top of the LOB. Further, $CT^{j}_{i,d,n}(q)$ is an *ex-ante* variable, measuring the price impact of a future transaction. By containing valuable information regarding investors' future trades, $CT^{j}_{i,d,n}(q)$ is a better proxy than the effective spread or the realized spread, both of which are *ex-post* measures of liquidity based on the prices of (sample) realized transactions.

Our second measure of liquidity captures market immediacy. For each trader type $j = \{DMM, OHFT, NON\ HFT\}$, stock i, day d, and intraday interval n, we calculate the total number of passively traded shares as follows:

$$IM^{j}_{i,d,n} = \sum_{k=1}^{K} V^{j}_{i,d,n,k}\ , \tag{2}$$

where k denotes the k-th trade in interval n, and $V^{j}_{i,d,n,k}$ is the corresponding number of traded shares. That is, $IM^{j}_{i,d,n}$ is an *ex-post* measure of liquidity that represents the total number of passively traded shares conditional on the type of the trader. For the sake of simplicity, we will refer to $CT^{j}_{i,d,n}(q)$ and $IM^{j}_{i,d,n}$ as CT (or $CT(q)$) and IM in our analysis.

3.2 Preparation of liquidity variables

To calculate the cost of trade (*CT*), we use the historical order and trade messages to replicate the trading process and re-build the order book. For immediacy (*IM*), we use the trade files, which include a buyer/seller initiated indicator. Thus, we are able to disentangle passive from active trading for each trader type.

After our initial calculations, according to equations (1) and (2), we follow a two-step process to prepare the variables for our analysis of liquidity commonality. In the first step, following Chordia et al. (2000), we de-trend the liquidity series through the following logarithmic transformation:[12]

$$L^{j}_{i,t} = \log\left(\frac{l^{j}_{i,d,n}}{l^{j}_{i,d,n-1}}\right), \tag{3}$$

where $j = \{DMM, OHFT, NON\ HFT\}$ denotes the type of the trader, and $l^{j}_{i,t}$ is either CT or IM. The time index t is defined such that $t \equiv N(d-1) + n$ where N is the number of total intraday observations with $n = 1, \dots, N$. Thus, each liquidity series consists of $T = N \times D$ consecutive intraday observations, where D is the number of total trading days in the sample with $d =$

[12] Chordia et al. (2000) use percentage changes, whereas we use logarithmic first differences.

$1, \dots, D$.[13] Chordia et al. (2000) argue that the use of changes in liquidity, instead of liquidity levels, is better for two reasons: a) since the aim is to investigate whether liquidity co-moves, it is more appropriate to use liquidity changes; and b) the use of liquidity changes reduces biases from non-stationarity issues related to the intraday adjustments of liquidity levels.[14] We standardize the liquidity changes, to remove any remaining periodic intraday components, using the following formula:

$$\left(L_{i,d,n}^{j} - mean\left(L_{i,n}^{j}\right)\right) / std\left(L_{i,n}^{j}\right), \tag{4}$$

where $mean\left(L_{i,n}^{j}\right)$ and $std\left(L_{i,n}^{j}\right)$ correspond to the across-days mean and standard deviation of liquidity, respectively, for intraday interval n (Hasbrouck and Seppi, 2001).

In the second step, we filter our liquidity series for firm-specific volatility and market price momentum, as well as for asynchronous trading effects, which are well known determinants of liquidity commonality (e.g., Chordia et al., 2000). To do so, we estimate the following regression equation:

$$L_{i,t}^{j} = A_i + B_{1,i}^{j} Vol_{i,t} + B_{2,i}^{j} Vol_{i,t-1} + B_{3,i}^{j} Vol_{i,t+1} + \Gamma_{1,i}^{j} MR_t + \Gamma_{2,i}^{j} MR_{t-1} + \Gamma_{3,i}^{j} MR_{t+1} + \omega_{i,t}^{j}, \tag{5}$$

where $j = \{DMM, OHFT, NON\ HFT\}$ denotes the type of trader. The dependent variable, $L_{i,t}^{j}$, is the firm-specific liquidity (either CT or IM), while the right-hand side of the equation includes the lead, concurrent, and lag terms of firm-specific volatility (in the form of standardized squared logarithmic returns, to remove time-of-day effects) and market performance (the return of the market portfolio is computed as the across-firm capitalization-weighted average logarithmic return).[15] In the remaining analysis, we employ the residual term $\omega_{i,t}^{j}$ as a measure of firm-specific liquidity for trader type j, filtered for volatility, market price effects, and time-of-day effects (e.g., Malceniece et al., 2019).

4. Econometric methodology

In this section, we present the econometric methodology we use to estimate liquidity commonality by trader type. We then provide a description of the test statistics computed for our three hypotheses (H1, H2, and H3).

[13] We exclude the opening and the closing sessions, as in Andersen and Bollerslev (1997).

[14] Note that we have applied the Augmented-Dickey-Fuller (ADF) and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests for non-stationarity and stationarity, respectively; our results indicate that our liquidity measures are free from non-stationarity.

[15] To calculate intraday returns, we use the mid-point price at the top of the LOB (Hasbrouck, 1991).

4.1 Estimation of trader type liquidity commonality

Following Anand and Venkataraman (2016), for each trader type we regress firm-specific liquidity on concurrent, lead, and lagged market-wide liquidity as follows:

$$\omega_{i,t}^{j} = b_{i,j}^{0} + b_{i,j}^{1}\omega_{M,t}^{j} + b_{i,j}^{2}\omega_{M,t-1}^{j} + b_{i,j}^{3}\omega_{M,t+1}^{j} + \epsilon_{i,t}^{j}, \quad (6)$$

where j denotes the trader type, $j \in \{DMM, OHFT, NON\ HFT\}$, M denotes "Market", and $\omega_{M,t}^{j}$ is market-wide liquidity supplied by trader type j. The adjusted $R_{i,j}^{2}$ obtained from equation (6) represents the variation of liquidity offered by trader type j for a specific stock i, in terms of the market-wide liquidity offered by the same trader type (j). Following previous studies, we use the adjusted $R_{i,j}^{2}$ as a summary measure of liquidity commonality for trader type j (e.g., Brockman et al., 2009; Karolyi et al., 2012; Malceniece et al., 2019).

To estimate equation (6), we need a proxy for market-wide liquidity, $\omega_{M,t}^{j}$. Following Hasbrouck and Seppi (2001), we use the Principal Component Analysis (PCA). PCA uses the singular value decomposition algorithm (SVD) to extract the common (market-wide) liquidity factor from the covariance matrix of the constructed liquidity series for trader type j, $\left[\omega_{i,t}^{j}\right]'$, where $'$ is the transpose operation. After applying the PCA algorithm, we use the first (market-wide) principal component as a proxy of $\omega_{M,t}^{j}$ in equation (6). To avoid additional correlation biases, in the regression for stock i we exclude that stock from the PCA estimation of $\omega_{M,t}^{j}$. [16]

Note that PCA describes common factors without requiring particular distributional assumptions (e.g., normality) (Joliffe, 2002). Subsequent statistical inference on the significance of the eigenvalues, however, assumes multivariate normality. If the original data are drawn from a normal population, then the standard error of the estimated eigenvalue is, asymptotically, of the magnitude $\lambda^{j}\sqrt{2/T}$, where λ^{j} is the eigenvalue and T the length of the time series at hand (Hasbrouck and Seppi, 2001). In our analysis, though, normality of the liquidity data is not plausible, and thus standard errors may be understated. Still, $\lambda^{j}\sqrt{2/T}$ can be used as an indicator of the statistical significance of λ (Hasbrouck and Seppi, 2001; Corwin and Lipson, 2010).

Whereas PCA estimates an unknown market-wide liquidity factor, both theoretical and empirical findings point toward a market average common liquidity factor. For instance, Acharya and Pedersen (2005) propose a liquidity-adjusted CAPM, where the liquidity of the market

[16] To infer the components (i.e., the eigenvalues and eigenvectors) of a correlation matrix, one has to standardize the input liquidity data, $\left[\omega_{i,t}^{j}\right]'$, to avoid biases due to potential differences in the distributional properties of the constructed series (i.e., differences in scaling). Our liquidity series are already standardized, according to equation (4); therefore, we omit this step.

portfolio has explanatory power on returns. When they test their model on a set of NYSE stocks, they find evidence that liquidity commonality is priced.[17] Accordingly, as a second proxy of market liquidity, $\omega_{M,t}^{j}$, in equation (6), we use the across-stocks capitalization-weighted average of liquidity, restricting the common factor to be equivalent to the liquidity of the market portfolio. As with PCA, in each (stock) regression, stock i is excluded from the calculation of market average liquidity. Our results (untabulated) are highly consistent with those obtained using the first principal component.[18]

4.2 Hypotheses testing

Our first hypothesis (H1) states that, due to the use of sophisticated technologies, HFTs' (DMMs' or OHFTs') liquidity supply co-moves across securities more than NON HFTs' liquidity supply does. To test this hypothesis, we statistically compare the across-stocks average co-movement in DMM and OHFT liquidity, measured by $\bar{R}_{DMM}^{2}$ and $\bar{R}_{OHFT}^{2}$, with the across-stocks average co-movement in NON HFT liquidity, measured by $\bar{R}_{NON\ HFT}^{2}$. We compute t-statistics over various interday and intraday market periods, as well as for different order sizes (see Section 5).

Our second hypothesis (H2) asserts that DMMs employing HFT algorithms are less diverse in their liquidity supply, compared to voluntary HFTs (OHFTs), across securities. To test this hypothesis, we statistically compare the across-stocks average levels of commonality in DMM and OHFT liquidity, as measured by $\bar{R}_{DMM}^{2}$ and $\bar{R}_{OHFT}^{2}$.

According to our third hypothesis (H3), cross-sectional co-movement in DMM, OHFT, and NON HFT liquidity increases with market stress. To test this hypothesis, we evaluate the relation between the obtained $R_{i,j}^{2}$s and market price volatility, assuming that the latter represents the overall level of market stress. Following Anand and Venkataraman (2016), we use the US CBOE VIX as an instrument for exogenous market volatility and estimate equation (6) over the two sub-periods of 25 days that exhibit the highest/lowest volatility. Subsequently, for each trader type we statistically compare the average level of co-movement in liquidity, $\bar{R}_{j}^{2}$, between the two volatility sub-periods. We conduct similar tests within the trading day, by comparing the across-stocks average level of liquidity co-movement, $\bar{R}_{j}^{2}$, between the opening, the middle of the

---

[17]Similarly, Watanabe and Watanabe (2008) theoretically analyze how liquidity risk affects asset pricing. Empirical evidence on the importance of liquidity risk in asset pricing is provided by Pastor and Stambaugh (2003), Gibson and Mougeot (2004), Sadka (2006), and Kim and Lee (2014) for the US stock markets; Bongaerts et al. (2011) for Credit Default Swaps; and Bao et al. (2011) for the bond market. Lee (2011) analyses the world pricing of liquidity commonality.

[18] These results are available upon request.

trading day, and the closing, as well as around the announcement of macroeconomic news at certain points in time (see Section 5.3.2). For these tests, our main driver is the intraday pattern of endogenous market volatility.

Because liquidity co-movement can be time varying (e.g., Watanabe and Watanabe, 2008), we additionally test the validity of our findings by employing a rolling window approach over the trading days (Kempf and Mayston, 2008). In this approach, we let w be a rolling window of N days. For each stock and for each rolling window, we estimate equation (6) to obtain the magnitude of liquidity co-movement (i.e., the $R^2_{i,j,w}$statistic). Accordingly, we calculate the across-days average CBOE VIX, V_w. To test the relation between volatility and liquidity co-movement, we run the following linear regression:

$$\Delta C^j_{i,w} = \alpha^j_i + \beta^j_i \Delta V_w + r^j_{i,w}, \tag{7}$$

where Δ is the first difference operator and $C^j_{i,w} \equiv R^2_{i,j,w}$ is the level of liquidity co-movement within window w.[19] As with equation (3), we employ first differences instead of levels to avoid biases due to potential non-stationarity in the rolling window series.

5. Descriptive analysis and empirical test results

5.1 Order flow and liquidity in the Paris market

We begin by presenting a descriptive analysis of the order flow and liquidity for each trader type. This exercise gives us insight into the relative contributions of each trader type to the total order placement activity. Note, however, that the level of aggressiveness in liquidity supply at the firm level does not imply co-movement across securities.

Table 1 reports summary statistics on order flow and trading activity for each trader type. The vast majority of orders are attributed to DMMs (85.6%), whereas OHFTs and NON HFTs are responsible for 13% and 1.3% of total orders, respectively. These percentages indicate the significance of DMMs' liquidity-supplying activity. DMMs are also responsible for a large percentage of modifications (77.5%) and cancellations (88.4%). This finding is not surprising,

[19] Note that because the $R^2_{i,j,w}$ statistic is bounded, it is not meaningful to interpret the magnitude of the estimated coefficients in equation (7). However, we can still safely consider the sign and statistical significance of the coefficients. We have also conducted the following logit transformation, $C^j_{i,w} = \log(R^2_{i,j,w}/(1 - R^2_{i,j,w}))$, which renders $R^2_{i,j,w}$ unbounded (Karolyi et al., 2012). Results using the logit transformation, $C^j_{i,w}$, are qualitatively very similar to those reported. We attribute this result to the fact that the commonality values ($R^2_{i,j,w}$) in our analysis are not extreme (i.e., close to 0 or 1).

as all DMMs in our sample are HFTs; i.e., they frequently implement submit-cancel strategies to minimize the risk of being picked off by other HFTs.

