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The impact of high frequency trading on market integrity: an empirical examination

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Contents

The impact of high frequency trading on market integrity: an empirical examination

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Abstract

This report empirically examines the relation between the increased incidence of High Frequency Trading (HFT) and metrics that proxy for market manipulation. Results suggest that there is a substantial increase in the level of electronic message traffic relative to trades, and thus HFT, on both the LSE and Euronext Paris over the 2006 – 2011 sample periods. Correlation estimates for variables that proxy for HFT and market manipulation metrics show a positive and statistically significant relation between HFT and Ticking, and a negative and statistically significant relation between HFT and Dislocation Price Alerts. Regression analysis reveals that the proxy for HFT is a statistically significant determinant of dislocation price alerts, but is not a significant determinant of ticking alerts, when controlling for on-market volume, daily volatility and daily returns, for both the LSE and Euronext Paris 2006 – 2011 sample periods.

1. Introduction

This report empirically examines the relation between the increased incidence of High Frequency Trading (HFT) and metrics that proxy for market abuse, particularly market manipulation. Algorithmic trading is commonly identified as the use of computer algorithms to automatically generate trading decisions through limit and market order submission, and manage such orders after submission (Hendershott, Jones, and Menkveld, 2011). Algorithmic traders (AT) are becoming an increasingly significant market participant, whose growing prevalence can be attributed to the increasing speed at which they can process signals and interact with the market. Despite a strong level of interest, there still remains a dearth of empirical research that directly examines the impact of Algorithmic trading on aspects of market quality; specifically integrity.

Recently, the CESR issued an open questionnaire to market participants on microstructural issues in European equity markets. For the MiFID regulatory review, the CESR noted that several technology-driven developments had intensified AT and HFT, and revealed their intention to assess those developments and the “potential effects on overall equity market structure and the efficiency of those markets in the EU” (CESR, 2010a). Respondents raised concerns that HFT activity might impose certain risks (CESR, 2010b), such as “increased bandwidth usage; order entry/deletion and rogue algorithms; increased market abuse with detection becoming more difficult in a fragmented and highly automated environment; sudden liquidity withdrawal; and potential de-correlation of prices from market fundamentals if trading strategies focused solely on short-term profits.”

In the Swinburne Report (European Parliament, 2010), the Committee on Economic and Monetary Affairs explores regulation of trading in financial instruments with respect to HFT. The Committee discusses several market microstructure issues, and motivated by the HFT Flash Crash (Easley, Lopez de Prado, and O’Hara, 2011), urges further investigation on costs and benefits of HFT, particularly on whether HFT provides real liquidity to markets, and whether there is potential for market abuse through manipulation.

As the source of an individual order or trade cannot be observed, this report uses a proxy similar to that used in Hendershott, Jones and Menkveld (2011) to examine the relation between HFT and market manipulation. Due to transaction cost and latency considerations, HFT servers do not rely on human intermediaries, but instead generate orders that are electronically routed to a specific trading venue. It can be inferred that the rate of electronic message traffic in an electronic limit order market directly relates to the level of HFT. Therefore, using a proxy for HFT based on a ratio between electronic messages entered into the limit order book and executed trades, this study examines the association between the increased incidence of HFT and identified periods of market manipulation. Sample periods from the LSE and Euronext Paris over a six-year period from 1 January, 2006 to 31 December, 2011, are examined.

Preliminary results suggest that there is a substantial increase in the level of electronic message traffic relative to trades, and thus HFT, on both the LSE and Euronext Paris over the 2006 – 2011 sample periods. Pearson Correlation Coefficient estimates for variables that proxy for HFT and market manipulation metrics show a positive and statistically significant relation between HFT and Ticking, and a negative and statistically significant relation between HFT and Dislocation Price Alerts. Further, regression analysis reveals that the proxy for HFT is a statistically significant determinant of dislocation price alerts, but is not a significant determinant of ticking alerts, when controlling for on-market volume, daily volatility and daily returns, for both the LSE and Euronext Paris samples.

2. Literature review

The existing literature that directly addresses AT and HFT is a small, but rapidly growing field, stimulated by the endogenous increase in AT and HFT, the availability of quality data, and the desire by several market participants to understand the role that AT and HFT plays in current market microstructure. HFT and AT are not synonymous despite sharing similar characteristics, and HFT is often viewed as a subset of AT (see Brogaard, 2010), where trading decisions are normally pre-designed and submissions are automated and executed without human intervention. AT is fundamentally employed in agency trading to achieve particular outcomes such as stealthily capturing liquidity, engaging in block trading in a manner that minimises information leakage, or simply minimising implementation shortfall.[1] HFT, as a subset of AT, is characterised by rapid order submissions and cancellations that normally are facilitated by exchanges offering co-location services. Further, Cvitanic and Kirilenk (2010) characterise HFT as not holding overnight positions, such that HFT realise profits from small deviations in prices across hundreds, if not thousands, of transactions throughout the day.

