

The impact of technology on market quality, organization and regulation

Iryna Veryzhenko Leboeuf

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Habilitation à Diriger des Recherches

Note de Synthèse

The impact of technology on market quality, organization and regulation

Iryna Veryzhenko Leboeuf

Defended on 14/12/2020

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Table des matières

Aknowledgment **2**

1 Introduction **3**

2 Computational simulations as a research tool in finance **4**

3 Where does market quality come from ? **8**

3.1 Increasing traders' rationality 8

3.2 Institutional design and individual behavior 13

4 High frequency trading: strategic competition between heterogeneous traders **18**

4.1 HFT Modeling in an Artificial Market Framework 19

4.2 The effect of heterogeneous HFTs on market quality 19

5 Regulatory policy and traders' behavior **25**

5.1 Cancelled order tax 25

5.2 Short-selling ban 27

5.3 Circuit breakers 29

5.4 Delayed market order execution 34

6 Ongoing research projects **36**

7 Other activities **39**

7.1 Scientific Communication 39

7.2 Teaching related to my research topics 40

7.3 Master thesis 40

List of publications **41**

Aknowledgment

This dissertation would not have been completed without the participation and support of many people.

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Dear Etienne, you are more than a co-author, you became my best friend. Despite the thousands of kilometers that separate us, I still feel your continuous support and encouragement.

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1 Introduction

Financial markets have recently seen a transition to fully automated and high-speed order executions, fragmentation and a larger heterogeneity of trading practices. The rise of high-frequency traders (HFTs) which refers to investors who use sophisticated computers for generating, routing, and executing orders over extremely short time intervals, is the major change in modern financial markets. Some studies view this evolution as beneficial since automation reduces the cost of liquidity provision and fast reaction to information improves market efficiency (Budish *et al.*, 2015; Menkveld and Zoican, 2017). Others argue that HFTs exploit their speed advantage to make profits at the expense of other market participants (O'Hara, 2015). Some HFTs are also blamed for being responsible for unusually turbulent market events (Kirilenko *et al.*, 2017) or for market manipulation (Lee *et al.*, 2013).

In the last decade, much research has been devoted to the understanding of the impact of technological changes and particularly high frequency trading on the quality of financial markets (its efficiency, stability, transparency, liquidity, and fairness). A large body of the literature is empirical (Brogaard *et al.*, 2017; Colliard and Hoffmann, 2017; Kirilenko *et al.*, 2017). Theoretical studies have also been growing in recent years (Biais *et al.*, 2015; Hoffman, 2014). Additional efforts to understand HFT are done by studies using agent-based models (Leal and Napoletano, 2017; Leal *et al.*, 2015; Manahov, 2016; Manahov *et al.*, 2014). The works presented in this document belong to this last stream of research.

Agent-based modeling (ABM) is a computational research approach in which individuals, their interactions and environment are explicitly represented as individual software components. ABM approach attempts to model financial markets as evolving complex systems of competing, autonomous interacting agents in order to analyze global system dynamics (Tesfatsion and Judd, 2006). This computational tool thus allows us to study financial problems based on more realistic assumptions regarding traders' heterogeneity, bounded-rationality, market non-equilibrium dynamics, etc.

My research works relying on agent-based simulation tools fall at the crossroads of information systems, artificial intelligence, and finance. My research interests cover two main topics: (1) the interrelation between individual behavior, market mechanisms, and

its resulting dynamics. This topic involves examining the evolution of market design, trading practices, and their effect on various dimensions of market quality such as liquidity, volatility, and informational and allocative efficiency [11,8]. (2) The second topic of interest is the effect of particular groups of market participants, especially HFTs, on different dimensions of market quality. In a series of papers, I test the ability of various market rules (delayed execution of market orders and circuit breakers) and constraints (financial transaction tax and short-selling ban) to reduce potential disruptive trading activities without altering the benefits investors – especially HFTs – can bring to markets [2, 5, 10, 13, 12]. My contributions have important implications for the regulation of HFT. In particular, I provide insights and give recommendations for regulators that can offer guidance on the market rules to be introduced. [1]