DMMs are the major traders in the Paris market. On average, 60.1% of total marketable orders stem from their accounts. We postulate that DMMs submit aggressive quotes to adjust their inventories and to eliminate market imbalances and stale quotes, or to profit from their ability to predict future order flows and price trends (see, also, the analysis in Malinova and Park (2015)). A significant percentage of marketable orders is associated with OHFTs (29.3%), whereas NON HFTs are responsible for the remaining 10.6%. Regarding trade size, the average marketable order size is 200 shares, whereas the average trade is 109 shares. These figures suggest that traders apply "slice and dice" techniques to avoid revealing their information and/or to better handle their execution costs.

Table 2 summarizes the liquidity supplying activity on the central LOB.[20] In particular, we report: a) the distribution of the LOB depth up to the best ten limits, and b) the percentage of available shares due to OHFTs, DMMs, or NON HFTs. To obtain this percentage, for each limit we calculate the sum of available shares associated with trader type j, divided by the sum of total outstanding shares. The top of the LOB is relatively thin, as the median depth is only 931 shares on both the buy and sell sides. Therefore, relatively small transactions (e.g., just over 1,000 shares) can consume liquidity deeper in the LOB, resulting in higher transaction costs for investors. Nonetheless, the small average trade size reported in Table 1 suggests that the majority of trades do not consume liquidity beyond the first limit; trades that do consume liquidity deeper in the LOB are less frequent. Notice also that the two sides of the LOB are almost symmetrical in depth up to the 10th best limit, hinting at the absence of significant supply/demand imbalances.

Looking at the percentage of shares offered by each trader category in Table 2, we see that the vast majority of queuing shares are associated with DMMs' and OHFTs' quotes. For example, at the top of the LOB, the percentage of immediacy offered by OHFTs and DMMs is 23.7% and 71.3%, respectively, on the buy side. The corresponding percentages on the sell side are 23.9% and 71.2%. We can readily infer that this provision of liquidity stems mostly from the implementation of HFT algorithms. Note, however, that deeper in the LOB (e.g., up to the 10th limit), the percentage of liquidity supplied by NON HFTs is relatively higher.

[20] The opening and closing sessions are excluded from the order flow analysis.

Table 3 compares liquidity by trader type, calculated according to equations (1) and (2). We report the average $CT_{i,d,n}^{j}(q)$ across stocks, days, and intraday intervals for $q = 1$ and $q = 200$ shares: $q = 1$ represents the most competitive quotes submitted by each trader category (i.e., the bid-ask spread); $q = 200$ is based on the distribution of the trade size. As reported in Table 1, the average transaction does not exceed 200 shares. For purposes of comparison, we divide $CT_{i,d,n}^{j}(q)$ by q to convert the unit to Euros-per-share-price impact. For immediacy, $IM_{i,d,n}^{j}$, we report the across-stocks, days, and intraday intervals percentages of passively traded shares for each trader type; that is, $[IM^{j}/(IM^{OHFT} + IM^{DMM} + IM^{NON\ HFT})] \times 100$. Notice, first, that HFTs' quotes are more competitive than NON HFTs', offering a lower cost of trade. This evidence is consistent with existing empirical findings on the positive effect of HFT on liquidity (e.g., Hendershott et al., 2011). Second, the cost of trade is higher for larger investors, indicating that market depth is an important parameter of market liquidity. Regarding immediacy, the most aggressive traders are DMMs (52% of total passively traded shares), followed by OHFTs (38%). NON HFTs are the least aggressive in providing the market with immediacy (10%).

5.2 Trader type liquidity commonality

We have shown that HFTs (both DMMs and OHFTs) play a critical role in firm-specific liquidity, representing, on average, almost 90% of available shares at the best quotes. In this section, we conduct our main empirical tests concerning the co-movement of trader-type liquidity.

Our findings are summarized in Table 4. We begin by presenting the results obtained from the PCA. To avoid biases due to missing observations and/or microstructure noise, we aggregate the 1-minute liquidity observations into 15-minute intervals, using the simple arithmetic average.[21] For each trader type, we report the first and second eigenvalues (λ_1^j and λ_2^j), together with the explained variance (%) for the first eigenvalue. Moreover, we present the across-stocks average adjusted $R_{i,j}^2$ statistic ($\bar{R}_j^2$), obtained from the estimation of equation (6); this statistic is the summary measure of liquidity co-movement in our analysis. Alongside it we

[21] Ait-Sahalia and Xiu (2017) show that sampling at too high of a frequency (e.g., 1 second) contaminates the data with microstructure noise, whereas using too low of a frequency (e.g., hourly) increases the ratio of the cross-sectional dimension against the number of observations (see also Osborne and Costello (2004) and de Souza et al. (2018)). In both cases, the PCA estimates may be less accurate. Ait-Sahalia and Xiu (2017) suggest an optimal sampling frequency of between 15 and 30 minutes. Thus, our use of a 15-minute interval has theoretical support. Note that originally sampling at a 1-minute frequency lets us examine the dynamics of liquidity co-movement around certain times during the trading day (e.g., around macroeconomic news announcements). We do not exclude the possibility of microstructure noise induced in our 1-minute liquidity series. Nonetheless, we are able to clearly identify the dynamics of co-movement around these events.

present the percentage of positive and significant (at the 5% probability level) $\hat{b}_{i,j}^1$ coefficient estimates, also from equation (6); these estimates represent the contemporaneous sensitivity of firm-specific liquidity to market liquidity (Chordia et al., 2000).

All first eigenvalues are well above unity. By contrast, all second eigenvalues are close to unity, indicating that trader type liquidity is primarily driven by market-wide factors. Additionally, all explained variances are higher than $(\lambda_1^j = 1)/\ 33 \approx 3.03\%$ (where 33 is the number of stocks in our sample); this result also implies significant cross-sectional liquidity co-variation for all trader types. Recall that, under normality, the standard error for λ_1^j should equal approximately $\lambda_1^j\sqrt{2/T}$. For example, for DMMs and $CT(q = 1)$, the standard error is $9.96\sqrt{2/(8{,}349)} = 0.1542$, where $T = 8{,}349$ is the total number of sampled intraday differences. Therefore, the first eigenvalue estimate is almost 65 times higher the magnitude of the standard error, implying that the eigenvalue is highly significant. Similar conclusions hold for the remaining eigenvalues. Notice also that the $\hat{b}_{i,j}^1$ coefficient estimates are statistically significant in all cases, further suggesting the presence of trader type liquidity commonality.[22]

Looking at the estimated $\bar{R}_j^2 s$ in Table 4, we find plenty of evidence to support our first hypothesis (H1). For $CT(q = 1)$, the first principal component explains almost 30.18% (16.90%) of total variation in DMM (OHFT) liquidity; the corresponding percentage for NON HFT liquidity is 11.38%. More importantly, the across-stocks average liquidity co-movement, $\bar{R}_{DMM}^2$ ($\bar{R}_{OHFT}^2$), obtained from the estimation of equation (6) for DMM (OHFT) liquidity, is equal to 26.06% (12.19%), whereas that for NON HFT liquidity, $\bar{R}_{NON\ HFT}^2$, is only 6.61%; this difference is statistically significant at the 5% probability level. Similar results hold for $CT(q = 200)$ and market immediacy (IM). Thus, HFT (DMM or OHFT) liquidity is associated with excessive co-movement, when compared to NON HFT liquidity.

[22] Chordia et al. (2000), using spread related measures of liquidity report, weak commonality for the NYSE. In particular, they find a low percentage of significant and positive contemporaneous b coefficient estimates, ranging from 14.29% to 34.65% depending on the liquidity measure, whereas we find 100% significant $\hat{b}_{i,j}^1$ coefficients. For each trader type, we have additionally estimated equation (6) in a single panel regression, using two-way clustered errors that account for cross-sectional correlations. Our results indicate, again, a highly significant $\hat{b}_{i,j}^1$ coefficient estimate. The difference in our results likely stems from the fact that Chordia et al. (2000) use a daily liquidity series of 254 days, whereas we use intraday data with thousands of observations. Thus, we obtain tighter confidence bounds and the null hypothesis $\hat{b}_{i,j}^1 = 0$ is frequently rejected. In other words, we are able to accurately detect deviations of $b_{i,j}^1$ from zero. Note, however, that to infer and, in turn, compare trader type liquidity commonality, we focus on the adjusted R^2 statistic, following Karolyi et al. (2012) and Malceniece et al. (2019). Further, Brockman et al. (2009) point out that one of the benefits of analyzing the adjusted R^2 statistic is that it is less subject to scaling effects compared to the $b_{i,j}^1$ coefficient.

Regarding our second hypothesis (H2), for our measure of immediacy the across-stocks average co-movement for OHFT, $\bar{R}^2_{OHFT}$, is 11.79%, whereas that for DMM, $\bar{R}^2_{DMM}$, is almost twice its magnitude at 23.3%. Similarly, for $CT(q = 1)$ and $CT(q = 200)$, the average commonality for OHFT, expressed by $\bar{R}^2_{OHFT,}$ is equal to 12.19% and 14.02%, respectively, while the corresponding values for DMM, shown by $\bar{R}^2_{DMM}$, are 26.06% and 32.52%. These differences are statistically significant at the 5% level. In support of this hypothesis, our findings indicate the importance of isolating compulsory (DMM) from voluntary (OHFT) liquidity supply when investigating the role of aggregate HFT activity in liquidity co-movement. This conclusion becomes even more relevant when we consider the fact that DMM liquidity accounts for more than 70% of total market liquidity (Table 2).

Concerning order size, our findings indicate that co-movement is higher deeper in the book for all types of traders. In the case of $CT(q = 200)$, the across-stocks averages $\bar{R}^2_{DMM}$, $\bar{R}^2_{OHFT}$, and $\bar{R}^2_{NON\ HFT}$ are 32.52%, 14.02%, and 11.16%, respectively, whereas in the case of $CT(q = 1)$ the corresponding percentages are 26.06%, 12.19%, and 6.61%. For all trader types, t-tests confirm that the increase in the average $R^2_{i,j}$ for larger orders is significant at the 5% probability level. These results are consistent with previous empirical findings that market depth is an important source of liquidity co-movement (e.g., Kempf and Mayston, 2008). Notice, also, that our findings concerning our first and second hypotheses (H1 and H2) are robust with respect to order size. That is, for both $CT(q = 1)$ and $CT(q = 200)$, co-movement in HFT liquidity is higher compared to co-movement in NON HFT liquidity, while DMM liquidity is less diverse compared to OHFT liquidity.

5.2.1 A robustness test

Our results demonstrate that the magnitude of liquidity co-variation varies across the groups of traders. This finding implies that trader-type liquidity commonality is driven by different, albeit not necessarily mutually exclusive, sets of information. Calculated pairwise correlation coefficients, $\rho_{\omega^{DMM}_{M,t},\omega^{OHFT}_{M,t}}$, $\rho_{\omega^{DMM}_{M,t},\omega^{NON\ HFT}_{M,t}}$, and $\rho_{\omega^{OHFT}_{M,t},\omega^{NON\ HFT}_{M,t}}$, are equal to 0.76, 0.42, and 0.46, respectively, implying that there are common cross-sectional liquidity variations across the groups of traders. To further explore this possibility, we perform a second set of regressions. Following Coughenour and Saad (2004), for each trader type j we relate liquidity $\omega^j_{i,t}$ to all trader-type principal components in a joint estimation:

$$\omega_{i,t}^{j} = c_{i,j}^{0} + c_{i,j}^{1}\omega_{M,t}^{DMM} + c_{i,j}^{2}\omega_{M,t-1}^{DMM} + c_{i,j}^{3}\omega_{M,t+1}^{DMM} + c_{i,j}^{4}\omega_{M,t}^{OHFT} + c_{i,j}^{5}\omega_{M,t-1}^{OHFT} + c_{i,j}^{6}\omega_{M,t+1}^{OHFT} + c_{i,j}^{7}\omega_{M,t}^{NON\,HFT} + c_{i,j}^{8}\omega_{M,t-1}^{NON\,HFT} + c_{i,j}^{9}\omega_{M,t+1}^{NON\,HFT} + e_{i,t}^{j}. \quad (8)$$

Note that the effect of near-multicollinearity on the accuracy of the coefficient estimates should be marginal, as long as the $R_{i,j}^2$ obtained from equation (8), as in our analysis, is not less than the $R_{i,j}^2$ obtained from separately regressing trader-type liquidity, $\omega_{i,t}^{j}$, on each individual component (Green, 1990; Coughenour and Saad, 2004); these results are available upon request.

Table 5 summarizes the results of estimating equation (8). For DMMs (i.e., $j = DMM$) and for $CT(q = 1)$, the percentages of statistically significant $\hat{c}_{i,j}^{4}$ and $\hat{c}_{i,j}^{7}$ coefficient estimates are 27.3% and 10%, respectively. Thus, the contemporaneous sensitivity of firm-specific DMM liquidity to the OHFT and NON HFT market-wide liquidity factors is not significant for the majority of securities in our sample. Conversely, 100% of $\hat{c}_{i,j}^{1}$ coefficient estimates, which represent the concurrent sensitivity of DMM firm-specific liquidity to the DMM common liquidity factor, are significant (at the 5% level). Further, the magnitudes of $\hat{c}_{i,j}^{4}$ and $\hat{c}_{i,j}^{7}$ coefficient estimates are, on average, equal to 0.008 and 0.004, respectively, whereas the average $\hat{c}_{i,j}^{1}$ is considerably higher (≈ 0.157).[23] Notice, additionally, that the average $\hat{c}_{i,j}^{1}$ (≈ 0.157) is slightly less than the level of concurrent sensitivity of DMM firm-specific liquidity to the DMM common liquidity factor, as reported in Table 4 ($\bar{b}_{i,j}^{1} = 0.164$). Similar conclusions can be drawn for the remaining trader types and measures of liquidity. Therefore, we infer that the firm-specific liquidity offered by trader type j is more likely to correlate with the market-wide liquidity offered by the same trader type (i.e., with $\omega_{M,t}^{j}$).[24]

Overall, the results shown in Table 5 suggest the presence of statistically significant, albeit rather weak, liquidity commonality across the groups of traders. This finding provides further support for our results on our first and second hypotheses (H1 and H2), as presented in Table 4.