HFT can be likened to AT in the sense that it is characterised by a broad range of active strategies employed by a diverse group of trading participants. These participants range from proprietary market-making firms to quantitative hedge funds. Their practices include a range of activities such as pseudo market-making and statistical arbitrage. Though many of these trading approaches derive from strategies that have always existed in markets, the speed with which they are able to be employed, as well as their reduced costs, are the predominant

[1] For a comprehensive list of definitions see Gomber, Arndt, Lutat and Uhle (2011).

differences.2 With these changes delivering significant competitive advantages to HFT participants, the dramatic growth in HFT over such a short-time horizon is significant.

Much of the existing literature examines the impact of AT on various measures of market quality. Due to the challenge of identifying AT, much of the extant research uses institutional data that contain a unique identifier, or proxies for AT or HFT. Cvitanic and Kirilenk (2010) offer one of the first theoretical models to directly address the impact of HFT on market quality; they simulate an electronic model populated by low latency (Human Traders), and then add an uninformed HFT. They find that the presence of the HFT lowers volatility and increases liquidity based on trading volume and inter-trade duration. Further, Jovanovic and Menkveld (2010) develop a theoretical model and provide empirical analysis that suggests that AT are better informed about recent news events than the average trader, and that their reaction time is faster and they trade in the correct direction.

Much of the empirical academic literature addresses these theoretical notions. For instance, Groth (2011) investigates the relationship between AT and volatility by examining all order book events on the Xetra trading platform from October 8, 2007 to October 12, 2007. Results show that AT participation does not significantly increase volatility levels, and does not reduce liquidity during periods of high volatility. Groth (2011) conveys that AT follow trading strategies that are as diverse as human strategies. In addition, Groth does not find evidence that AT demand more liquidity than humans.

Domowitz and Yegerman (2005) examine the execution costs of ITG buy-side clients with respect to different AT providers. They suggest AT is less expensive than the alternative human execution means, based on a measure of implementation shortfall. This finding is robust “considering trade difficulty, differences in markets, side of trade, and volatility”. The superiority of AT performance applies only for order sizes up to 10% of average daily volume, suggesting that for the 2004 sample, algorithms may not yet be sophisticated enough for large orders.

Hendershott, Jones, and Menkveld (2011) examine the impact of AT on liquidity for NYSE stocks over the sample period December 2, 2002 to July 31, 2003. The study documents the first empirical analysis that develops a proxy for AT, based on scaled electronic messages on the limit order book. The study finds that quoted and effective spreads narrow with increased AT activity. Further, the study also finds support for the proposition in Chaboud, Chiquoine, Hjalmarsson, and Vega (2009) and Chordia, Roll, and Subrahmanyam (2011) that AT is one of the key drivers of smaller average trade sizes.

Hendershott and Riordan (2011) analyse the impact of AT on the Deutsche Bourse over a 13-day trading period from January 1, 2008 to January 18, 2008. Their results suggest that AT contribute 52% of trading volume via marketable orders, and that effective spreads are smaller than quoted spreads. Market participants seldom submit marketable orders for depth levels greater than the best bid or ask prices. AT are present in 68% of trades with traded volume less than 500 shares, and 23% of trades with traded volume greater than 1,000 shares. This leads the authors to infer that AT use small trades to hide market sensitive information.

[2] While the nature of trading strategies employed has not significantly changed over time, the mix of participants organising and executing HFT strategies has fundamentally changed over this period.

Hasbrouck and Saar (2010) observe electronic order book “strategic runs” as a proxy variable for HFT. “Runs” consist of linked order book submissions, cancellations and executions over 10-minute intervals throughout the trading day for NASDAQ stocks between October 2007 and June 2008. They find that low latency trading decreases short-term volatility and increases depth over the sample period. During periods of high volatility, HFT reduces volatility in smaller stocks more than in larger stocks.

