A Reexamination of High Frequency Trading Regulation Effectiveness in an Artificial Market Framework

Iryna Veryzhenko, Lise Arena, Etienne Harb and Nathalie Oriol

Abstract In this paper we analyze the impact of the French cancel order tax on market quality measured by market liquidity and volatility. Additionally, this paper raises the question whether this tax leads to reduction of high-frequency trading (HFT) activities and a declining in trading volume. Moreover, we test market rules that have not been yet introduced using artificial market framework.

Keywords High frequency trading market regulation · Market liquidity and volatility · Agent-based modeling

1 Introduction

The historical evolution of information systems on financial markets has shown their increasing role in traders' activities. They are responsible as well for the emergence of new forms of volatility. Financial markets have became increasingly swift and reactive, yet increasingly sensitive, leading to the amplification of a global instable climate. Accordingly, there is a growing body of literature on the rise of algorithmic trading and high frequency traders' influence on market quality. Empirical evidence [4, 30] shows positive correlation between HFT and increasing volatility which gives rise to the hypothesis that HFT activities are purely speculative and destabilize

I. Veryzhenko(✉)
Labex ReFi, LIRSA-CNAM, Paris, France
e-mail: iryna.veryzhenko@cnam.fr

L. Arena · N. Oriol
GREDEG-Université Nice Sophia-Antipolis, Nice, France
e-mail: {lise.arena,nathalie.oriol}@gredeg.cnrs.fr

E. Harb
Essca Research Lab, Boulogne-Billancourt, Paris, France
e-mail: etienne.harb@essca.fr

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trading strategies. Yet, others also argue that most HFT trading volume contributes to liquidity provision or at least, that there is no evidence of increasing volatility [17, 20]. Quantitative trading strategies, supporting high frequency trading, increases the number of smaller orders and enables more efficient allocation, price discovery and market liquidity [1, 5, 10].

To identify the responsibilities for (in)stability and market (in)efficiencies is difficult due to the limited ability of regulators and researchers to establish the "real drivers" of assets price dynamics. First, because of the "3V" characteristics of financial big data (Volume, Velocity and Variety), as well as the dark and shadow trading flows that escape from regulatory monitoring. The evolving nature of financial markets also makes the study complicated. According to Cliff and Northrop [12], financial markets have became "ultra large scale complex socio technical systems". Thus, their analysis as purely technical systems (computer science literature) or purely agent system (financial literature) is reductionist. Order flows and price discovery process are the result of trader-to-machine, machine-to-machine, and trader-to-trader non-trivial interactions. Investors are not external users of the systems [8], they are vital components within the system, even if today, they can be outside of the running process. Hence, their IT-centric behavior, as much as their social coordination are keys to understand macroscopic events such as a new type of market instability.

The introduction of a "good" HFT regulation is not a simple task, since HFTs are heterogeneous and have heterogeneous impacts on market quality. Then, a "good" regulation should be the most predictable and adaptive one. Predictable because its positive and negative potential effects should be well-understood ex ante. And adaptive, because regulators must have appropriate tools to evaluate the impact of new rules ex post for readjustments.

In this paper we estimate the effect of HFTs on market quality and trading activity and address the question of a "good" HFT regulation in the artificial financial market. This computational-experimental approach enables us to perform several tests, to validate some hypotheses and, eventually, to make preliminary suggestions to regulators about setting some rules in order to stabilize the market and limit speculation. The use of a simulation platform allows us to shed some new light on the non-linear relationship between local behavior based on traders' strategies and global behavior of that system characterized by its unstable nature. To this extent, the use of a simulation platform is in line with Simon's *"Science of the Artificial"* [29] that claims that computational intelligence (seen as intelligent devices in the artificial intelligence field) is needed to understand complex systems. Agent-based artificial markets allow us to reproduce main features of real trading on the fine grain and to test trading rules not applied by regulator in the real market. Here, we use ArTifcial Open Market (ATOM) [6] as a software-defined intelligent device which is a highly flexible simulations platform and allows different parameterization of microstructure and traders' behavior for different scenarios. To the best of our knowledge, this paper is the first attempt to examine the effect of french HFT cancel order tax implemented on August 1st, 2012 on trading activities and market quality in the artificial market framework. Based on the first results, the government estimated that the tax on HFT generated no revenue in 2012. This paper seeks to shed some new light on this phenomenon. Especially, we try to figure out whether this regulatory policy has reduced high-frequency activities, discouraged speculative transactions, and, as a result, we identify the effect on market quality. We settle two scenarios. The first one is without any taxes. This case is considered as a benchmark and a control group for statistical test. The second scenario proposes a market under tax regulations. We compute a wide range of measures of liquidity and volatility to account for different dimensions of market quality. To estimate the impact of this new regulation on the market quality measure, we use a difference-in-difference technique (DiD).