[23] In line with Coughenour and Saad (2004), for $j = DMM$ we have tested the following restrictions: $\hat{c}_{i,j}^{1} = \hat{c}_{i,j}^{4}$ and $\hat{c}_{i,j}^{1} = \hat{c}_{i,j}^{7}$. Our results reject the restriction in both cases at the 5% probability level, indicating that the differences between the coefficient estimates are statistically significant. We obtain similar findings for $j = OHFT$ and $j = NON\ HFT$.

[24] A limitation in our analysis is that we cannot observe traders' IDs. Thus, we cannot directly distinguish the firms that provide liquidity across the securities, within each trader type.

5.3 Time varying liquidity commonality

In this section, we present our test results regarding our third hypothesis (H3), examining whether our findings on our first and second hypotheses (H1 and H2) are robust with respect to liquidity variation over time.

5.3.1 Interday evidence

Table 6 presents the estimation results from our tests of trader-type liquidity co-movement and market volatility. As explained in Section 4.2, we initially estimate equation (6) over the two sub-periods of 25 days that exhibit the highest/lowest volatility. For all trader types, co-movement in the cost of trade (CT) is elevated on days of high volatility compared to normal trading days. Additionally, for these two periods the across-stocks average $R_{i,j}^2$ ($\bar{R}_j^2$) significantly differs (at the 5% probability level). In terms of supplying immediacy (IM), DMM and OHFT commonality rises on days of high volatility. By contrast, co-movement in the NON HFTs' supply of immediacy remains unaltered with respect to volatility. In line with our third hypothesis (H3), the evidence indicates that liquidity commonality increases during periods of higher price uncertainty.

At this point, it is useful to statistically compare commonality in liquidity among the three types of traders within the two volatility sub-periods. As shown in Table 6, co-movement in DMM and OHFT liquidity is consistently higher, compared to co-movement in NON HFT liquidity; the corresponding differences in the across-stocks average $R_{i,j}^2$ are statistically significant (at the 5% probability level) for both CT and IM. Similarly, we find that co-movement is higher in DMM liquidity when compared to that of OHFT liquidity. Thus, our central findings, regarding our first and second hypotheses (H1 and H2), hold both in less turbulent periods and in periods of increased market stress.

In Figure 2, we present the results from our rolling window analysis tests (see Section 4.2). A visual inspection of the evolution of $\bar{R}_{j,w}^2$ (i.e., rolling window liquidity commonality) against volatility V_w (represented by the CBOE VIX) reveals: a) that the two variables are highly correlated, and b) the time-varying nature of liquidity co-movement. For space issues, we suppress the $CT(q = 200)$ variable, which is also highly correlated with volatility. Notice that co-movement in HFT (either DMM or OHFT) liquidity is consistently higher, compared to co-movement in NON HFT liquidity, for both CT and IM. Similarly, DMM liquidity exhibits higher co-variation, compared to OHFT liquidity. These findings further verify the robustness of our results regarding our first and second hypotheses (H1 and H2).

Our estimation results for equation (7) are presented in Table 6. With a rolling window of $N = 25$ days, these results verify the positive relation between co-movement in the cost of trade (CT) and volatility, for all trader types. For immediacy (IM), the positive relation is verified only in the case of HFTs (both DMMs and OHFTs), further indicating the importance of HFT as a source of liquidity commonality.

In addition to equation (7), which reveals the effect of exogenous market volatility on trader-type liquidity co-variation, we regress firm-specific liquidity on volatility, for each trader type, using the following equation:

$$\Delta L_{i,w}^{j} = \gamma_i^j + \delta_i^j \Delta V_w + y_{i,w}^j, \tag{9}$$

where $L_{i,w}^{j}$ is the daily average liquidity in window w and, as before, V_w is volatility represented by the CBOE VIX. Our results, reported in Table 6, show that firm-specific liquidity (CT or IM) is positively related to volatility for all types of traders. This evidence corroborates our central results, that systematic liquidity risk significantly increases during turbulent market periods and that this risk is higher with respect to the liquidity offered by DMMs and OHFTs.

5.3.2 Intraday evidence

Figure 3 depicts the intraday evolution of the cost of trade $CT(q = 1)$ and immediacy (IM), aggregated in 15-minute intervals. Again, for space issues, we suppress the case for $CT(q = 200)$, which has a very similar pattern with $CT(q = 1)$. Additionally, we plot endogenous intraday volatility (in the form of squared logarithmic returns) in 1-minute frequencies. Volatility is significantly high at the beginning of the continuous session, reflecting the intensity of price adjustments after the market's opening. During the middle of the day, volatility drops, then it slightly increases at the closing, creating an inverse J-shaped pattern for the full day. The cost of trade exhibits a similar pattern, whereas intraday immediacy is U-shaped, indicating the intensity of trading during the post-open and pre-close market periods.

Driven by the visual evidence of Figure 3, we split our 15-minute liquidity data into three intraday periods to test for time-of-day effects on liquidity co-movement. The three periods are: a) the post-opening period, from 09:00 CET to 12:00 CET; b) the midday period, starting at 12:00 CET and ending at 14:45 CET; and c) the pre-closing period, from 14:45 CET to 17:30 CET. For each period, we estimate equation (6) to infer the level of trader type co-movement in liquidity.

Figure 4 presents our results for the cost of trade $CT(q = 1, 200)$ and for immediacy (IM), for each trader type. Notice, first, that co-movement (for both CT and IM) is higher in DMM liquidity compared to that of OHFT. NON HFT liquidity exhibits the lowest cross-sectional co-variation. Results of t-tests for the equality of the across-stocks average $R^2_{i,j}$ among the trader groups indicate that these differences are significant at the 5% level. Thus, our main comparison results hold at the intraday level, supporting our first and second hypotheses (H1 and H2).

Intraday co-movement in the cost of trade $CT(q = 1)$ is U-shaped, while immediacy follows an upside-down U-shape, for all market participants. Hence, during the more volatile intraday periods (opening and closing), the systematic risk of trading cost is relatively increased. Conversely, the systematic risk of immediacy is of less concern during the opening and the closing periods, but increases during the midday period. Again, we have tested the differences in the average $R^2_{i,j}$ among the three intraday periods and our results reject the null hypothesis of equality for all types of traders, supporting our third hypothesis (H3). Altogether, our findings point out the importance of market timing as a source of liquidity risk in organized trading.

Figure 3 illustrates two distinct volatility spikes at 14:30 CET and 16:00 CET, corresponding to the announcement of European and US macroeconomic news (Kurov et al., 2016; Megarbane et al., 2017). To examine co-movement in trader-type liquidity around such deterministic events, we randomly select to focus on 14:30 CET. We first estimate an extended version of equation (6) over the full sample period (using the 1–minute liquidity data), including 1-minute dummy variables, D_τ, with $\tau = \{-4, -3, \dots, +5, +6\}$, from 14:25 CET to 14:36 CET (that is, around 14:30 CET). Results from these regression estimations, as presented in Table 7, suggest that one minute before the event, the spread $CT(q = 1)$ imposed by DMMs and OHFTs increases sharply ($\overline{D}_0^{DMM}$ and $\overline{D}_0^{OHFT}$ are 0.49 and 0.25, respectively, and both significant at the 5% level), whereas this is not the case for NON HFTs' quotes ($\overline{D}_0^{NON\ HFT}$ is 0.03 and not significant). By contrast, $CT(q = 200)$ significantly increases for all market participants, further suggesting that order size is an important parameter in the assessment of liquidity risk. Notice, however, that in the case of $CT(q = 200)$, NON HFTs' reactions take place two minutes before the event ($\overline{D}_{-1}^{NON\ HFT}$ is 0.20 and significant at the 5% level), whereas DMMs and OHFTs react, on average, one minute before the event ($\overline{D}_0^{DMM}$ and $\overline{D}_0^{OHFT}$ are 0.40 and 0.36, respectively; both significant at the 5% level). For immediacy offered by DMMs and OHFTs, we find consecutive decreases minutes before the event ($\overline{D}_{-4}^{DMM,OHFT}, \overline{D}_{-3}^{DMM,OHFT}, \dots, \overline{D}_0^{DMM,OHFT}$ are found to be negative and significant at the 5% level), whereas there are no particular changes in NON HFTs' supply of immediacy. Lastly, we observe an increase in DMMs' supply of immediacy minutes after the announcement time ($\overline{D}_{+3}^{DMM}$ and $\overline{D}_{+4}^{DMM}$ are 0.22 and 0.15, respectively; both significant at the 5% level).

We next assess liquidity co-movement. To this end, we fix the 1-minute interval and estimate equation (6) over the trading days. We repeat this procedure minute by minute from 14:25 CET to 14:36 CET, in line with the firm-specific liquidity analysis presenting above (see Table 7). Figure 6 plots the across-stocks average $R_{i,j}^2$ ($\bar{R}_j^2$) for $CT(q = 1)$, $CT(q = 200)$, and IM. Our findings are revealing: One minute before the event time, DMMs sharply increase their spreads, raising the cost of trade $CT(q = 1, 200)$ in a systematic manner which, in turn, elevates the level of liquidity risk. The same result holds true for OHFTs, but the magnitude of liquidity co-movement is significantly lower. For NON HFTs and for $CT(q = 1)$, this feature is almost negligible.[25] For the same trader type, however, $CT(q = 200)$ systematically increases two minutes before as well as two minutes after the event, again suggesting that order size plays an important role in liquidity commonality. Conversely, there are no significant changes in the co-movement of NON HFT liquidity a minute around the event time for $CT(q = 1, 200)$.

Looking at immediacy (IM), co-movement substantially increases just after the announcement time for all market participants. Notice, also, that co-movement in the supply of immediacy by DMMs and OHFTs is higher, compared to that of NON HFTs; this finding is consistent with our first hypothesis (H1). Confirming our results on our second hypothesis (H2), we find co-movement in DMMs' supply of immediacy to be considerably higher, compared to that of OHFTs. Computed t-statistics verify that these differences are significant at the 5% probability level, on average across the securities.

To sum up, our findings demonstrate that HFT (whether DMM or OHFT) is a significant source of liquidity risk around scheduled announcements of macroeconomic news. Nonetheless, the substantial level of commonality in DMM liquidity implies that co-movement in aggregate HFT liquidity is likely to be associated with market makers' common inventory handling activities.

6. Conclusions

In this paper we investigate the role of high-frequency traders (HFTs) in liquidity commonality for the CAC 40 Index constituents listed on the Euronext Paris Exchange. The literature on microstructure theory has focused more on the impact of HFT on firm-specific liquidity, whereas

[25] t-tests corroborate the visual evidence that for $CT(q = 1)$, co-movement in NON HFTs' liquidity supply remains at the same level, on average across securities, around 14:30 CET. In contrast, the increase of co-movement in HFTs' (DMMs' or OHFTs') liquidity supply is found to be statistically significant at the 5% level, on average.

liquidity co-movement has received less attention thus far.

Our analysis shows that HFTs exhibit higher co-variation in their liquidity supply compared to NON HFTs, in line with existing evidence that the use of sophisticated algorithms enhances the diffusion of information across securities. Nonetheless, we demonstrate that a certain fraction of the excessive co-variation in HFT liquidity is likely to be related to the activities of DMMs (e.g., through common inventory handling strategies). Our results indicate, also, that order size and market timing are important sources of liquidity co-movement.

Our analysis has implications for both investors and policy makers. First, investors face increased costs of trade when willing to execute orders that consume liquidity deeper in the LOB. Therefore, “slice and dice” techniques are more suitable for handling large orders. Second, securities that are heavily traded by HFTs are likely to be associated with elevated levels of systematic risk, particularly when market stress is higher. Indeed, liquidity commonality is a dynamic process and, thus, timing should be considered in risk assessment by portfolio managers. Third, policy makers in the Paris market should consider new regulations that will enhance the liquidity provision process when price uncertainty is higher. For example, imposing a maximum quoted spread limit on DMMs may improve market welfare, reducing the risk of liquidity dry-ups during turbulent trading periods (Bessembinder et al., 2015).

References

Acharya, V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics, 77*, 375–410.

Ait-Sahalia, Y., & Xiu, D. (2017). Using principal component analysis to estimate a high dimensional factor model with high-frequency data. *Journal of Econometrics, 201*, 384–399.

Ait-Sahalia, Y., & Saglam, M. (2017a). High frequency market making: Implications for liquidity. Unpublished working paper. Available at SSRN: 2908438.

Ait-Sahalia, Y., & Saglam, M. (2017b). High frequency market making: Optimal quoting. Unpublished working paper. Available at SSRN: 2331613.