My HDR report proceeds as follows. Section 2 presents the underlying philosophy of agent-based modeling and how simulations can help us better understand, interpret and explain the phenomena we analyze. Section 3 turns to the issues on the relation between institutional design, market participant behavior and market quality. Sections 4 and 5 address different aspects related to high frequency trading: the effect of HFT on market quality, the profitability of this trading practice, as well as the institutional and regulatory design to deal with these trading practices. In section 6, I present my ongoing projects and further developments of my research agenda.

2 Computational simulations as a research tool in finance

The paper *"On the Design of Agent-Based Artificial Stock Markets"*[6] co-written with Olivier Brandouy and Philippe Mathieu introduces the research approach, agent-based modeling, used in a series of papers, its advantages and limits, the difficulty of constructing agent-based models and architectural choices.

ABM aims at analyzing complex systems by representing each of its microscopic components individually and by simulating the behavior of the entire system, keeping track of all the individual elements and their interactions over time. With ABM, complex dyna-

1. Two of our papers have been submitted to the regulators and have gotten insightful feedbacks. Veryzhenko *et al.* (2017b) was submitted to Nicolas Megarbane, Autorité des Marchés Financiers. Oriol and Veryzhenko (2018a) was submitted to Dobrislav Dobrev, Federal Reserve Board of Governors.

mics are studied using a bottom-up approach. An ABM experiment starts with specifying the capabilities and parameters of its individual components called the agents. The principle of ABM is that the global system behavior emerges out of the interactions between these agents and their common environment. Although, there is no universally accepted definition of the term "agent", we propose the definition by Wooldridge and Jennings (1995) as *"a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives"*. The representation of an agent varies from a simple rule [2] to complex software components involving artificial-intelligence, or even humans.

In our case, the market is the environment and the agents are those who trade on this market. The environment is characterized by a set of rules (for instance price-time priority in order execution) and restrictions (for instance short selling ban or limited borrowing).

ABM begins with assumptions about agents and their interactions and then uses computer simulation to generate histories that can reveal the dynamic consequences of these assumptions. ABM researchers can investigate how large-scale effects arise from the micro-processes of interactions among agents. Running the ABM multiple times allows to capture different possible scenarios for the output driven by agent interactions. These interactions can produce different aggregate behaviors for the system like equilibrium, patterns and cycles, or bubble and crashes. ABM allows to compare not only the end results of the model but also the overall trajectories that lead to the final outputs.

While theoretical studies often rely on strong restrictive assumptions (e.g. representative agent) and empirical studies report the aggregate effect of heterogeneous traders, agent-based studies are able to make a particular focus on individual agents or groups of agents with different tastes, skills, and beliefs. Therefore, the agent-based approach provides a better overall view not only on the global system but also on the evolution of particular groups of participants.

Axelrod and Tesfatsion (2005) point out specific goals pursued by ABM. First, agent-based models can provide *normative* investigation, as it allows to determine the output of different designs and to identify the features that improve the performance of the

2. Wooldridge and Jennings (1995) provide a mathematical formalization of the agent. Agent's environment is characterized as a set of environment states $S = \{s_1, s_2, ...\}$ that the agent can influence only partially. The influence of agents is a set $A = \{a_1, a_2, ...\}$ through which agents can affect the environment $actions : S \longrightarrow A$

system. Second, agent-based models can provide useful *heuristics* of market phenomena, as they allow to understand economic system behaviors under alternatively specified initial conditions. Also, ABM can shed some new light on causal mechanisms in social systems. Finally, agent-based modeling can help researchers to get advance in *methodological* issues, as it provides the methods and tools needed to undertake the rigorous study of social systems through controlled computational experiments. In a nutshell, ABM represents a methodological approach that allows the rigorous testing, refinement, and extension of existing theories that have proved to be difficult to formulate and evaluate using standard statistical and mathematical tools.