2 The Model

2.1 Traders Strategies

Trading process is a trade-off between execution cost and benefits generated by transaction (decreased risk exposure, increased return, etc). So trading is determined not only by the global strategy (for instance, utility maximization), but also by "technical" details, like order timing, order volume, type of order, etc. Johnson [22] presents factors that motivate an agent to be more aggressive or more patient in his order submission, they can be classified based on liquidity, price and time relevance.

To keep our model as simple as possible for tractability reasons, we focus only on three groups of traders: slow fundamentalists, high-frequency "contrarians" and high-frequency directional traders.

Fundamentalists are driven by the true (fundamental) asset's value. The fundamental value of each stock evolves according to a jump process $V_t = V_{t-1} + \delta_t$, where $\delta_t \sim N(0, \sigma)$. As the agents are bounded rational (or noisily informed), the fundamental value is biased by ϵ_i, which determines the accuracy of the agent i to interpret the fundamental information $W_t = V_t + \epsilon_i$, $\epsilon_i \sim N(0, \sigma_W)$. Agents are heterogeneous with respect to their parameter ϵ_i. To make a buy/sell decision an agent compares the stock's current price P_t with fundamental value W_t. The price fixing mechanism is inspired from the paper of Chan *et al.* [9] and summarized in Table 1. The fundamentalists submit their orders according to procedure described in Table 1. To summarize, agents buy undervalued stocks and sell overvalued stocks according to their beliefs. They stop trading when they are out of cash or stocks.

High Frequency Traders

High frequency trading refer to strategies relying on fast algorithm for order generation using very fast access to trading platforms and market information. HFTs have short holding periods and trade frequently. They take long and short position of the market and trade near the best-ask and best-bid.

The high frequency traders adopt directional strategies [23]. They try to get benefit from anticipation of price variations $|\frac{P_t - P_{t-n}}{P_{t-n}}| > \Delta_i$. The agents are heterogeneous with respect to the parameter Δ_i of minimal price variation and its? interpretation.

Table 1 The order-submission procedure. P_{ask} denotes a best ask price, P_{bid} best bid price, α_t ask tick size, β_t bid tick size, Q_t is a volume of the order issued at the moment t, N_{t-1} is a number of stocks hold by an agent at moment $t-1$, C_{t-1} is available cash hold by an agent at moment $t-1$, $U(x_1, x_2)$ the uniform distribution in the interval $[x_1, x_2]$

Conditions	Order type
Existing bid, existing ask	
$W_t > P_{ask}$	bid market order
$W_t < P_{bid}$	ask market order
$P_{bid} < W_t < P_{ask}$	bid/ask order with probability 50%/50% at price $\sim U(P_{bid}, P_{ask})$
Order book is empty	
with probability 1/2	limit ask order at $W_t + \alpha_t$, $Q_t \sim U(1, N_t - 1)$
with probability 1/2	limit bid order at $W_t - \beta_t$, $Q_t \sim U(1, C_t/(W_t - \beta_t))$
Empty bid side, existing ask	
$W_t > P_{ask}$	bid market order, $Q_t \sim U(1, C_t/P_{ask})$
$W_t \leq P_{ask}$	limit bid order at $W_t - \beta_t$, $Q_t \sim U(1, C_t/(W_t - \beta_t))$
Existing bid side, empty ask side	
$W_t < P_{bid}$	ask market order, $Q_t \sim U(1, N_t - 1)$
$W_t \geq P_{bid}$	limit ask order at $W_t + \alpha_t$, $Q_t \sim U(1, N_t - 1)$

According to Brogaard *et al.* [7] some part of HFTs act as liquidity providers meaning that they buy (sell) stocks whose prices have been declining (increasing) in the last 10 to 100 seconds. We will call this group of traders *contrarians*. The other group called *?trend followers?* buys (sells) when stock value has been increasing (declining) over last n time stamps. As we observe on average 4000 trades per day, it represents about 0.13 trades per trading round, thus the parameter n is settled in the limit [2; 15]. They have also different trading frequencies, how often they update their positions: cancel pending order and submit a new one. The high-frequency traders do such revision more often than fundamentalists.