Anagnostidis, P., Papachristou, G., & Thomaidis, N. S. (2016). Liquidity commonality in order-driven trading: Evidence from the Athens Stock Exchange. *Applied Economics, 48*, 2007–2021.

Anand, A., & Venkataraman, K. (2016). Market conditions, fragility, and the economics of market making. *Journal of Financial Economics, 121*, 327–349.

Andersen, T. G., & Bollerslev, T. (1997). Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance, 4*, 115–58.

Aragon, G. O., & Strahan, P. E. (2012). Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy. *Journal of Financial Economics, 103*, 570–587.

Bao, J., J. Pan, & Wang, J. (2011). The illiquidity of corporate bonds. *Journal of Finance, 66*, 911–946.

Benos, E., Brugler, J., Hjalmarsson, E., & Zikes, F. (2017). Interactions among High-Frequency Traders. *Journal of Financial and Quantitative Analysis, 52*, 1375–1402.

Bessembinder, H., Hao, J., & Zheng, K. (2015). Market Making Contracts, Firm Value, and the IPO Decision. *Journal of Finance, 70*, 1997–2028.

Boehmer, E., Li, D., & Saar, G. (2018). The Competitive Landscape of High-Frequency Trading Firms. *The Review of Financial Studies, 31*, 2227–2276.

Bongaerts, D., Driessen, J., & de Jong, F. (2011). Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market. *Journal of Finance, 66*, 203–240.

Boyson, N., Stahel, C. W., & Stulz, R. M. (2010). Hedge fund contagion and liquidity shocks. *Journal of Finance, 65*, 1789–1816.

Brockman, P., & Chung, D. (2002). Commonality in Liquidity: Evidence from an Order-Driven Market Structure. *Journal of Financial Research, 25*, 521–539.

Brockman, P., Chung, D., & Pérignon, C. (2009). Commonality in Liquidity: A Global Perspective. *Journal of Financial and Quantitative Analysis, 44*, 851–882.

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High frequency trading and price discovery. *Review of Financial Studies, 27*, 2267–2306.

Brunnermeier, M., & Pedersen, L. H. (2009). Market Liquidity and Funding Liquidity. *The Review of Financial Studies, 22*, 2201–2238.

Cao, C., & Petrasek, L. (2014). Liquidity Risk and Institutional Ownership. *Journal of Financial Markets, 21*, 76–97.

Cao, M., & Wei, J. (2010). Commonality in Liquidity: Evidence from the Option Market. *Journal of Financial Markets*, *13*, 20–48.

Carrion, A. (2013). Very fast money: High-frequency trading on the NASDAQ. *Journal of Financial Markets, 16*, 680–711.

Cespa, G., & Foucault, T. (2014). Illiquidity contagion and liquidity crashes. *The Review of Financial Studies, 27*, 1615–1660.

Chaboud, A., Chiquoine, B., Hjalmarsson, E., & Vega, C. (2014). Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market. *Journal of Finance, 69*, 2045–2084.

Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics, 56*, 3–28.

Chordia, T., Sarkar, A., & Subrahmanyam, A. (2005). An empirical analysis of stock and bond market liquidity. *The Review of Financial Studies, 18*, 85–129.

Clark-Joseph, A. D., Ye, M., & Zi, C. (2017). Designated market makers still matter: Evidence from two natural experiments. *Journal of Financial Economics, 126*, 652–667.

Comerton-Forde, C., Hendershott, T., Jones, C., Moulton, P., & Seasholes, M. (2010). Time variation in liquidity: The role of market maker inventories and revenues. *Journal of Finance, 65*, 295–331.

Corwin, S., & Lipson, M. (2011). Order Characteristics and the Sources of Commonality in Prices and Liquidity. *Journal of Financial Markets, 14*, 47–81.

Coughenour, J., & Saad, M. (2004). Common Market Makers and Commonality in Liquidity. *Journal of Financial Economics, 73*, 37–69.

Dang, T. L., Moshirian, F., Wee, C. K. G., & Zhang, B. (2015a). Cross-listings and liquidity commonality around the world. *Journal of Financial Markets, 22*, 1–26.

Dang, T. L., Moshirian, F., & Zhang, B. (2015b). Commonality in news around the world. *Journal of Financial Economics, 116*, 82–110.

de Souza, J. B., Reisen, V. A., Franco, G. C., Ispany, M., Bondon, P., & Santos, J. M. (2018). Generalized additive models with principal component analysis: an application to time series of respiratory disease and air pollution data. *Journal of the Royal Statistical Society C, 67*, 453–480.

Domowitz, I., Hansch, O., & Wang, X. (2005). Liquidity, Commonality and Return Co–movement. *Journal of Financial Markets, 8*, 351–376.

Fernando, C. (2003). Commonality in Liquidity: Transmission of Liquidity Shocks across Investors and Securities. *Journal of Financial Intermediation, 12*, 233–254.

Foran, J., Hutchinson, M. C., & O'Sullivan, N. (2015). Liquidity Commonality and Pricing in UK Equities. *Research in International Business and Finance, 34*, 281–293.

Garleanu, N., & Pedersen, L. H. (2007). Liquidity and risk management. *American Economic Review, 97*, 193–197.

Gibson, R., & Mougeot, N. (2004). The Pricing of Systematic Liquidity Risk: Empirical Evidence from the US Stock Market. *Journal of Banking & Finance*, *28*, 157–178.

Gissler, S. (2017). Lockstep in Liquidity: Common Dealers and Co-Movement in Bond Liquidity. *Journal of Financial Markets, 33*, 1–21.

Gorton, G., & Metrick, A. (2010). Haircuts. *Federal Reserve Bank of St. Louis Review 92*, 507–519.

Gromb, D., & Vayanos, D. (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics, 66*, 361–407.

Hameed, A., Kang, W., & Viswanathan, S. (2010). Stock market declines and liquidity. *Journal of Finance, 65*, 257–293.

Hasbrouck, J. (1991). Measuring the Information Content of Stock Trades. *Journal of Finance, 46,* 179–207.

Hasbrouck, J., & Seppi, D. (2001) Common Factors in Prices. Order Flows and Liquidity. *Journal of Financial Economics, 59*, 383–411.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011). Does algorithmic trading improve liquidity? *Journal of Finance, 66*, 1–33.

Hendershott, T., & Riordan, R. (2013). Algorithmic trading and the market for liquidity. *Journal of Financial and Quantitative Analysis, 8*, 1001–1024.

Huberman, G., & Halka, D. (2001). Systematic Liquidity. *Journal of Financial Research, 24*, 161–178.

Jain, P. K., Jain, P., & McInish, T. H. (2016). Does high-frequency trading increase systemic risk? *Journal of Financial Markets, 31*, 1–24.

Joliffe, I. T. (2002). *Principal Component Analysis*. (2nd ed.). Berlin, Heidelberg, New York: Springer-Verlag.

Kamara, A., Lou, X., & Sadka, R. (2008). The divergence of liquidity commonality in the cross-section of stocks. *Journal of Financial Economics, 89*, 444–466.

Karolyi, G. A., Lee, K.-H., & van Dijk, M. A. (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics, 105*, 82–112.

Karnaukh, N., Renaldo, A., & Soderlind, P. (2015). Understanding FX liquidity. *The Review of Financial Studies, 28*, 3073–3108.

Kurov, A., Sancetta, A., Strasser, G., & Wolfe, M. H. (2016). Price drift before US macroeconomic news: private information about public announcements? European Central Bank, Working Paper 1901.

Kempf, A., & Mayston, D. (2008). Liquidity commonality beyond best prices. *Journal of Financial Research, 31*, 25–40.

Kim, S.-H., & Lee, K.-H. (2014). Pricing of liquidity risks: Evidence from multiple liquidity measures. *Journal of Empirical Finance, 25*, 112–133.

Kirilenko, A., Kyle, A. S., Samadi, M., & Tuzun, T. (2017). The flash crash: High-frequency trading in an electronic market. *The Journal of Finance, 72*, 967–998.

Klein, O., & Song, S. (2018). Multimarket High-Frequency Trading and Commonality in Liquidity. Unpublished working paper. Available at SSRN: 2984887.

Lee, K.-H. (2011). The world price of liquidity risk. *Journal of Financial Economics 99*, 136–161.

Longstaff, F. A. (2004). The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices. *The Journal of Business,* 77, 511–526.

Malceniece, L., Malcenieks, K., & Putniņš, T. J. (2019). High Frequency Trading and Co-Movement in Financial Markets. *Journal of Financial Economics* (forthcoming).

Malinova, K., & Park, A. (2015). Liquidity Provision and Market Making by HFTs. Report prepared for the Investment Industry Regulatory Organization of Canada.

Mancini, L., Ranaldo, A., & Wrampelmeyer, J. (2013). Liquidity in the foreign exchange market: measurement, commonality, and risk premiums. *Journal of Finance, 68*, 1805–1841.

Marshall B. R., Nguyen, N. H., & Visaltanachoti, N. (2013). Liquidity commonality in commodities. *Journal of Banking & Finance*, *37*, 11–20.

Megarbane, N., Saliba, P., Lehalle, C. A., & Rosenbaum, M. (2017). The behaviour of high-frequency traders under different market stress scenarios. *Market Microstructure and Liquidity, 3*, 1850005.

Moshirian, F., Qian, X., Wee, C. K. G., & Zhang, B. (2017). The determinants and pricing of liquidity commonality around the world. *Journal of Financial Markets 33*, 22–44.

Næs, R., Skjeltorp, J. A., & Ødegaard, B. A. (2011). Stock Market Liquidity and the Business Cycle. *Journal of Finance, 66*, 139–176.

Næs, R., & Skjeltorp, J. A. (2006). Order book characteristics and the volume-volatility relation: Empirical evidence from a limit order market. *Journal of Financial Markets, 9*, 408–432.

Nagel, S. (2012). Evaporating liquidity. *The Review of Financial Studies, 25*, 2005–2039.

Osborne, J. W., & Costello, A. B. (2004). Sample size and subject to item ratio in principal component analysis. *Practical Assessment, Research & Evaluation, 10*, 1–9.

Pastor, L., & Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy, 111*, 642–685.

Pu, X. (2009). Liquidity commonality across the bond and CDS markets. *Journal of Fixed Income, 19*, 26–39.

Qian X., Tam, L., & Zhang, B. (2014). Systematic liquidity and the funding liquidity hypothesis. *Journal of Banking & Finance. 45*, 304–320.

Rösch, C., & Kaserer, C. (2013). Market Liquidity in the Financial Crisis: The Role of Liquidity Commonality and Flight-To-Quality. *Journal of Banking & Finance, 37*, 2284–2302.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics, 80*, 309–349.

SEC (2010). Securities and Exchange Commission: Concept release on equity market structure. Available at https://www.sec.gov/rules/concept/2010/34-61358.pdf.

Subrahmanyam, A., & Zheng, H. (2016). Limit order placement by high-frequency traders. *Borsa Istanbul Review, 16*, 185–209.

Wang, J. X. (2013). Liquidity commonality among Asian equity markets. *Pacific-Basin Finance Journal, 21*, 1209–1231.

Watanabe, A., & Watanabe, M. (2008). Time-varying liquidity risk and the cross-section of stock returns. *Review of Financial Studies, 21*, 2449–2486.

Watanabe, M. (2014). A model of stochastic liquidity. Unpublished working paper. Available at SSRN: 413983.

Zhang, Z., Cai, J., & Cheung, Y. L. (2009). Explaining country and cross-border liquidity commonality in international equity markets. *Journal of Futures Markets, 29*, 630–65.

TABLES

Table 1: Order flow and trade summary

	HFT		NON HFT
ORDER FLOW	OHFT (%)	DMM (%)	NON HFT (%)
Non-marketable orders	13.0	85.6	1.3
Cancelled by member	11.2	88.4	0.5
Modified by member	18.9	77.5	3.6
Marketable orders	29.3	60.1	10.6
TRADE SIZE	Minimum	Median (50%)	90%
Marketable order size (shares)	1	200	764
Trade size (shares)	1	109	268

Note: This table summarizes order flow and trade statistics. For order flow, for each stock we calculate the total number (across days) of submitted non-marketable orders by OHFTs, DMMs, and NON HFTs. In our calculations we include limit orders that are not aggressive (i.e., not triggering a trade), pegged orders, and stop orders. Then, we calculate the percentage (%) of trader-type submissions relative to total submitted orders and report the across-stocks mean percentage. Accordingly, we calculate and report the across-stocks mean percentage for modifications, cancellations, and submissions of marketable orders (i.e., aggressive market and limit orders triggering trades). For trade size, for each stock we aggregate across days all marketable order sizes and all trade sizes. Then, we report the across-stocks minimum, median, and 90% percentile.