Brogaard (2010) examines the market impact of 26 HFT firms who cover 120 NASDAQ stocks. Given the study’s backdrop of the Global Financial Crisis from 2007 to 2008, results illustrate that HFT provide liquidity in short-term periods of high volatility, but that this effect lessens as the time horizon increases. The results in Menkveld (2011) are consistent with those from Brogaard (2010); HFT is most concentrated in market positions that execute within short time horizons. The author notes that the search for low transaction fees encourages HFT to actively search for low-cost trading platforms. These cost efficiencies may then be passed on to investors in the form of reduced bid-ask spreads. The demand for minimal transaction costs and quick execution are therefore posited by the study as key drivers in the push for market fragmentation.

3. Data and descriptive statistics

This study uses data from the LSE and Euronext Paris over the six-year period from 1 January, 2006 to 31 December, 2011. The sample contains all common stocks that can be matched in both the Trades and Quotes (TAQ) database, sourced from Reuters DataScope Tick History, provided by SIRCA. The fields contain, for each stock and date, (i) the number of order updates, (ii) the number of trades, and for each date; (iii) a ticking the market metric, (iv) dislocation of end of day price metric for the entire sample. The time series data set contains 1,480 (1,535) daily observations for the LSE (Euronext Paris) sample.

Table 1 presents descriptive statistics for the key HFT and market manipulation fields for both the LSE and Euronext Paris sample periods. The average daily HFT proxy is 15.41 for the LSE sample, and higher at 21.34 for the Euronext Paris sample (with an accompanying higher variance and range). The average daily ticking is 308.4 for the LSE, and higher for Euronext Paris at 994.5. End of Day Dislocation Price Alerts are qualitatively similar across both samples, with averages of 1.174 and 1.716 for the LSE and Euronext Paris samples, respectively.

Table 1. Descriptive statistics.

This table presents descriptive statistics for the LSE (Panel A) and Euronext Paris (Panel B) sample period (1/1/2006 – 31/12/2011) for all listed stocks for the HFT Proxy, Ticking, and End of Day Dislocation Price Alerts. For each of these variables, N denotes the number of average daily observations, Mean denotes the average daily value, Std Dev denotes the Standard Deviation of the daily value, as well as Minimum and Maximum average daily values.

		N	Mean	Std Dev	Minimum	Maximum
Panel A: LSE Sample						
HFT Proxy		1,480	15.41	9.530	4.201	59.32
Ticking		1,480	308.4	210.4	26	2,392
Dislocation Price Alert		1,480	1.174	2.025	0	23
Panel B: Euronext Paris Sample						
HFT Proxy		1,535	21.34	15.27	2.924	115.3
Ticking		1,535	994.5	849.7	95	14,775
Dislocation Price Alert		1,535	1.716	2.031	0	23

Figures 1 and 2 present the trend in the HFT proxy for the LSE and Euronext Paris, respectively, over the 2006-2011 sample periods. There is a marked increase in the daily average of the ratio of orders to trades (HFT proxy) from 2006 to the end of 2011 in both samples, while trends are relatively similar with spikes in 2010 – 2011, a decline into 2011, and then further increases for the remainder of the 2011 sample period. The ratios are consistently larger in magnitude for the Euronext Paris sample.

Figure 1. HFT Proxy – LSE.