The volume of bid order is determined as follow $Q_t \sim U(1, \triangle \times \lfloor \frac{C_{t-1}}{P_t} \rfloor)$, where $U(x_1, x_2)$ uniform distribution in the limit $[x1, x2]$, C_{t-1} is allowed cash, P_{t-1} is observed market price, and $\triangle$ is borrowing rate. $\triangle > 1$ if borrowing is allowed. The volume of ask order is determined as $Q_t \sim U(1, \triangle \times S_{t-1})$, where S_{t-1} is a number of held stocks, $\triangle$ is a short selling rate. $\triangle > 1$ if short selling is allowed. According to Boehmer *et al.*[5] HFT increase a number of smaller order, thus in current simulations HFTs are attributed initially less equities than fundamentalists. However, we recognize the importance of quantity as a choice variable and that our volume submission is a simplification of a real one, which depends on risk aversion. We believe results are not too sensitive to this aspect.

Tax is not directly implemented into the agents decision making as they are taxed at the end of the trading day and only operations exceeding 80% of the total threshold are taxed. Specifically, traders can cancel and modify up to 80% of their orders free of charge. Moreover, in the real market a trader prefers to cancel an unprofitable operation, to accept potential losses and to conclude a new more profitable transaction. HFTs stop trading when they are out of cash or stocks, in such a way we test how the tax on canceling makes high frequency activities unprofitable.

Each limit order is submitted as a Good-Till-Cancelled (GTC). Agents can have only one pending order in the order book, so they have a possibility to cancel their unexecuted order and resubmit at different limit prices. All parameters are detailed in Table 2.

2.2 Timing

We use a simulated time approach meaning that the platform attributes a time stamp to each event. So time is considered to be discrete with millisecond granularity, 30 600 000 milliseconds that represents a trading round of 8.5 hours [24]. At each millisecond, one of the traders is uniformly picked to make a trading decision. The simulator always start by the group of HFT in such a way this group of agents has faster access to an order book, then the group of fundamentalists is activated. Each agent has a choice to do nothing, to cancel a pending non-executed or partially executed order and to send a market or limit order. The traders are heterogeneous with respect to their trading frequency.

3 Econometric Analysis

HFT Activity Proxies. In this paper we estimate the HFT activities as a special group of traders. First, we focus on evolution of Order-to-Trade Ratio (*OTR*) with introduction of the cancel order tax. Order-to-Trade ratio is calculated for all HFT agents, and not for each member separately, over all orders they submit and the trades that result. The numerator includes all types of orders. The denominator includes all trades with HFT agent as a counterpart.

To address the HFT activity, as a subclass of algorithmic trading, we also use a measure proposed by Hendershott *et al.* [19]: $alg - trad = -\frac{\text{Dollar Volume}}{\text{Message Traffic}}$, where Message traffic is the sum of the number of trades, and the number of quote revisions and cancellations, calculated based on the intraday trades and entire order book. Later in this paper this measure will be called Algorithmic Trading (AT) ratio.

Market Liquidity. Measuring liquidity by volume is the most intuitive way, as by definition, liquidity is the ability to trade large volume order without affecting a price in a significant manner. First, we compute *log dollar volume*, as follow $ln\ (Q_t \times P_t)$ where P_t is the transaction price at the moment t, and Q_t is traded volume at the moment t. This measure captures the facility to turn around a position [11].

We include also *depth* into our study, that is measured as the average number of shares that can be traded at the best bid and ask quotes [18]. *Euro depth* is calculated as the average of the sum of the number of shares quoted at the ask price plus the number of shares quoted at the bid price, times their respective quoted prices [18].

Table 2 Parameters and their initialization used in simulations

Parameter	Value	Description
N_{fund}	1000	Number of fundamentalists
N_{HFT}	500	Number of HF traders
$C_{0,i}$	[1 000 000; 2 000 000]	Initial cash attributed at moment 0 to the agent i
$S_{0,i}^{fund}$	[100; 1000]	Number of stocks attributed at moment 0 to the fundamentalist i
$S_{0,i}^{HFT}$	[10; 200]	Number of stocks attributed at moment 0 to the HFT i
tax_C	{0%, 0.01%, ...0.1%}	the tax on orders canceled under a determined time span
tax_A	0.2%	the tax on acquisition of securities
N_{rounds}	30 600 000	Number of rounds per day
N_{days}	60	Number of days

Another widely used measure of liquidity is bid-ask spread. The spread is defined based on the lowest price at which someone is willing to sell (best ask) and the higher price at which someone is willing to buy (best bid). We focus on different dimensions of this measure: *effective spread, realized spread, and quoted spread.* The smaller the spreads are, the more liquid the market is.