ATOM

For some studies [3, 4, 5, 2, 13] presented later in this manuscript, I use ArTificial Open Market (ATOM)[3] developed by the team of computer scientists from Lille University (Brandouy *et al.*, 2013). It is a highly flexible simulation platform that allows different parameterizations of the market structure and traders' behaviors.

The platform offers three main interacting modules: (i) the "market microstructure" module, which allows to define the mechanism of order routing and price setting, (ii) "economic world", which provides exogenous information on corporate developments, dividends, and coupon changes, and (iii) the "agent" component, which allows to model multiple types of agents with different utility functions, beliefs, and strategies. Thus, ATOM allows to model traders who take into account exogenous (for instance expected returns or estimated risks) and endogenous information (post transaction information generated by agents' interactions), as well as restrictions (bans on short sale or borrowing), and market mechanism rules they account for in the definition of their trading strategies.

In Brandouy *et al.* (2013), we detail the various aspects regarding the programming (construction) of artificial stock markets parametrization. A key element in all multi-agents systems is a scheduler, that is the modeling of a time scale. A scheduler manages the moment when agents act, orders are executed, and prices are set. A scheduler can be represented as a set of loops (or rounds) in the simulations. Within each round, agents have an opportunity to express their decisions, i.e. buy, sell or do nothing. The simulator

3. http://atom.univ-lille1.fr

can pick agents randomly to make their decisions (to trade or to do nothing), but it is also possible to define a strict ordering of "agent interrogation". This allows us, for example, to model faster or privileged access to the order book for some traders.

The number of rounds determines the time granularity of the simulations. For instance, 30 600 rounds can represent a daily trading session of 8.5 hours at second frequency. Imposing a strict and realistic scheduling enables us to construct a sound and plausible correspondence between simulation rounds and calendar time. ATOM links price-setting methods (Call auction or continuous trading) to chronological rounds. In such a way, ATOM is able to replicate the time structure of the trading day of a real financial trading platform. For example, it is possible to replicate a Euronext-like trading session with an opening batch auction phase, real-time matching according to continuous double auction, a pre-closing order accumulation phase, and a closing batch auction (Euronext, 2017). In addition, ATOM's high flexibility allows us to change the order of the various trading phases and to study issues like delayed opening or frequent batch auctions in lien of continuous trading.

Timing is a key issue in investment decision making. Some agents make hundreds of transactions daily, while others rebalance their portfolio weekly or even at monthly frequency. In ATOM, this is featured by giving agents the possibility to decline the proposition from the simulator to act. For example, let assume that a trading day consists of 30,600 seconds (rounds) and an agent rebalances his portfolio once per month. He will send orders once over $30,600 \times 22$ rounds (22 business days). High-frequency traders have an opportunity to react at each round (second).

An important feature of ATOM is its ability to include human-beings in the simulation loop together with artificial agents. ATOM can be installed on a central server and multiple users can access to ATOM's order book or communicate with market maker over network. The presence of human agents does not alter the way the scheduler operates. At each round, the simulator asks human and artificial agents with a random or strictly defined order to express their intentions.

3 Where does market quality come from ?

The evolution of market organization and trading practices are intertwined. Traders adjust their behavior to the set of rules set by market operators and regulators impose new rules, requirements, and restrictions in response to trading practices. This chapter presents my analysis of the bidirectional effect of market mechanisms and trading practices on the properties of a market and its quality.