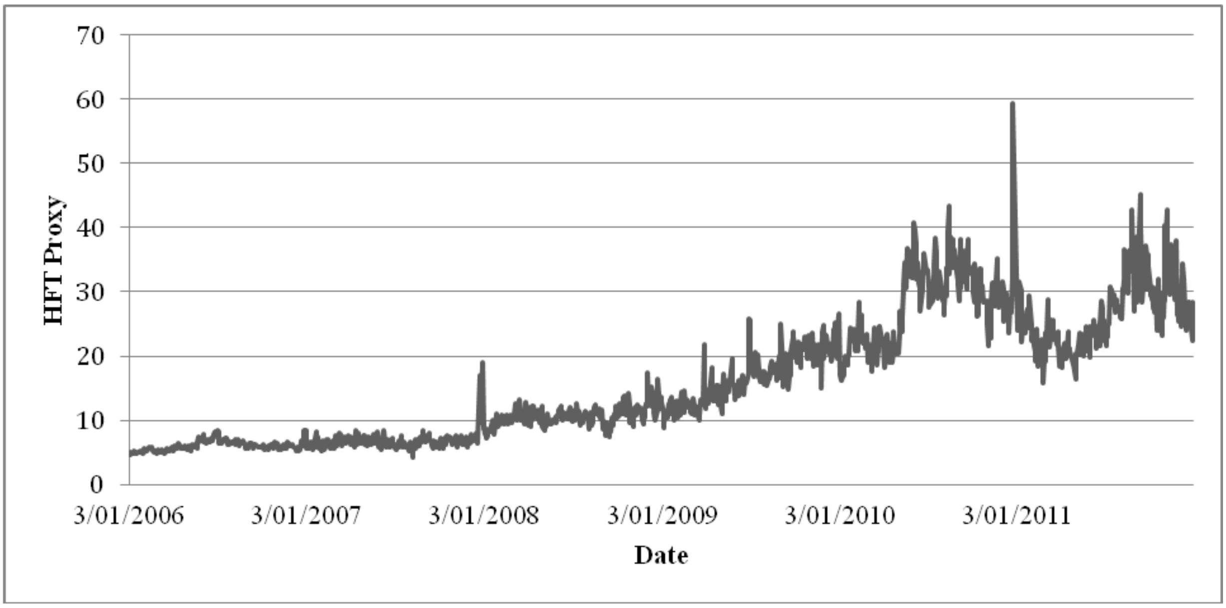
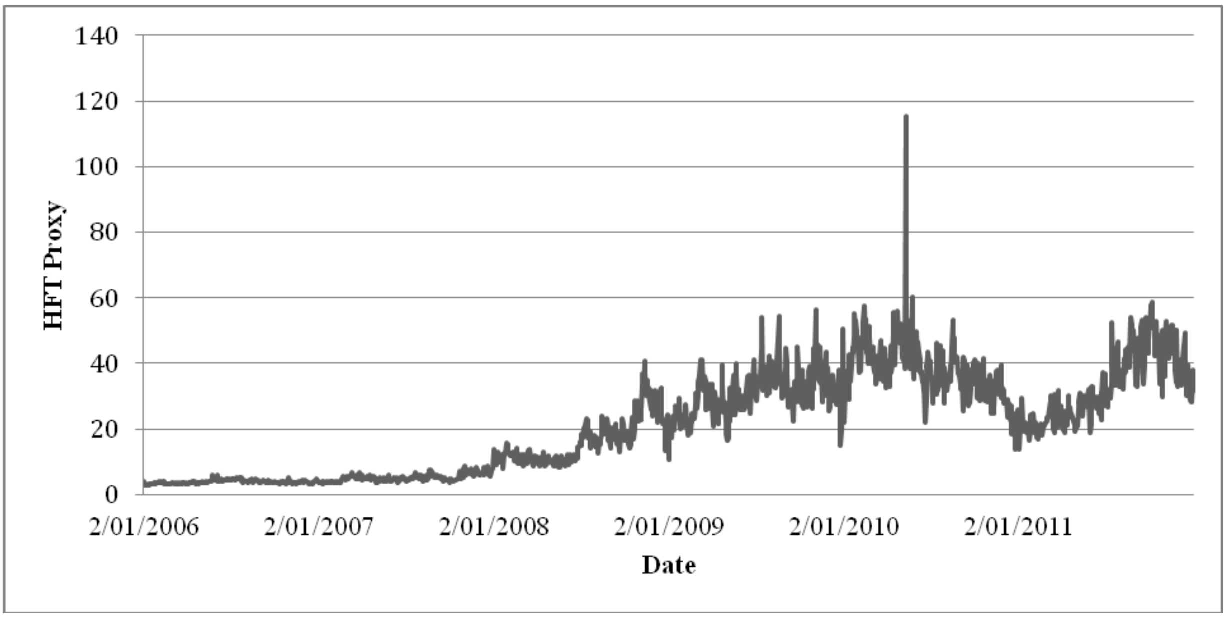


Figure 2. HFT Proxy – Euronext Paris.



4. Research method

It can be inferred that the rate of electronic message traffic is a proxy for the amount of HFT. This proxy is commonly used by market participants, including consultants Tabb Group, as well as exchanges and other market venues (Hendershott, Jones, and Menkveld, 2011). Generally, electronic message traffic includes order submissions, cancellations, and trade reports. Therefore using a proxy for HFT based on a ratio between electronic messages on the limit order book and executed trades, this study examines the association between any increased incidence of HFT and identified periods of market manipulation. The proxies for market manipulation include End of Day Dislocation Price Alerts and Ticking.