Volatility. We proxy volatility by the squared return R^2 and absolute return $|R|$.

Market Efficiency. We measure informational efficiency by the absolute deviation between the price $P_{t,k}$ and fundamental value $F_{t,k}$, $\frac{100}{T}\sum_{t=1}^{T}|\frac{P_{t,k}-F_{t,k}}{F_{t,k}}|$.

4 Simulations and Discussions

We run several computational experiments. In the first experiment set, later called *different tax regimes*, for each run, all parameters are fixed, with the exception of cancel order tax, which varies from 0% to 1% with 0.01% step. These settings allow us to study the tax impact on HFT activities. For each settled tax the simulations are repeated 100 times in order to get more representative results. The parameters used in the simulations are listed in Table 2. The estimation of these parameters is inspired by the papers of [24, 26, 27].

In other series of experiments, all parameters are fixed, with the exception of tax that switches from 0.0% to 0.01% in the middle of trading period (60 days). This later is used to analyze the impact of the new regulation on the market using difference in difference technique.

Using real order book data we cannot directly observe whether a particular order is generated by an algorithm. For this reason, the rate of electronic message traffic is used as a proxy for the amount of AT. The advantage of agent-based simulations is that we can easily identify a sender for each order and estimate the activity level of HFT, that is not an easy task with real market data. As in these simulations HF traders are event driven agents, we first estimate how many orders they send to the market and how many of them are canceled under different tax regimes. We also use AT proxies widely applied in the literature to study real market order book.

Table 3 Activity measures of high-frequency traders under different tax regimes. This table reports different proxies for HFT activity. *OTR* – Order-to-Trade Ratio. *alg trad* a proxy for algorithmic trading, which is defined as the negative of trading volume divided by the number of messages. Each metric is an average of 100 simulations. Linear regression coefficients are computed based on the total sample. Signif. codes: 0 ’***’, 0.001 ’**’, 0.01 ’*’, 0.05 ’.’, 0.1 ’ ’, 1.

Tax	*OTR*	*alg trad*
0.00%	173.04563	-1603
0.01%	78.35619	-4753
0.02%	67.74425	-6964
0.03%	74.08699	-7720
0.04%	71.93468	-8197
0.05%	82.19863	-8765
0.06%	75.01937	-8878
0.07%	69.69344	-7333
0.08%	76.05431	-8046
0.09%	65.04254	-9896
0.10%	69.41141	-11184
coef.	-502.00	-65118.2
p-value	0.0833 .	0.001234**
R^2	0.2183	0.6716

From Table 3 we can report a dramatic decrease in Order-to-Trade ratio with tax introduction, but our findings don’t provide the undisputed evidence of clear linear relationship between the tax and Order-to-Trade ratio. The Order-to-Trade ratio is about 173:1 in untaxed market, and about 72:1 (average value for market with cancel order tax). Table 3 reports the slope coefficients for linear regression, when the dependent variable is OTR or $alg - trad$. The coefficient of -502.00 implies that increased cancel transaction tax decreases Order to Trade ratio by 5.020.

For untaxed market, there is about $1, 603 of trading volume per electronic message, and it increases dramatically with tax increase to $11, 184 per electronic message for 0.1% of tax. Table 3 shows that there is a significant negative relationship between the the tax and our measure of AT, *alg-trad*, which is the negative of dollar volume per electronic message. Higher tax removes faster HFTs who are characterized by high number of small volume orders. Thus, it is clear that higher tax leads to less of HFT activities.

4.1 Difference-in-Difference

To understand the impact of tax on market quality metrics, we run extensive simulations of 30 days before and after the introduction of 0.01% tax on cancel and update orders. Each of such simulations results on average by 250000 intraday trades and millions of messages. These data are analyzed with *difference in difference* technique.