3.1 Increasing traders' rationality

In Brandouy *et al.* (2012) [8] and Biondi and Veryzhenko (2018) [11], we investigate the extent to which the emergence of realistic stylized facts (statistical properties of returns, volume and trading time) and realistic price dynamics is driven by market mechanisms and by strategic traders' behavior. Both papers attempt to reconcile two streams of the literature: the first one attributes the emergence of stylized facts to market mechanisms (Cliff *et al.*, 1997; Gode and Sunder, 1993; Ladley and Schenk-Hoppe, 2009), while the second one imputes it to agents' behavior and heterogeneity (Hommes, 2006; LeBaron *et al.*, 1999; Levy *et al.*, 2000; Lux, 2009). We assume that each of these components may contribute to explaining market properties.

An important stage in the validation of any agent-based model is the test of its ability to generate realistic stylized facts. In Brandouy *et al.* (2012)[8], we compare the statistical properties of returns and prices generated by our market simulator to those observed on a real dataset, namely high frequency data on order flow and trades from the Paris Euronext Stock Exchange. This dataset covers 37 CAC40 stocks for the month of August 2002 (22 trading days).

Brandouy *et al.* (2012)[8] contributes to the literature on Zero Intelligence Traders (ZITs) introduced by Gode and Sunder (1993). ZITs are agents who behave randomly and have no optimization strategies. Therefore, in a market populated with only ZITs, the observed properties produced by our model are attributed solely to market structure. If some properties do not emerge from a ZIT model, this implies that one has to consider the interaction between strategic behaviors and market mechanisms. As such, our simulation approach allows us to disentangle the effects of strategies and market mechanisms,

respectively, on the observed market statistical properties.

More concretely, our model considers 1,000 agents who trade on a continuous order driven market. At each time step, they choose one action among the following: i) do nothing ii) post a buy limit order iii) post a sell limit order iv) send a buy market order v) send a sell market order, and vi) cancel a pending order. The central limit order book collects the demands and supplies and translates them into transactions. We use Euronext dataset to calibrate the proportion of market to limit orders as well as the number of canceled orders. The ratio of market orders to limit orders is set to 1:3, while the probability to cancel an order is 33%. Moreover, we assume that agents buy and sell with equal probabilities (50% each). These parameters are of particular importance, since they directly impact market liquidity and market volatility.

While the existing literature (Challet and Stingchcombe, 2001; Maslov, 2000) models non-strategic agents who trade a single unit order size, we model a realistic order size based on real market data. This is important as volume has a significant impact on returns. To account for size, we divide all agents into two sub-categories which we call "Big fishes" and "Small fishes", based on the size of orders they submit to the central order book. In accordance with the Euronext dataset, the ratio of big-to-small fishes is set to 1 over 5.

We also focus on five well-known and well-reported types of zero-intelligence traders (see Table 1). The introduction of the most basic agent type called ZIT_U is inspired by the work of Maslov (2000). Agents in this category send orders whose price and volume are uniformly drawn from a given interval, the boundaries of which are calibrated based on Euronext market data. Agents ZIT_N issue orders whose price and volume are drawn from a normal distribution whose mean and standard deviation match those of the Euronext dataset. As traders from these two categories receive no information, have no learning capabilities and act randomly, the effects we highlight on price dynamics are the sole outcome of market design.

In a second step, we consider agents with larger cognitive abilities in order to test the necessary level of agents' intelligence to generate realistic price dynamics within the limit order book market architecture. Agents $SZIT_U$ rely on order book information to determine the parameters of their orders. Bid order price limits are randomly drawn from the interval $[b_{min}, b_{max}]$, and ask order price limits are drawn from $[a_{min}, a_{max}]$, where b_{min},

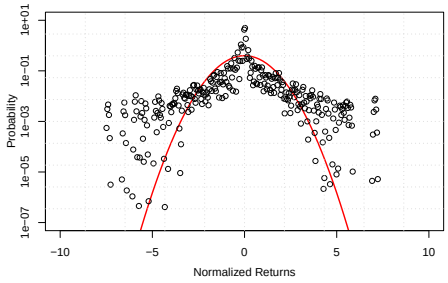
b_{max}, a_{min}, a_{max} are the minimum and maximum of daily bids and asks observed in the Euronext order book.