Dislocating the end-of-day price (Ni, Pearson, and Poteshman, 2005) involves influencing closing prices such that they do not represent the true forces of supply and demand. The determination of closing prices is important as these are the values used as inputs by investors and derivatives contracts. Price manipulation can be achieved through the release of misleading information or through trading strategies which deliberately cause order imbalances. Dislocation of the end-of-day price is generally characterised by attempts towards the end of a trading period to move a stock price away from its fair value through aggressive trading. Potential motivations for manipulating end-of-day prices include:

- To modify the value of managed funds. Fund managers may dislocate the closing price in an attempt to alter the appearance of their performance and increase their ranking relative to competitors. This may be particularly associated with end-of-month or end-of-quarter reporting periods;
- To profit from derivatives positions in the underlying stock;
- To obtain a favourable price in pre-arranged off-market trades;
- To alter their customers' inference of broker execution ability;
- To maintain a stock's listing on an exchange with minimum price requirements;
- To gain inclusion in an index near stock index rebalancing days and;
- To avoid margin calls

However, not all abnormal closing prices are the result of deceitful trading strategies. Some reasons why stock prices may naturally close at unusual levels include:

- Announcements or changes in underlying instruments near the close, or during the closing auction, may cause large price movements;
- Brokers with a mandate to sell certain quantities of stock may be forced to become aggressive to liquidate before the end of the trading day;
- Some market participants may not like to hold inventory overnight and are obliged to liquidate at the close, irrespective of price;

- Participants who enter large market orders at the closing auction may unwittingly cause large price movements if they are not mindful of the indicative closing price, or the amount of depth available, on the opposite side of the book.

In this report, attempts to mark the close are measured as abnormally large end-of-day price changes which exceed pre-determined stock-specific thresholds. For each stock and trading day, the price change of the last 15 minutes of trading is compared to a distribution of historical price changes occurring during the previous 30 trading days.

$$\Delta EOD_i = \frac{P_{eod,i} - P_{eod-15m,i}}{P_{eod-15m,i}} \quad (1)$$

$$\overline{\Delta EOD_i} = \frac{1}{30} \sum_{t=-31}^{t=-1} \Delta EOD_i \quad (2)$$

Where ΔEOD is the return between the closing price and the price 15-minutes prior to the close, $\overline{\Delta EOD}$ is the average return over a rolling window of 30 trading days prior to the day being analysed, and σ_i is the standard deviation of ΔEOD_i over the same period. Manipulative behaviour is suspected when an end-of-day price change exceeds 3 standard deviations (above or below) from the mean of the distribution of prior observations.

$$\textit{Potential Positive Manipulation if } R_i > \overline{\Delta EOD_i} + 3 * \sigma_i \quad (3)$$

$$\textit{Potential Negative Manipulation if } R_i < \overline{\Delta EOD_i} - 3 * \sigma_i \quad (4)$$

End-of-day prices that are not the result of the genuine forces of supply and demand are likely to exhibit next-day price reversion. Instances of abnormal end-of-day price changes which are followed by a price reversion of 50% or more on the open of the next trading day are considered successful attempts at marking the close. These are referred to as instances of “End of Day Price Dislocation” (“Dislocation Price Alert”).

Ticking refers to the change in price of a security from trade to trade initiated by a one-lot order, such that the price of the stock changes from the previous trade’s price. The ticking manipulation metric is a proxy for intraday price manipulation; specifically a price movement that is linked to the trading activities of one specific trader. Ticking is calculated as a simple count of the instances where a one-lot order executes leading to a change in price; further, it has the potential to proxy for intraday manipulation motivated by short-term price movements. Given that HFT is synonymous with high-frequency low-volume trades through both limit and market orders, ticking provides an interesting and novel proxy that examines the link between HFT and intraday price manipulation.

Given that the research method examines the relation between HFT and Market Manipulation via proxies, consideration needs to be given to the fact that the individual measures that proxy for HFT, and End of Day and Intraday Market manipulation are proxies. Proxies for manipulation may capture the impact of other factors such as volatility and intraday price movements; as such, regressions are used to control for such external factors.

The research approach involves two stages. Using a Pearson Correlation Coefficient matrix, the relation between the HFT Proxy and the proxies for market manipulation are examined. Further, regression models are developed that examine the relation between various proxies for suspected market abuse through time, and the proxy for HFT. Regressions are also estimated that control for endogenous increases in trading volume and volatility. The natural logarithmic difference is taken for each of the regression variables to control for non-stationarity.

The time-series regressions for Dislocation Price Alert and Ticking on the respective LSE and Euronext Paris HFT Proxies, controlling for on-market trading volume, are specified as follows:

$$MA_{i,t} = \alpha_0 + \beta_1 HFT_{i,t} + \beta_2 MKT_{i,t} + \varepsilon_{i,t} \quad (5)$$

where $MA_{i,t}$ represents either the Dislocation Price Alert or Ticking metrics in sample period *i* at time-interval *t*, $HFT_{i,t}$ represents the HFT Proxy, and $MKT_{i,t}$ represents on-market volume in each of *i* sample periods. On-market volume represents the total number of shares traded on-market for each of the specific exchanges.