Table 2: Limit order book (LOB) summary statistics

Depth sell	*Min*	*10%*	*20%*	*30%*	*40%*	*Median*	*60%*	*70%*	*80%*	*90%*	*Max*
Level 1	1	186	338	505	700	931	1,233	1,684	2,514	5,165	818,620
Level 2	1	400	659	929	1,247	1,631	2,107	2,772	4,137	9,561	824,424
Level 3	1	646	993	1327	1,709	2,162	2,719	3,535	5,203	12,368	826,000
Level 4	1	788	1,166	1,531	1,935	2,384	2,944	3,819	5,640	12,731	824,377
Level 5	1	852	1,239	1,620	2,042	2,515	3,124	4,050	5,906	12,889	820,341
Level 6	1	712	1,052	1,385	1,758	2,194	2,746	3,581	5,316	12,168	818,435
Level 7	1	554	845	1,131	1,461	1,864	2,379	3,138	4,665	10,039	819,622
Level 8	1	365	595	822	1,089	1,425	1,888	2,588	3,957	8,367	817,848
Level 9	1	252	437	622	834	1,104	1,477	2,067	3,221	6,423	814,229
Level 10	1	193	345	500	679	906	1,223	1,745	2,782	5,559	826,228
Depth buy	*Min*	*10%*	*20%*	*30%*	*40%*	*Median*	*60%*	*70%*	*80%*	*90%*	*Max*
Level 1	1	182	333	500	698	931	1,238	1,698	2,528	5,154	1,290,496
Level 2	1	400	669	949	1,277	1,676	2,178	2,880	4,335	9,820	1,177,613
Level 3	1	648	1,007	1,350	1,736	2,192	2,754	3,595	5,372	12,414	1,299,336
Level 4	1	797	1,182	1,548	1,946	2,401	2,957	3,812	5,660	12,647	1,299,449
Level 5	1	854	1,244	1,622	2,026	2,491	3,084	3,994	5,875	12,695	1,296,033
Level 6	1	714	1,058	1,393	1,758	2,186	2,737	3,549	5,282	11,961	1,295,198
Level 7	1	557	851	1,138	1,465	1,864	2,376	3,110	4,595	9,854	1,294,451
Level 8	1	370	600	828	1,093	1,426	1,885	2,570	3,884	8,157	1,294,155
Level 9	1	254	439	621	830	1,097	1,462	2,039	3,133	6,196	1,293,893
Level 10	1	195	345	500	674	896	1,205	1,706	2,706	5,363	614,445

	Sell side			*Buy side*		
	HFT		NON HFT	HFT		NON HFT
LOB depth	OHFT (%)	DMM (%)	NON HFT (%)	OHFT (%)	DMM (%)	NON HFT (%)
Level 1	23.9	71.2	5.0	23.7	71.3	5.1
Level 2	13.3	84.9	1.8	12.9	85.4	1.7
Level 3	13.0	85.6	1.4	12.6	86.1	1.3
Level 4	13.0	85.4	1.6	12.6	86.0	1.4
Level 5	13.1	84.6	2.3	12.7	85.3	2.1
Level 6	13.9	82.6	3.5	13.5	83.3	3.2
Level 7	13.8	81.6	4.7	13.4	82.4	4.2
Level 8	13.9	80.7	5.4	13.6	81.6	4.9
Level 9	13.7	79.5	6.8	13.3	80.5	6.2
Level 10	13.2	78.5	8.4	12.9	79.5	7.6

Note: This table reports the distribution of depth (hidden plus visible) in shares up to the best 10 limit levels of the LOB (for each limit we aggregate shares across days and stocks), on the buy and the sell side. Additionally, we present the available liquidity on the LOB (for each level-limit) offered by OHFTs, DMMs, and NON HFTs. Liquidity is calculated as the across days and stocks average percentage of total outstanding shares for each trader category, relative to the total number of outstanding shares on the LOB, for each limit. Statistics are reported for both the buy and the sell side and up to the 10 best limits of the constructed LOB. The LOB is constructed in 1-minute frequencies. The total number of CAC 40 sample stocks is 33, and the total number of trading days is 253 for year 2015, excluding 2015/04/29, 2015/12/24, and 2015/12/31.

Table 3: Summary of liquidity measures

	HFT		NON HFT
	DMM	OHFT	NON HFT
CT (q=1)	0.025*	0.039*	0.210
CT(q=200)	0.026*,**	0.049*,**	0.265**
IM	52%	38%	10%

Note: This table presents aggregate liquidity statistics for each trader type (DMM, OHFT, and NON HFT). For the cost of trade, $CT_{i,d,n}^{j}(q) = \int_{0}^{q}[S_{i,d,n}^{j}(Q) - D_{i,d,n}^{j}(Q)]dQ$, we report the average across stocks, days, and intraday intervals (1 min frequency), for each trading category and for depths (i.e., order sizes) q=1 and q=200 shares. Additionally, for purposes of comparison, we divide $CT_{i,d,n}^{j}(q)$ by q to convert the unit in Euros per share price impact. For immediacy, $IM_{i,d,n} = \sum_{k=1}^{K} V_{i,d,n,k}$, we calculate the total number of passively traded shares for each trader type across stocks, days, and intraday intervals (1 min frequency). Then we calculate and report the percentage of passively traded shares for each investor type, relative to the total trading volume. Single asterisks denote rejection of the null hypothesis, at the 5% probability level, that the average cost of trade offered by HFTs (DMMs or OHFTs) is equal to the average cost of trade offered by NON HFTs. Double asterisks denote rejection of the null hypothesis, at the 5% probability level, that the average $CT_{i,d,n}^{j}(q = 1)$ is equal to the average $CT_{i,d,n}^{j}(q = 200)$.

Table 4: Trader type liquidity commonality

	1st eigenvalue (λ_1^j)	2nd eigenvalue (λ_2^j)	Explained variance (λ_1^j)	Average $R_{i,j}^2$: $\bar{R}_j^{\,2}$	Positive and significant $b_{i,j}^1$	Average $b_{i,j}^1$: $\bar{b}_{i,j}^1$
CT (q=1)						
$\boldsymbol{j}$ = DMM	9.96	0.92	30.18%	26.06%*,**	100%	0.164
$\boldsymbol{j}$ = OHFT	5.58	1.11	16.90%	12.19%*	100%	0.148
$\boldsymbol{j}$ = NON HFT	3.76	1.29	11.38%	6.61%	100%	0.131
CT (q=200)						
$\boldsymbol{j}$ = DMM	11.98	0.88	36.30%	32.52%*,**	100%	0.167
$\boldsymbol{j}$ = OHFT	6.16	1.15	18.66%	14.02%*	100%	0.151
$\boldsymbol{j}$ = NON HFT	5.23	1.54	15.84%	11.16%	100%	0.144
IM						
$\boldsymbol{j}$ = DMM	8.95	1.15	27.43%	23.30%*,**	100%	0.160
$\boldsymbol{j}$ = OHFT	5.39	1.13	16.50%	11.79%*	100%	0.148
$\boldsymbol{j}$ = NON HFT	2.90	1.09	10.00%	5.97%	100%	0.131

Note: This table reports the results for trader type liquidity commonality. We first filter the 15-minute liquidity series (*CT* or *IM*) for volatility (*Vol*) and market performance (*Market Return*), for each stock and for each trader type (DMM, OHFT, and NON HFT), by estimating equation (5): $L_{i,t}^j = A_i + \mathrm{B}_{1,i}^j Vol_{i,t} + \mathrm{B}_{2,i}^j Vol_{i,t-1} + \mathrm{B}_{3,i}^j Vol_{i,t+1} + \Gamma_{1,i}^j MR_t + \Gamma_{2,i}^j MR_{t-1} + \Gamma_{3,i}^j MR_{t+1} + \omega_{i,t}^j$. Then, we use the filtered liquidity series ($\omega_{i,t}^j$) as input in the PCA algorithm, to obtain the first (market-wide) principal component ($\omega_{M,t}^j$, where M denotes "Market"). Finally, for each trader type we regress firm-specific liquidity on the obtained lead, lag, and concurrent first principal component in equation (6): $\omega_{i,t}^j = b_{i,j}^0 + b_{i,j}^1 \omega_{M,t}^j + b_{i,j}^2 \omega_{M,t-1}^j + b_{i,j}^3 \omega_{M,t+1}^j + \epsilon_{i,j,t}$. Regarding the PCA, we report the first eigenvalue and the corresponding explained variance (%), as well as the second eigenvalue, for each trader type. Next, we present the across-stocks average adjusted $R_{i,j}^2$ statistic as a summary measure of liquidity co-movement for each trader type. Single asterisks denote rejection of the null hypothesis that between HFT (DMM or OHFT) and NON HFT, the across-stocks average difference in the adjusted $R_{i,j}^2$ is equal to zero. Double asterisks denote rejection of the null hypothesis that between DMM and OHFT, the across-stocks average difference in the adjusted $R_{i,j}^2$ is equal to zero. We additionally present the percentage of positive and significant $b_{i,j}^1$ coefficient estimates (representing contemporaneous liquidity co-movement) out of the 33 regression equations, along with the average coefficient estimates. Standard errors are Newey-West adjusted for serial correlation and heteroskedasticity.

Table 5: Liquidity co-movement across groups of traders

	CT (q=1)							*CT (q=200)*							*IM*						
$\boldsymbol{j = DMM}$	$\bar{R}_J^{\,2}$	$\bar{c}_{i,j}^{1}$	(%)	$\bar{c}_{i,j}^{4}$	(%)	$\bar{c}_{i,j}^{7}$	(%)	$\bar{R}_J^{\,2}$	$\bar{c}_{i,j}^{1}$	(%)	$\bar{c}_{i,j}^{4}$	(%)	$\bar{c}_{i,j}^{7}$	(%)	$\bar{R}_J^{\,2}$	$\bar{c}_{i,j}^{1}$	(%)	$\bar{c}_{i,j}^{4}$	(%)	$\bar{c}_{i,j}^{7}$	(%)
	26.13	0.157	100	0.008	27.3	0.004	10	32.59	0.162	100	0.005	33.3	0.004	24.2	24.60	0.155	33	0.005	15.2	0.005	6.1
$\boldsymbol{j = OHFT}$	$\bar{R}_J^{\,2}$	$\bar{c}_{i,j}^{1}$	(%)	$\bar{c}_{i,j}^{4}$	(%)	$\bar{c}_{i,j}^{7}$	(%)	$\bar{R}_J^{\,2}$	$\bar{c}_{i,j}^{1}$	(%)	$\bar{c}_{i,j}^{4}$	(%)	$\bar{c}_{i,j}^{7}$	(%)	$\bar{R}_J^{\,2}$	$\bar{c}_{i,j}^{1}$	(%)	$\bar{c}_{i,j}^{4}$	(%)	$\bar{c}_{i,j}^{7}$	(%)
	12.53	0.024	78.8	0.120	100	0.011	39.4	14.32	0.018	63.6	0.130	100	0.006	21.2	13.21	0.019	27.3	0.118	100	0.027	30.3
$\boldsymbol{j = NON\ HFT}$	$\bar{R}_J^{\,2}$	$\bar{c}_{i,j}^{1}$	(%)	$\bar{c}_{i,j}^{4}$	(%)	$\bar{c}_{i,j}^{7}$	(%)	$\bar{R}_J^{\,2}$	$\bar{c}_{i,j}^{1}$	(%)	$\bar{c}_{i,j}^{4}$	(%)	$\bar{c}_{i,j}^{7}$	(%)	$\bar{R}_J^{\,2}$	$\bar{c}_{i,j}^{1}$	(%)	$\bar{c}_{i,j}^{4}$	(%)	$\bar{c}_{i,j}^{7}$	(%)
	6.86	0.006	27.3	0.013	48.5	0.118	100	32.59	0.006	36.4	0.007	39.4	0.135	100	24.60	0.005	12.1	0.031	51.5	0.096	100

Note: For each trader type j, we relate liquidity, $\omega_{i,t}^{j}$, to all trader-type principal components (concurrent lead and lag) in the joint estimation equation (8): $\omega_{i,t}^{j} = c_{i,j}^{0} + c_{i,j}^{1}\omega_{M,t}^{DMM} + c_{i,j}^{2}\omega_{M,t-1}^{DMM} + c_{i,j}^{3}\omega_{M,t+1}^{DMM} + c_{i,j}^{4}\omega_{M,t}^{OHFT} + c_{i,j}^{5}\omega_{M,t-1}^{OHFT} + c_{i,j}^{6}\omega_{M,t+1}^{OHFT} + c_{i,j}^{7}\omega_{M,t}^{NON\ HFT} + c_{i,j}^{8}\omega_{M,t-1}^{NON\ HFT} + c_{i,j}^{9}\omega_{M,t+1}^{NON\ HFT} + e_{i,t}^{j}$. For each trader type, we report the across-stocks average adjusted $R_{i,j}^{2}$ and the across-stocks average concurrent coefficient estimates (time t), together with the corresponding percentages of statistically significant coefficient estimates (at the 5% probability level). Standard errors are Newey-West adjusted for serial correlation and heteroskedasticity.

.