Table 4 The impact of the tax introduction on stock market liquidity and volatility. Difference in difference analysis. ln(Volume) = ln(Number of traded shares × Price). *% Bid-Ask spread* = $\frac{1}{2} \times \left(\frac{Ask_{it} - Bid_{it}}{M_{it}}\right) \times 100$, $M_{it} = \frac{Ask_{it} + Bid_{it}}{2}$, where Ask_{it} and Bid_{it} are the posted ask price and bid price. Depth = $\frac{Q_t^{bid} + Q_t^{ask}}{2}$ where Q_t^{bid} is the best bid size, Q_t^{ask} is the best ask size. Euro depth = $\frac{Q_t^{bid} \times Bid_{it} + Q_t^{ask} \times Ask_{it}}{2}$. $R_t = log(P_t/P_{t-1})$ is the log return. R_t^2 and $|R_t|$ are respectively squared and absolute returns. Signif. codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ', 1

Volume			
Tax	(s.e.)	adj. R^2	p-value
0.02721	1.112	0.002651	0.38663
half Bid/ask spread			
Tax	(s.e.)	adj. R^2	p-value
0.116941	0.4288	0.01605	$< 2e - 16^{***}$
% Bid/ask spread			
Tax	(s.e.)	adj. R^2	p-value
2.739e-05	0.0001123	0.01402	$< 2e - 16^{***}$
Depth			
Tax	(s.e.)	adj. R^2	p-value
-21.5402	33.04	0.06075	$< 2e - 16^{***}$
Euro depth			
Tax	(s.e.)	adj. R^2	p-value
-57671	99950	0.05916	$< 2e - 16^{***}$
Effective spread			
Tax	(s.e.)	adj. R^2	p-value
0.114501	0.44	0.01319	$< 2e - 16^{***}$
Squared return			
Tax	(s.e.)	adj. R^2	p-value
0.05286	16.51	0.0001181	0.910
Absolute return			
Tax	(s.e.)	adj. R^2	p-value
0.045090	0.8858	0.0001501	0.000105***
% Deviation from fundamental			
Tax	(s.e.)	adj. R^2	p-value
1.835e-04	6.748	0.001329	0.00422**

A difference-in-difference [2] is a widely used technique to estimate the impact of a policy change or some other shock on population. We consider two groups and two periods case. One population is exposed to cancel order tax.

$$Y_i = \beta_0 + \beta_1 \cdot D^{treated} + \beta_2 \cdot D^{tax} + \tau \cdot \overbrace{D^{treated} \cdot D^{tax}}^{treated \times tax} + \epsilon_i \tag{1}$$

We regress liquidity and volatility metrics Y_i on a set of treatment indicators that include a dummy variable picking out the treated group $D^{treated} \in \{0, 1\}$, a dummy indicating an after tax period $D^{tax} \in \{0, 1\}$ and the interaction of those two dummies $treated \times tax$. τ is a parameter of interest. If the tax has an significant effect on dependent variables it will appear as a significant coefficient on the $treated \times tax$.

Based on the figures presented in Table 4, we can report a reduction of market liquidity after introduction of HFT tax. The bid/ask spread increases by 2.739e-05%, and effective spread increase by 0.114501. The wider spread measures, the less liquid is the stock. Our results confirm that the tax introduction alters the market liquidity as stated by of Haferkorn [16] and Meyer [25] who investigated the impact of the French FTT on market liquidity. It also converges with the results of [3], [28] who find a negative relationship between transaction tax and market liquidity and recently with the results of Friederich [14] who studies the impact of the implemented penalty on OTR in Italian stock market. At the same time we report the depth and euro depth declines and increased volatility. The impact we find of HFT tax on volatility meets the results of [15, 21, 28]. Additionally, the introduction of the tax increases the deviation from the fundamental by 1.835e-04 percents, that demonstrate a deterioration of market efficiency.

Our results show that financial transaction taxes on canceled orders decrease liquidity, significantly increase volatility, deteriorate market efficiency.

5 Conclusions

Modern financial markets can be considered as adaptive complex socio-technological "system of systems". They are based on softwares which evolve and learn from experience (machine learning). They are also complex, as they allow emergent practices and behaviors that cannot totally be planned ex-ante. In such a manner, SMA and the difference-in-difference methodology are a consistent approach to back-test new rules and delimit their different impacts [12].

As an illustration, we run two experiments in the agent-based artificial market: i) different tax regimes ii) tax introduced in the middle of trading period. Based on our findings, we report that introduction of cancel order tax reduces only slightly HFT activities, but it significantly affects market liquidity, increases market volatility and deteriorates the market efficiency. We conclude, that it is difficult to dissuade investors from entering into unproductive trades and eliminate negative outputs of HFT (such as price manipulations) through tax without altering the benefits of HFT like liquidity provision and efficient price discovery.

Thus, one would agree with [25] and [13] that an FTT is sensitive to many aspects as the composition of the trading floor population, the characteristics of the asset treated and the market microstructure. Policy makers and regulators need to separate the FTTs objectives (collect revenues for financing the burdens of the financial crisis, curb speculative trading, etc.) in order to design an appropriate tax with a clearer view of its costs and benefits.

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