The regression is constructed across each of the samples such that the relation between either Dislocation Price Alert or Ticking and HFT can be examined using both the LSE and Euronext Paris sample periods. The t-statistics for each of the HFT and volume coefficients, and predictive R^2 values, are used to examine the relation between the variables across each of the samples.

The time-series regressions of either Dislocation Price Alert or Ticking on the respective LSE and Euronext Paris HFT Proxies, controlling for on-market trading volume, intraday volatility, and returns, are specified as follows:

$$MA_{i,t} = \alpha_0 + \beta_1 HFT_{i,t} + \beta_2 MKT_{i,t} + \beta_3 VOL_{i,t} + \beta_4 r_{i,t} + \varepsilon_{i,t} \quad (6)$$

where $MA_{i,t}$ represents either the Dislocation Price Alert or Ticking metrics in sample period *i* at time-interval *t*, $HFT_{i,t}$ represents the HFT Proxy, $MKT_{i,t}$ represents on-market volume, $VOL_{i,t}$ represents daily volatility, and $r_{i,t}$ represents daily return in each of *i* sample periods. Daily volatility is calculated as the sample indexes' high divided by low, while daily return is calculated as the sample indexes' closing price divided by the open.

The regression is constructed across each of the samples such that the relation between either Dislocation Price Alert or Ticking and HFT can be examined for both the LSE and Euronext Paris sample periods, after controlling for on-market volume, daily volatility, and daily returns. The t-statistics for each of the coefficients, and predictive R^2 values, are used to examine the relation between the variables across each of the samples.

5. Results

Tables 2 and 3 report Pearson Correlation Coefficients and accompanying p-values that test the Null Hypothesis of no correlation between the two respective variables for the LSE and Euronext sample periods, respectively. Table 2 shows a positive and statistically significant correlation between the HFT proxy and Ticking for the LSE, with a coefficient of 0.3025. Results suggest a statistically significant negative relation between the HFT proxy and the Dislocation Price Alert, with a coefficient of -0.4097. Table 3 shows a positive and statistically significant correlation between the HFT proxy and Ticking for Euronext Paris, with a coefficient of 0.3522. Results suggest a statistically significant negative relation between the HFT proxy and the Dislocation Price Alert, with a coefficient of -0.1945.

When comparing results in Tables 2 and 3 for the LSE and Euronext Paris samples, correlations are similar in sign, but differ in magnitude. The correlation between the HFT proxy is greater for the LSE sample compared to the Euronext Paris sample – while the correlation coefficients are considerably lower when considering the relation between the HFT proxy and the Dislocation Price Alert. The significant relation between the HFT and market manipulation proxies motivates further examination through regression analysis, controlling for various endogenous factors.

Table 2. Pearson correlation coefficients – LSE.

This table presents Pearson correlation coefficients, and accompanying p-values, that test the null hypothesis of no correlation between variables; HFT Proxy, Ticking, and Dislocation Price Alert. Pearson correlation coefficients measure the strength of the association between the two variables, ranging between -1 and +1. The sample period is 1 January, 2006 to 31 December, 2011 (1,480 trading days) for all stocks traded on the LSE.

**** indicates 0.05 level of significance, * indicates 0.01 level of significance.**

Pearson Correlation Coefficients, N = 1,480 Prob > |r| under H_0: Rho=0				
		HFT Proxy	Ticking	Dislocation Price Alert
HFT Proxy		1		
Ticking		0.3025*	1	
Dislocation Price Alert		-0.4097*	-0.2637*	1

Table 3. Pearson correlation coefficients – Euronext Paris.

This table presents Pearson correlation coefficients, and accompanying p-values, that test the null hypothesis of no correlation between variables; HFT Proxy, Ticking, and Dislocation Price Alert. Pearson correlation coefficients measure the strength of the association between the two variables, ranging between -1 and +1. The sample period is 1 January, 2006 to 31 December, 2011 (1,535 trading days) for all stocks traded on Euronext Paris. ** indicates 0.05 level of significance, * indicates 0.01 level of significance.