Agents $AZIT$ are inspired by a model presented by Farmer *et al.* (2005). In this model, there are two types of zero-intelligence agents. First, patient agents ($AZIT_P$) send limit buy orders whose price limits are drawn from a uniform distribution between zero and a_{min}, and sell orders limits are drawn from the interval $[b_{max}, \infty)$. Second, impatient ZIT ($AZIT_I$) send market orders with a random volume in the interval $[V_{min}, V_{max}]$, where V_{min} and V_{max} are the minimum and maximum trade sizes computed also based on the Euronext data.

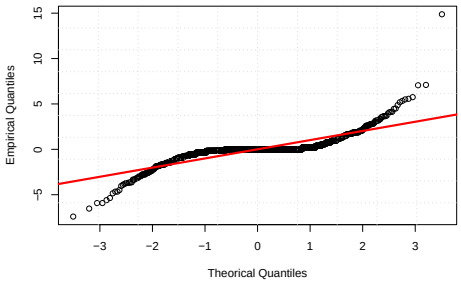
Trend calibrated agents ($TZIT$) pick a price determined based on the equation $P_t = P_{min} + (P_{max} - P_{min}) \times \gamma_t \times \delta_t$, where P_{min} and P_{max} are the minimum and maximum prices over a given period, and parameter γ_t is geared at reproducing the tendency of a given price series. It can also be considered as the sensitivity to trend information. Parameter δ_t generates additional randomness. Each trading day is divided into $n = 50$ sub-intervals to compute minimum and maximum prices over a given sub-interval. Based on these information, agents can track the global price trend and forecast price dynamics in the very short run.

Finally, for each day and each stock in the Euronext dataset, we run a set of five simulations (scenarios) which correspond to five families of ZITs. We check the ability of each scenario to generate statistics similar to those of the market used for calibration. For each scenario, we estimate the distribution of means, standard deviations, skewness, kurtosis of returns, their autocorrelation coefficients at orders 1 and 2, the slope of the decay function of their autocorrelation, and the sensitivity of volatility to volume. These outputs are compared to the real sample of CAC40 equities returns using the two-sample Kruskal-Wallis test, the Flinger-Policello test and the Wilcoxon test.

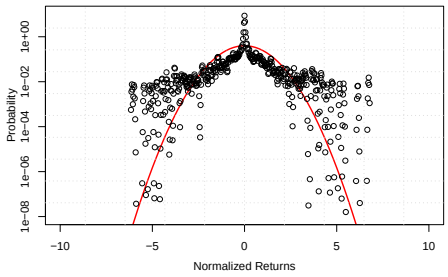
We find that basic types of agents $UZUT_U$, $TZIT$, $AZIT$ with completely random behavior are able to generate returns following a non-Gaussian distribution (see Figure 1). Hence, this statistical property of returns can be attributed to the limit order book market mechanism itself and it does not require strategic behavior from traders. Yet, the price dynamics we observe significantly differ from those observed on real data (see Figure 2). Neither higher moments of returns nor autocorrelation-based stylized facts can



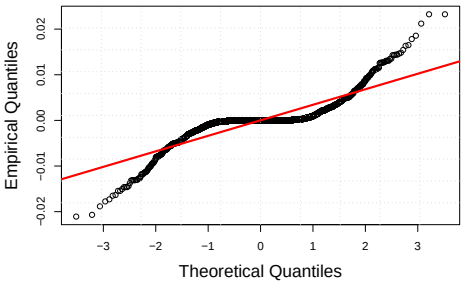
(a) Renault return series. Fat Tails (Normalized Returns)



(b) Renault return series. QQ-Plot



(c) Unconstrained ATOM ZIT. Fat Tails (Normalized Returns)