Table 6: Liquidity co-movement and volatility

	CT (q=1)	*CT (q=200)*	*IM*
VOLATILITY LOW			
$\bar{R}^2_{DMM}$	25.91% [b, c]	33.33% [b, c]	21.80% [b, c]
$\bar{R}^2_{OHFT}$	9.83% [b]	10.73% [b]	11.60% [b]
$\bar{R}^2_{NON\ HFT}$	5.21%	8.87%	7.49%
VOLATILITY HIGH			
$\bar{R}^2_{DMM}$	29.79% [a, b, c]	36.04% [a, b, c]	26.16% [a, b, c]
$\bar{R}^2_{OHFT}$	14.72% [a, b]	18.16% [a, b]	13.77% [a, b]
$\bar{R}^2_{NON\ HFT}$	9.54% [a]	13.56% [a]	7.67%
EQUATION (7)			
DMM: $\bar{\beta}$	0.469*	0.361*	0.766*
($\bar{t}$-statistic)	(2.888)	(2.525)	(3.019)
OHFT: $\bar{\beta}$	0.830*	0.915*	0.802*
($\bar{t}$-statistic)	(2.539)	(2.876)	(2.336)
NON HFT: $\bar{\beta}$	1.096*	0.850**	0.244
($\bar{t}$-statistic)	(2.023)	(1.766)	(0.260)
EQUATION (9)			
DMM: $\bar{\delta}$	0.159*	0.152*	0.745*
($\bar{t}$-statistic)	(4.597)	(4.438)	(3.925)
OHFT: $\bar{\delta}$	0.160*	0.107**	0.535*
($\bar{t}$-statistic)	(2.530)	(1.836)	(3.108)
NON HFT: $\bar{\delta}$	0.305*	0.272*	0.460**
($\bar{t}$-statistic)	(3.275)	(2.873)	(1.683)

Note: This table reports the results from the principal component analysis with respect to market volatility. We initially select two 25-day subsamples of highest/lowest volatility to estimate equation (6), $\omega^j_{i,t} = b^0_{i,j} + b^1_{i,j}\omega^j_{M,t} + b^2_{i,j}\omega^j_{M,t-1} + b^3_{i,j}\omega^j_{M,t+1} + \epsilon_{i,j,t}$, for each stock and for each trader type (OHFT, DMM, and NON HFT.). We report the across-stocks average adjusted $R^2_{i,j}$ as a measure of liquidity co-movement. "a" denotes rejection of the null hypothesis (at the 5% probability level) that, for trader type $j \in \{DMM, OHFT, NON\ HFT\}$, the across-stocks average $R^2_{i,j}$s between the high and the low volatility periods are equal. "b" denotes rejection of the null hypothesis (at the 5% probability level) that the across stocks average $R^2_{i,j}$s between HFT (DMM or OHFT) and NON HFT are equal (within the volatility period). "c" denotes rejection of the null hypothesis (at the 5% probability level) that the across-stocks average $R^2_{i,j}$s between DMM and OHFT are equal (within the volatility period). Then, for rolling windows (w) of N=25 days, we estimate equation (6) to obtain $R^2_{i,j,w}$. We also calculate the average CBOE VIX (across the 25 days) as an instrument for exogenous market volatility, V_w. Using the rolling window estimates, for each stock and for each trader type, we regress changes in the level of co-movement on changes in the level of volatility in equation (7): $\Delta C^j_{w,i} = \alpha^j_i + \beta^j_i \Delta V_w + r^j_{w,i}$, where $C^j_{w,i} \equiv R^2_{i,j,w}$. Moreover, we regress changes in the level of firm-specific liquidity (calculated as the average liquidity across the 25 days for each trader type) on changes in volatility, in equation (9): $\Delta L^{i,j}_w = \gamma^j_i + \delta^j_i \Delta V_w + y^{i,j}_w$. We report the across-stocks average coefficient estimates, $\bar{\beta}$ and $\bar{\delta}$, for equations (7) and (9), respectively, together with the corresponding average t-statistics for the significance of the coefficient estimates. Asterisks denote significance at the 5% probability level, whereas double asterisks denote significance at the 10% probability level. Standard errors are Newey-West adjusted for serial correlation and heteroscedasticity.

Table 7: Liquidity around macroeconomic news announcements

1-min Interval	14:25-14:26	14:26-14:27	14:27-14:28	14:28-14:29	**14:29-14:30**	**14:30-14:31**	14:31-14:32	14:32-14:33	14:33-14:34	14:34-14:35	14:35-14:36
					CT (q=1)						
Dummy	$\bar{D}^j_{-4}$	$\bar{D}^j_{-3}$	$\bar{D}^j_{-2}$	$\bar{D}^j_{-1}$	$\bar{D}^j_{0}$	$\bar{D}^j_{+1}$	$\bar{D}^j_{+2}$	$\bar{D}^j_{+3}$	$\bar{D}^j_{+4}$	$\bar{D}^j_{+5}$	$\bar{D}^j_{+6}$
$j =$ DMM	0.02	-0.01	0.01	0.04	**0.49***	**-0.28***	**-0.12****	-0.06	0.03	0.00	-0.01
$j =$ OHFT	0.01	-0.02	0.00	0.02	**0.25***	-0.08	-0.08	0.00	0.01	0.00	-0.01
$j =$ NON HFT	0.00	-0.01	-0.01	0.08	0.03	0.08	-0.03	-0.05	0.00	-0.01	0.00
t-statistic	$\bar{t}^j_{-4}$	$\bar{t}^j_{-3}$	$\bar{t}^j_{-2}$	$\bar{t}^j_{-1}$	$\bar{t}^j_{0}$	$\bar{t}^j_{+1}$	$\bar{t}^j_{+2}$	$\bar{t}^j_{+3}$	$\bar{t}^j_{+4}$	$\bar{t}^j_{+5}$	$\bar{t}^j_{+6}$
$j =$ DMM	0.32	-0.18	0.19	0.70	7.69	-4.44	-1.90	-0.94	0.46	-0.07	-0.15
$j =$ OHFT	0.18	-0.29	-0.03	0.37	3.94	-1.32	-1.24	0.04	0.16	-0.04	-0.14
$j =$ NON HFT	0.00	-0.20	-0.12	1.26	0.50	1.26	-0.43	-0.75	0.05	-0.24	-0.05
					CT (q=200)						
Dummy	$\bar{D}^j_{-4}$	$\bar{D}^j_{-3}$	$\bar{D}^j_{-2}$	$\bar{D}^j_{-1}$	$\bar{D}^j_{0}$	$\bar{D}^j_{+1}$	$\bar{D}^j_{+2}$	$\bar{D}^j_{+3}$	$\bar{D}^j_{+4}$	$\bar{D}^j_{+5}$	$\bar{D}^j_{+6}$
$j =$ DMM	0.02	0.00	0.03	0.05	**0.40***	**-0.22***	**-0.13***	-0.08	0.03	0.00	-0.01
$j =$ OHFT	0.01	-0.01	0.00	0.03	**0.36***	**-0.17***	**-0.11****	0.00	0.01	0.00	-0.01
$j =$ NON HFT	0.01	-0.01	0.00	**0.20***	0.03	0.06	-0.01	**-0.16***	0.00	-0.01	0.00
t-statistic	$\bar{t}^j_{-4}$	$\bar{t}^j_{-3}$	$\bar{t}^j_{-2}$	$\bar{t}^j_{-1}$	$\bar{t}^j_{0}$	$\bar{t}^j_{+1}$	$\bar{t}^j_{+2}$	$\bar{t}^j_{+3}$	$\bar{t}^j_{+4}$	$\bar{t}^j_{+5}$	$\bar{t}^j_{+6}$
$j =$ DMM	0.28	-0.06	0.48	0.83	6.03	-3.33	-2.16	-1.28	0.41	-0.03	-0.18
$j =$ OHFT	0.16	-0.19	0.07	0.47	5.75	-2.73	-1.83	-0.06	0.08	-0.04	-0.17
$j =$ NON HFT	0.18	-0.18	-0.03	3.18	0.46	0.96	-0.24	-2.51	-0.03	-0.24	-0.02
					IM						
Dummy	$\bar{D}^j_{-4}$	$\bar{D}^j_{-3}$	$\bar{D}^j_{-2}$	$\bar{D}^j_{-1}$	$\bar{D}^j_{0}$	$\bar{D}^j_{+1}$	$\bar{D}^j_{+2}$	$\bar{D}^j_{+3}$	$\bar{D}^j_{+4}$	$\bar{D}^j_{+5}$	$\bar{D}^j_{+6}$
$j =$ DMM	**-0.18***	**-0.23***	**-0.22***	**-0.27***	**-0.29***	-0.08	-0.08	**0.22***	**0.15***	0.04	0.05
$j =$ OHFT	**-0.16***	**-0.20***	**-0.19***	**-0.21***	**-0.16***	0.08	-0.06	0.01	-0.06	-0.08	-0.06
$j =$ NON HFT	-0.08	-0.09	-0.08	-0.09	-0.06	0.01	-0.02	-0.01	-0.01	-0.02	-0.01
t-statistic	$\bar{t}^j{}_{-4}$	$\bar{t}^j{}_{-3}$	$\bar{t}^j{}_{-2}$	$\bar{t}^j{}_{-1}$	$\bar{t}^j{}_{0}$	$\bar{t}^j{}_{+1}$	$\bar{t}^j{}_{+2}$	$\bar{t}^j{}_{+3}$	$\bar{t}^j{}_{+4}$	$\bar{t}^j{}_{+5}$	$\bar{t}^j{}_{+6}$
$j =$ DMM	-2.87	-3.69	-3.52	-4.35	-4.54	-1.34	-1.31	3.45	2.43	0.63	0.81
$j =$ OHFT	-2.62	-3.22	-3.06	-3.29	-2.47	1.24	-0.98	0.23	-0.91	-1.29	-0.99
$j =$ NON HFT	-1.20	-1.38	-1.32	-1.37	-0.97	0.20	-0.37	-0.16	-0.14	-0.34	-0.18

Note: This table reports our results for the evolution of trader type liquidity, at the firm level, around the announcement of European and US macroeconomic news at 14:30 CET. We calculate liquidity every 1 minute and, subsequently, we use the full sample to estimate equation (5): $L^j_{i,t} = A_i + \mathrm{B}^j_{1,i}Vol_{i,t} + \mathrm{B}^j_{2,i}Vol_{i,t-1} + \mathrm{B}^j_{3,i}Vol_{i,t+1} + \Gamma^j_{1,i}MR_t + \Gamma^j_{2,i}MR_{t-1} + \Gamma^j_{3,i}MR_{t+1} + \omega^j_{i,t}$. In turn, we employ the filtered liquidity series, $\omega^j_{i,t}$, to estimate an extended version of equation (6), $\omega^j_{i,t} = b^0_{i,j} + b^1_{i,j}\omega^j_{M,t} + b^2_{i,j}\omega^j_{M,t-1} + b^3_{i,j}\omega^j_{M,t+1} + Dummies + \epsilon_{i,j,t}$, where we include 1-minute dummy variables, D_τ, with $\tau = \{-4, -3, \ldots, +5, +6\}$, from 14:25 CET to 14:36 CET (that is, around 14:30 CET). We report the across-stock average estimated coefficients for the dummy variables, together with the corresponding average t-statistics, for each trader type and each liquidity measure (CT or IM). Asterisks denote significance at the 5% probability level. Double asterisks denote significance at the 10% probability level. Standard errors are Newey-West adjusted for serial correlation and heteroskedasticity.

FIGURES

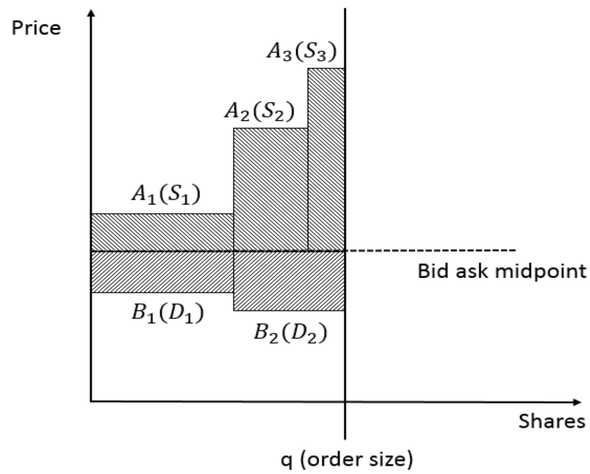
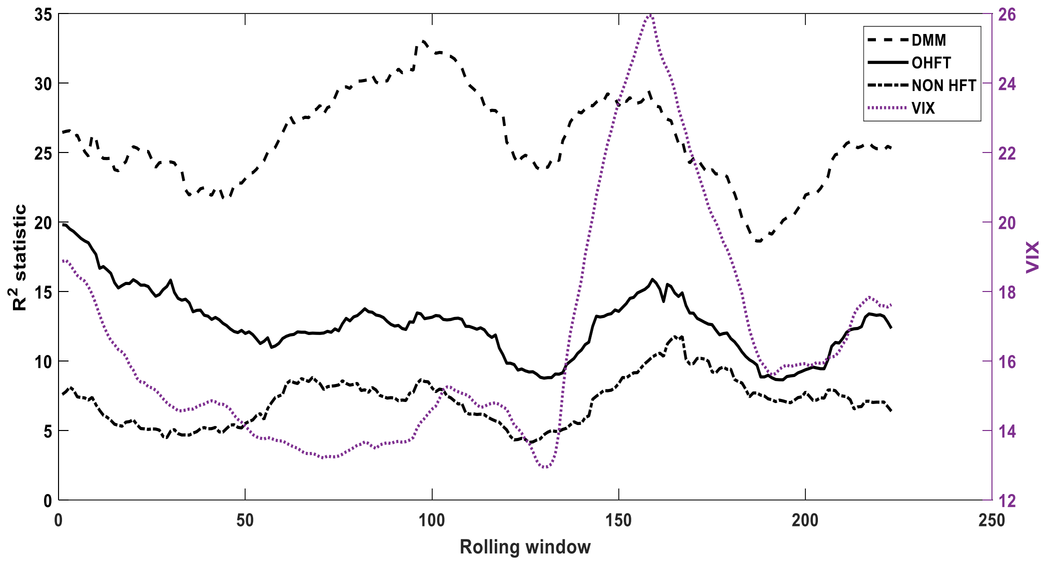


Figure 1: Calculation of (il)liquidity for a hypothetical order size of q shares and for a hypothetical order book state: A_1, A_2, and A_3 are the best three ask limits, and S_1, S_2, and S_3 are the corresponding quantities. Similarly, on the buy side, B_1 and B_2 are the two best bids, while D_1 and D_2 are the corresponding quantities. The shaded area between the supply-demand schedule represents the total round-trip cost for an order of q shares at time t, $l_t(q)$, which is represented by equation $l_t(q) = \int_0^q [S_t(Q) - D_t(Q)]dQ$ in integral form.