Pearson Correlation Coefficients, N = 1,535 **Prob > $\vert r \vert$ under H_0: Rho=0**				
		HFT Proxy	Ticking	Dislocation Price Alert
HFT Proxy		1		
Ticking		0.3522*	1	
Dislocation Price Alert		-0.1945*	0.0811*	1

Due to the significant level of correlation and the apparent trending in Figures 1 and 2, Table 4 examines Augmented Dicky-Fuller (ADF) and Phillips-Perron (PP) Tests of Stationarity for HFT and market manipulation proxies. Results for both tests suggest that the natural logarithm of HFT Proxy, Ticking, Dislocation Price Alert, Daily Volume, Intraday Return and Intraday Volatility are non-stationary. Given that the time series variables are non-stationary, they are converted into stationary returns by taking first log differences for all further regression analyses.

Table 4. Tests of stationarity: LSE and Euronext Paris.

This table presents tests of stationarity for LSE and Euronext Sample periods, presented in Panels A and B, respectively. ADF refers to the Augmented Dickey–Fuller test (Dickey and Fuller, 1979) and PP to the Phillips-Peron test (Phillips and Perron, 1988). The null hypothesis of the presence of a *unit root* is tested for the natural logarithm of HFT Proxy, Ticking, Dislocation Price Alert, Daily Volume, Daily Return and Daily Volatility.

*** indicates 0.05 level of significance, ** indicates 0.01 level of significance.**

		HFT Proxy	Ticking	Dislocation Price Alert	Daily Volume	Daily Return	Daily Volatility
Panel A: Tests of Stationarity for LSE Sample							
ADF		-8.139**	-10.99**	-19.42**	-15.20**	-27.30**	-11.04**
PP		-10.33**	-16.02**	-28.71**	-21.20**	-41.10**	-16.82**
Panel B: Tests of Stationarity for Euronext Sample							
ADF		-5.222**	-9.021**	-22.20**	-14.20**	-28.50**	-12.46**
PP		-6.383**	-12.89**	-31.95**	-18.29**	-42.62**	-17.64**

Table 5 presents results for regressions of the Dislocation Price Alert and Ticking proxies against the HFT Proxy, controlling for on-market trading volume. The sample consists of all on-market trades executed each day on the LSE (Panel A) and Euronext Paris (Panel B) during the sample period. *t*-statistics and Adjusted R-Squared values are reported to measure the statistical significance of the relation between the market manipulation and HFT Proxies.

Results in Panel A for the LSE suggest that the HFT proxy has a negative and statistically significant effect on dislocation price alerts, with a coefficient of -0.1606; this suggests that an increase in HFT is associated with lower dislocation price alerts. Further, greater trading volume, represented by on-market volume, has a positive and statistically significant effect on the dislocation price alerts, suggesting that an increase in trading volume is associated with heightened dislocation price alerts. The adjusted R-Squared of the regression is 0.2079.

Results for the second regression in Panel A, using Ticking as the dependent variable, shows that the HFT proxy coefficient is negative, and *not* a statistically significant determinant of Ticking. Further, greater trading volume, represented by on-market volume, has a positive and statistically significant relation with ticking, suggesting that an increase in trading volume is associated with heightened levels of ticking.

Results in Panel B for the Euronext Paris sample suggests that the HFT proxy has a negative and statistically significant effect on dislocation price alerts, with a coefficient of -0.1184; an increase in HFT is associated with lower dislocation price alerts. Further, greater trading volume, represented by on-market volume, has a positive and statistically significant effect on dislocation price alerts, suggesting that an increase in trading volume is associated with heightened dislocation price alerts. The adjusted R-squared of the regression is 0.1527.

Further, results for the second regression in Panel B, using Ticking as the dependent variable, suggest that the HFT proxy has an insignificant effect on ticking alerts; an increase in HFT is *not* associated with an increase in ticking. Further, greater trading volume, represented by on-market volume, has a positive and statistically significant effect on ticking, suggesting that an increase in trading volume is associated with heightened levels of ticking.

Table 5. Regressions LSE and Euronext Paris: dislocation price alert and ticking.

This table presents results for regressions of Dislocation Price Alert and Ticking separately on HFT Proxy. The sample period describes trading spanning 1 January, 2006 to 31 December, 2011, and consists of all on-market trades executed every day on the LSE (Panel A) and Euronext Paris (Panel B). *t*-statistics and Adjusted R^2 values are reported to measure the statistical significance of the relation between HFT Proxy and either Dislocation Price Alert or Ticking, controlling for exogenous changes in On-Market Volume. ** indicates 0.05 level of significance, * indicates 0.01 level of significance.

	Dislocation Price Alert	Ticking
Panel A: LSE		
Intercept	0.0003	0.0030**
HFT Proxy	-0.1606**	-0.0010
On-Market Volume	0.4934**	0.0035**
Adj R-Sq	0.2097	0.0285
Panel B: Euronext Paris		
Intercept	0.0003	0.0033**
HFT Proxy	-0.1184**	-0.0009
On-Market Volume	0.6106**	-0.0002
Adj R-Sq	0.1527	0.0001

Table 6 presents results for regressions of Dislocation Price Alert, controlling for volume, volatility and daily returns. Results in Panel A for the LSE sample suggest that the HFT proxy has a negative and statistically significant effect on dislocation price alerts, after controlling for daily market volume, daily volatility and daily returns, with a coefficient of -0.1549; this suggests that an increase in HFT is associated with fewer dislocation price alerts. Further, volume has a positive and statistically significant effect on dislocation price alerts, suggesting that an increase in trading volume is associated with increased alerts. Daily volatility and returns both have negative coefficients. Results for the second regression in Panel A, using ticking as the dependent variable, suggests that the HFT proxy is *not* a statistically significant determinant of ticking. Further, trading volume is a positive and statistically significant determinant of Ticking, while daily return is a statistically significant negative determinant of ticking; daily volatility is not a statistically significant determinant of ticking.

Results in Panel B for the Euronext Paris sample suggest that the HFT proxy has a negative and statistically significant effect on dislocation price alerts, after controlling for volume, volatility and returns, with a coefficient of -0.1664; this suggests that an increase in HFT is associated with fewer dislocation price alerts. Further, volume and volatility have positive and statistically significant effects on dislocation price alerts, while daily returns have a negative and statistically significant effect. Results for the second regression in Panel B, using ticking as the dependent variable, suggest that the HFT proxy is *not* a statistically significant determinant of ticking alerts, after controlling for volume, volatility and returns. Volatility has a negative and statistically significant effect on ticking, while daily returns and on-market volume are not statistically significant.

Table 6. Regressions LSE and Euronext Paris: dislocation price alert and ticking.

This table presents results for regressions of Dislocation Price Alert and Ticking separately on HFT Proxy. The sample period describes trading spanning 1 January, 2006 to 31 December, 2011, and consists of all on-market trades executed every day on the LSE (Panel A) and Euronext Paris (Panel B). *t*-statistics and Adjusted R^2 values are reported to measure the statistical significance of the relation between HFT Proxy and either Dislocation Price Alert or Ticking, controlling for exogenous changes in On-Market Volume, Daily Volatility and Daily Returns. ** indicates 0.05 level of significance, * indicates 0.01 level of significance.

		Dislocation Price Alert		Ticking
Panel A: LSE				
Intercept		0.0001		0.0030**
HFT Proxy		-0.1549**		-0.0013
On-Market Volume		0.5074**		0.0029**
Daily Volatility		-2.074		0.0251
Daily Return		-1.998*		-0.0462**
Adj R-Sq		0.2124		0.0328
Panel B: Euronext Paris				
Intercept		0.0006		0.0033**
HFT Proxy		-0.1664**		-0.0003
On-Market Volume		0.4775**		0.0014
Daily Volatility		7.785**		-0.1021*
Daily Return		-6.908**		0.0137
Adj R-Sq		0.1916		0.0017

6. Summary

The key findings of this report are as follows:

- Over the 2006 – 2011 sample periods, there is a considerable increase in the HFT proxy on the LSE and Euronext Paris markets.

- There is a statistically significant negative correlation between the HFT proxy and End of Day Price Dislocation Alerts for both LSE and Euronext Paris markets.

- There is a statistically significant positive correlation between the HFT proxy and Ticking for both LSE and Euronext Paris markets.

- Regression analysis that controls for non-stationarity suggests that; for the LSE sample period, HFT is a statistically significant negative determinant of End of Day dislocation Price Alerts, when controlling for on-market trading volume, daily volatility and daily returns. When considering Ticking as the dependent variable, regressions for the LSE sample suggest that the HFT proxy is *not* a statistically significant determinant of Ticking, when controlling for on-market trading volume, daily volatility and daily returns.

- Regression analysis that controls for non-stationarity suggests that; for the Euronext Paris sample period, HFT is a statistically significant negative determinant of End of Day dislocation Price Alerts, when controlling for on-market trading volume, daily volatility and daily returns. When considering Ticking as the dependent variable, regressions for the Euronext Paris sample suggest that the HFT proxy is *not* a statistically significant determinant of Ticking, when controlling for on-market trading volume, daily volatility and daily returns.

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