Cost of trade: *CT (q=1)*



Immediacy: *IM*

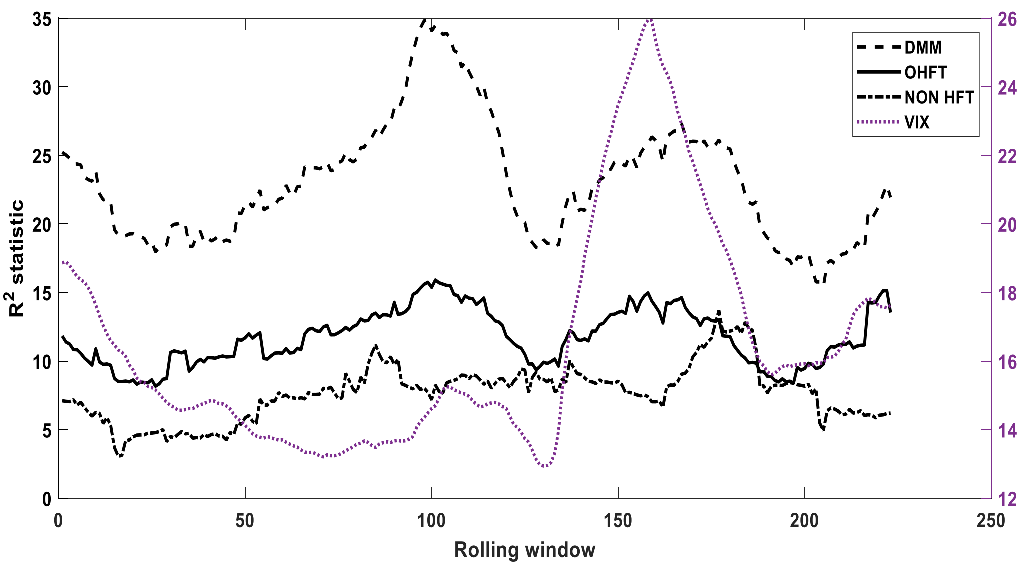


Figure 2: Dynamics of trader type liquidity co-movement and volatility through time. For rolling windows of 25 days, we estimate equation (6), $\omega_{i,t}^{j} = b_{i,j}^{1}\omega_{M,t}^{j} + b_{i,j}^{2}\omega_{M,t-1}^{j} + b_{i,j}^{3}\omega_{M,t+1}^{j} + \epsilon_{i,j,t}$, for each trader type and for each stock, to obtain the level of co-movement $R_{i,j,w}^{2}$. Rolling window volatility is calculated as the average CBOE VIX across the 25 days.

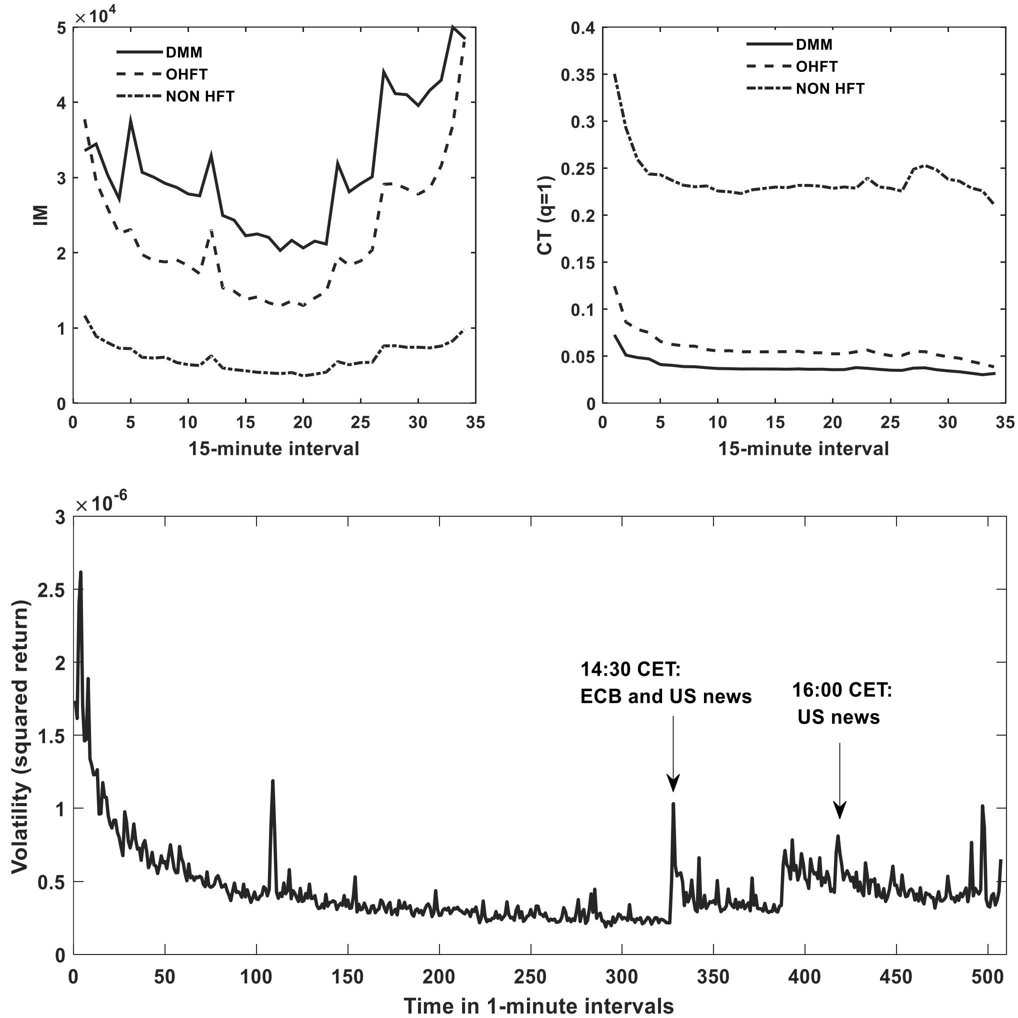
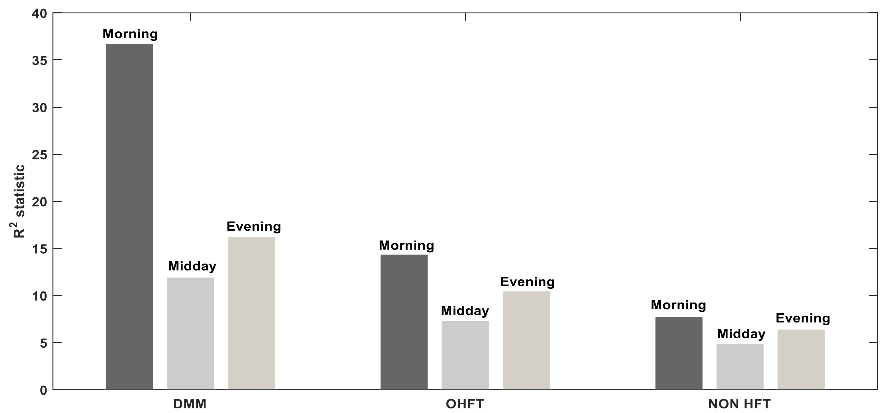
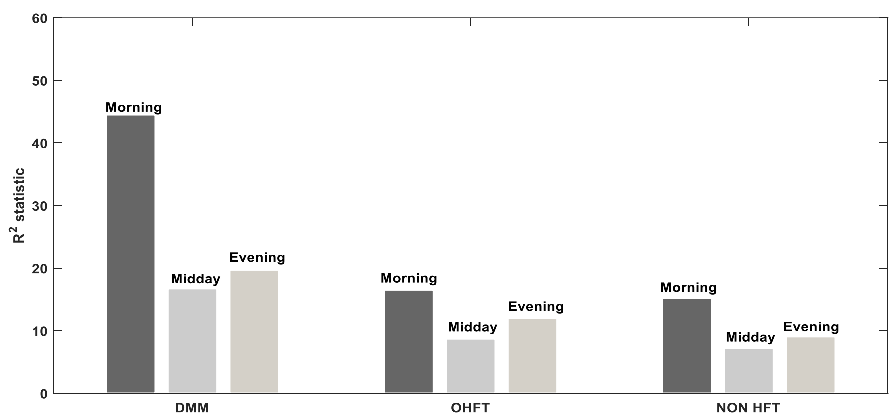


Figure 3: Top left graph: The across-stocks and days average immediacy, *IM*, in 15-minute intervals, for each trader type. Top right graph: The across-stocks and days average cost of trade, *CT (q=1)* in 15-minute intervals, for each trader type. Bottom graph: The across-stocks and days average volatility pattern in 1-minute frequency, in the form of squared 1-minute logarithmic returns. CET denotes Central European Time. ECB denotes Central European Bank.

Cost of trade: CT (q=1)



Cost of trade: CT (q=200)



Immediacy: *IM*

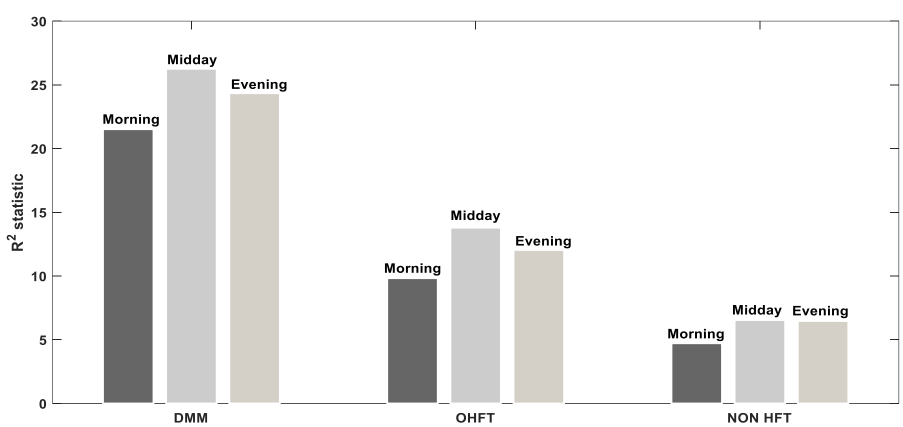
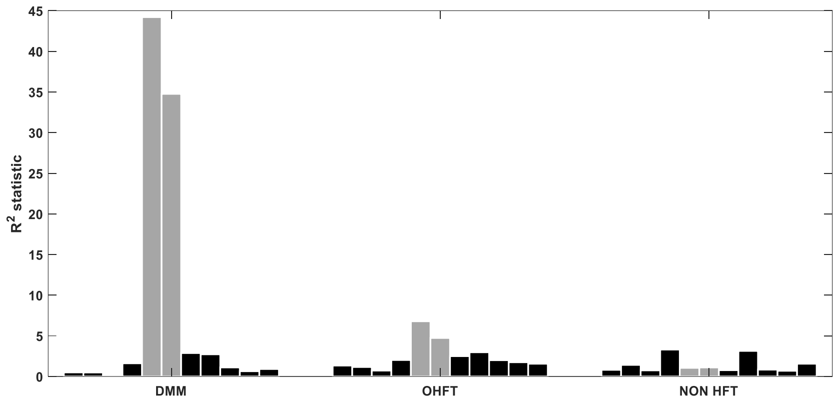
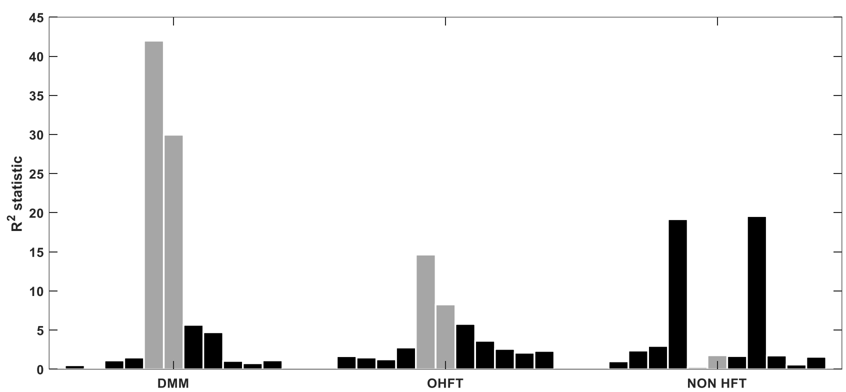


Figure 4: The across-stocks average $R^2_{i,j}$, obtained by estimating equation (6), $\omega^j_{i,t} = b^1_{i,j}\omega^j_{M,t} + b^2_{i,j}\omega^j_{M,t-1} + b^3_{i,j}\omega^j_{M,t+1} + \epsilon_{i,j,t}$, for each trader type and for three intraday sub-periods: the post-opening period, extending from 09:00 to 12:00, the midday period, from 12:00 to 14:45, and the pre-closing period from 14:45 to 17:30.

Cost of trade: CT (q=1)



Cost of trade: CT (q=200)



Immediacy: IM

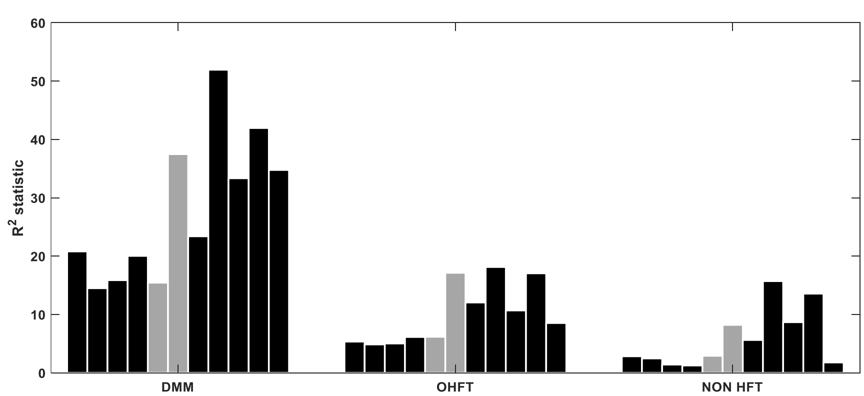


Figure 5: The across-stocks average $R^2_{i,j}$ obtained from the estimation of equation (6), $\omega^j_{i,t} = b^1_{i,j}\omega^j_{M,t} + b^2_{i,j}\omega^j_{M,t-1} + b^3_{i,j}\omega^j_{M,t+1} + \epsilon_{i,j,t}$, for each trader type and in 1-minute intervals around 14:30 CET. Results are reported for the two measures of liquidity, *CT* and *IM*. In each plot, the left grey bar corresponds to one minute before the announcement time, whereas the right grey bar corresponds to one minute after the announcement time.

Appendix A

Market making on the Euronext platform

In January 2011, Euronext Paris announced the introduction of a designated market making scheme ("Supplementary Liquidity Provision" or SLP), meant to enhance the provision of liquidity for specific baskets of blue chip stocks (including, for example, stocks from the Amsterdam Exchange and the CAC 40 Indices). The program was officially launched on April 1, 2011. According to the original market making scheme, the main obligations for SLPs are: a) to be present at least 95% of the time on both sides of the market during the continuous trading session, b) to be present at the best limits of the LOB for a minimum of 10% of total continuous trading session time, and c) to display a minimum volume of at least 5,000 Euros at the best limit (on average). Moreover, in compensation for providing liquidity to the market, SLPs are allowed to raise profits from transaction rebates that are fixed by market authorities. In May 2013, Euronext Paris announced a new round of applications for a revised version of the SLP program, inviting existing SLPs to renew their contracts, as well as recruiting new firms interested in participating in the market making process. In the revised version of the program, the percentage of minimum time presence at the best limits was increased from 10% to 25%, and a fourth rule was added: d) SLPs shall deliver a minimum passive execution level of 0.70% of the value of the executed volume, expressed in percentages of the aggregate monthly volume traded on Chi-X, BATs, Turquoise, and NYSE Euronext. This percentage was increased from 0.70% to 1% in December 2013. Further, the CAC 40 stocks were merged into a single basket (basket C), together with 20 other blue chip stocks, whereas smaller (i.e., midcap) stocks were included in a second basket (basket A). The revised SLP program started operating in June 2013.

On November 1, 2015, the SLP program was revised to include three different market making profiles. The first market making profile is the standard SLP profile, described above, with a 20-35% minimum time presence at the best limits, depending on the contract. The second and third profiles are based on the standard profile, but include additional requirements. Specifically, the second profile requires a market making ratio of at least 90% across the two baskets, and a minimum of 35% time presence at the best limits during the continuous session. The third profile includes a BBO (Best Bid Offer) setting counter fixed at 5%, together with an additional constraint imposing an average lifetime of 2 seconds for all canceled/replaced orders. It is worth noting that the rebates offered to market makers in the SLP program have been revised several times since it was launched in 2011.

In parallel with the SLP program, on January 2, 2015, Euronext Paris launched a second market making scheme to further enhance the liquidity provision process, the Market Making Program (MMP). The MMP concerns only registered members of Euronext markets who trade solely on their own account. It also includes a wide variety of securities, such as the Euronext 100 components and the LP Next 150 components. As in the SLP program, the MMP requirements focus on the minimum time presence on both sides of the book, which is set at 80%, and the minimum passive share volume, which depends on the securities for which the market maker is responsible (e.g., 5,000 Euros for the Euronext 100 components). However, the MMP members are obliged to maintain a maximum quoted spread of 2%, in contrast to SLPs, who have no maximum spread obligations. A second notable difference between the SLP and the MMP schemes is that the MMP does not offer rebates. However, for a member who actively participates in the MMP program, the Exchange considers his total MMP activity in the determination of his trading fees in the cash market (i.e., similar to a discount).[26]

It is important to stress that in our data sample, designated market makers (DMMs) are exclusively SLPs (see also the analysis in Megarbane et al. (2017) for year 2015). Therefore, DMMs are free from maximum spread restrictions, much like voluntary liquidity providers.

[26] Information on the details of the liquidity providing programs is retrieved from the following documents:
- Info flash 13 January 2011: Launch of the SLP program on European blue chips.
- Info flash 26 March 2012: Annual renewal of the SLP program on European blue chips.
- Info flash 9 May 2013: Call for applications for the revised SLP program.
- Info flash 1 October 2013: The maximum rebate for SLPs is reduced by 0.02bps to 0.20 bps.
- Info flash 2 December 2013: The minimum passive executed volume for SLPs is increased to 1.0% per basket.
- Info flash 31 October 2014: Revision of maker/taker fees for SLPs.
- Info flash 18 December 2014: Announcement of the MMP program that will be launched on January 2, 2015.
- Info flash 1 September 2015: Announcement of the termination of the SLP program on October 30, 2015.
- Info flash 16 October 2015: Announcement of the new SLP program that will start on November 1, 2015.
- Info flash 23 October 2015: Announcement of the rebates in the new SLP scheme.
The abovementioned documents are available on the NYSE Euronext Paris site, on the page Cash-Info Flash news: https://www.euronext.com/fr/membership/info-flashes

The CAC 40 sample

Table A1: The stock sample

Company name	*ISIN code*	*Shares*	*Trading Volume*	*Capitalization (Euros)*	*Capitalization (Euros) on 02/01/2015*
Credit Agricole	FR0000045072	2,614,015,740.1	7,253,113.1	32,179,328,647.3	28,082,386,937.0
SAFRAN	FR0000073272	417,029,585.0	1,187,796.6	27,024,469,380.3	21,289,360,314.0
Air Liquide	FR0000120073	344,372,956.7	950,001.2	39,132,905,650.5	34,956,260,921.0
Carrefour	FR0000120172	736,860,393.3	3,028,299.2	21,550,130,363.2	18,427,966,268.0
Total	FR0000120271	2,408,583,095.4	7,405,730.4	107,880,345,890.5	101,139,109,856.0
LOreal	FR0000120321	560,066,598.4	736,015.3	91,284,227,421.3	76,750,474,024.0
Accor	FR0000120404	233,125,442.6	1,149,155.6	10,462,977,234.1	8,580,318,982.9
Bouygues	FR0000120503	337,174,703.4	1,144,818.1	11,657,165,999.8	10,085,488,296.0
Sanofi	FR0000120578	1,313,980,317.7	3,202,467.7	115,781,819,701.8	100,107,021,686.0
Axa	FR0000120628	2,445,553,285.5	7,874,472.1	56,147,002,314.0	46,642,141,535.0
Danone	FR0000120644	651,083,803.9	1,784,504.2	39,505,389,736.4	34,674,637,120.0
Pernod Ricard	FR0000120693	265,421,592.0	563,973.6	27,755,041,828.4	24,177,252,815.0
Lvmh	FR0000121014	507,917,338.3	992,864.1	80,122,790,709.2	66,434,077,646.0
Michelin Nom.	FR0000121261	186,017,212.4	704,988.3	16,796,446,091.3	13,798,103,216.0
Kering	FR0000121485	126,262,610.1	348,524.0	20,972,659,766.6	19,912,754,263.0
Essilor Intl	FR0000121667	216,010,991.2	569,859.2	23,633,015,914.1	19,604,490,724.0
Schneider Electric	FR0000121972	586,002,513.4	2,077,114.3	36,544,401,082.7	35,042,511,032.0
Veolia Environn.	FR0000124141	562,335,282.0	2,382,231.7	10,763,676,172.5	8,257,401,947.7
Saint Gobain	FR0000125007	565,675,835.9	2,288,403.5	22,764,684,960.0	19,758,776,153.0
Cap Gemini	FR0000125338	168,392,927.1	718,881.9	13,188,217,528.1	9,835,208,093.9
Vinci	FR0000125486	595,543,297.5	1,865,040.3	33,014,792,098.9	26,800,901,356.0
Vivendi	FR0000127771	1,361,815,505.8	5,568,525.9	29,874,128,039.4	27,718,846,175.0
Publicis Groupe	FR0000130577	221,890,999.2	866,904.9	14,771,493,128.1	13,105,260,584.0
Societe Generale	FR0000130809	805,762,502.0	4,376,110.2	34,114,044,313.4	28,471,578,300.0
BNP Paribas	FR0000131104	1,246,061,221.8	4,263,113.8	67,410,498,828.3	61,580,723,485.0
Technip	FR0000131708	115,825,682.4	941,479.8	6,098,156,742.1	5,611,962,346.9
Renault	FR0000131906	295,722,284.0	1,296,214.3	24,867,112,222.4	17,713,764,812.0
Orange	FR0000133308	2,648,885,383.0	9,153,648.1	39,613,715,898.9	37,243,328,485.0
Engie	FR0010208488	2,435,285,011.0	6,347,321.6	42,178,513,187.7	47,025,353,562.0
Alstom	FR0010220475	309,983,344.8	1,298,851.1	8,696,642,885.0	8,323,201,770.6
Legrand	FR0010307819	265,976,503.8	698,700.3	13,405,312,620.4	11,507,795,869.0
Airbus Group	NL0000235190	786,797,085.4	2,770,421.8	46,316,736,124.9	32,585,990,902.0
Valeo	FR0000130338	79,462,540.0	436,004.0	10,559,820,738.9	8,212,453,509.0

Table A1 (continued)

Securities listed constantly on CAC 40 during 2015 but not negotiated directly on the Euronext platform		
Company name	*ISIN code*	*Platform of negotiation*
Solvay	BE0003470755	Belgium
Uniball-Rodamco	FR0000124711	the Netherlands
ArcelorMittal Reg	LU0323134006	Luxembourg

Securities not listed constantly on CAC 40 during 2015		
Company name	*ISIN code*	*Number of days listed on CAC 40 during 2015*
LafargeHolcim Ltd	CH0012214059	122
Lafarge	FR0000120537	131
Peugeot	FR0000121501	199
Klepierre	FR0000121964	8
Alcatel-lucent	FR0000130007	250
Electricite de France	FR0010242511	248
Lafarge	FR0012750396	5
Alcatel-lucent	FR0013046646	7
Gemalto	NL0000400653	57

Note: The final sample of 33 stocks from the CAC 40. Reported are the daily average number of company shares, trading volume (in shares), and market capitalization for the period: 01/01/2015 to 31/12/2015 (256 trading days). The last column reports the market capitalization for each company on the starting day of the intraday sample period examined in this analysis (02/01/2015). Securities that are constantly listed on CAC 40 during 2015, but are not negotiated on the Paris platform (and thus LOB data are not available), as well as securities that are not listed on CAC 40 during all of 2015, are also reported. These securities are excluded from the analysis.

THE AMF-BEDOFIH Euronext Paris database structure

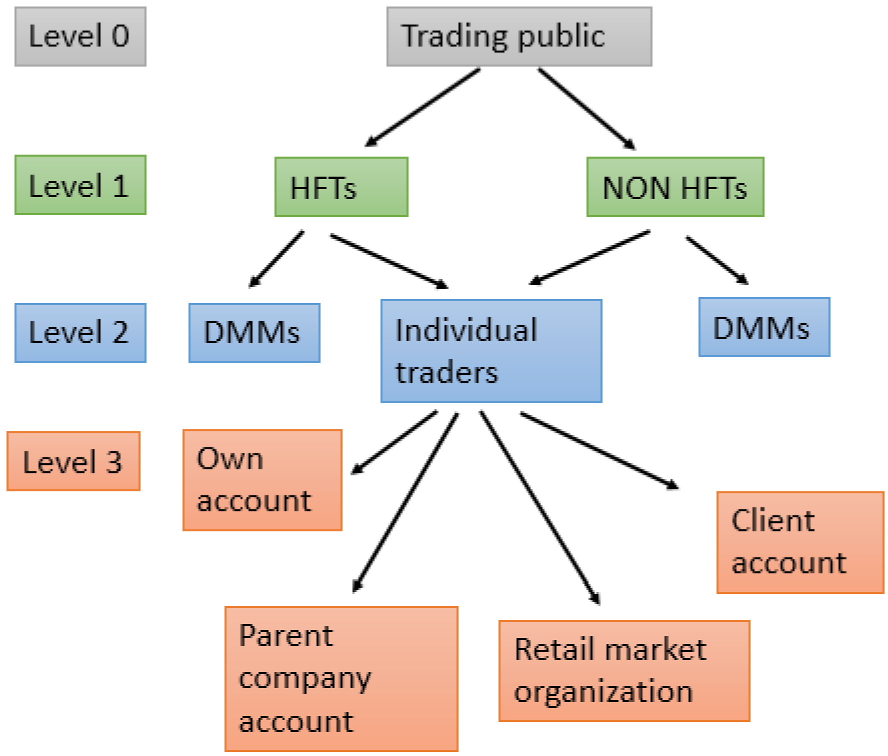


Figure A1: The AMF-BEDOFIH Euronext Paris database structure. The Level 2 classification, employed here, is based on the HFT and DMM flags.