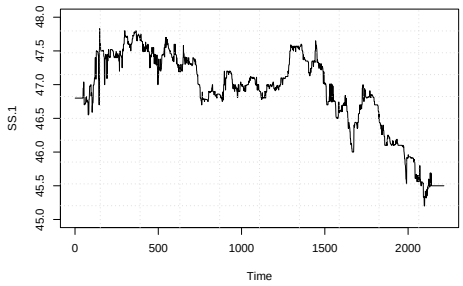


(d) Unconstrained ATOM ZIT. QQ-Plot

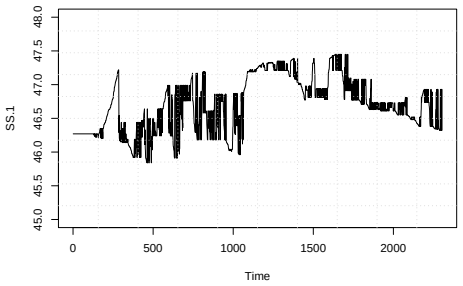
FIGURE 1 – Qualitative Stylized facts, Real market data vs. simulated data

Acronym	Name	Description
$UZIT_U$	Unconstrained ZIT with uniform price distribution	$p_t \sim U[min(P_t), max(P_t)]$
$UZIT_N$	Unconstrained ZIT with normal price distribution	$p_t \sim N(\mu_P, \sigma_P)$
$SZIT_U$	Statistically calibrated ZIT	The boundaries of order size and price are determined based on order book data. Price of ask orders are drawn from $[a_{min}, a_{max}]$, bids are drawn from $[b_{min}, b_{max}]$
$TZIT_N$	Trend calibrated agents	Trend following agents. $P_t^n = P_{min}^n + (P_{max}^n - P_{min}^n) \times \gamma_t \times \delta_t$ where γ_t is a trend sensitivity $\gamma_t = \gamma_{t-1} - (1/\theta) \times t$ with $t \in [0, \theta]$. It allows to track the underlying trend with a certain level of accuracy. The bigger θ, the more accurate the fit. Parameter δ_t denotes noise, $\delta_t \sim logN(0, 1)$. Daily price series is divided into 50 subsets that determine the periods of calibration.
$AZIT$	Aggressive ZIT	Agents are heterogeneous with respect to their relative aggressiveness. Patient agents ($AZIT_P$) send limit buy orders with prices uniformly drawn in the interval $[0; a_{min}]$ and sell orders limit from $[b_{max}; \infty)$. Impatient ZIT ($AZIT_I$) send market orders. There are 2/3 of $AZIT_P$ and 1/3 of $AZIT_I$

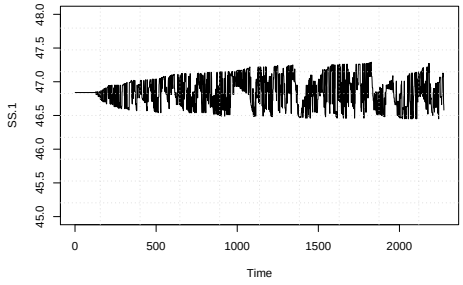
TABLE 1 – Summary of agents' strategies. p_t is the price of the order sent at moment t, $min(P_t)$ $max(P_t)$ are the minimum and maximum daily prices of real price series. The size of all orders is uniformly drawn from the interval $[min(V)\,;\, max(V)]$, P_{max}^n, P_{min}^n are the maximum and minimum prices respectively over the subperiod n.



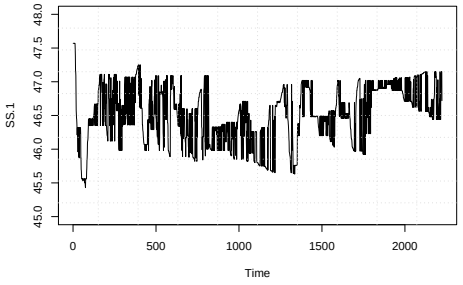
(a) Renault S.A., real



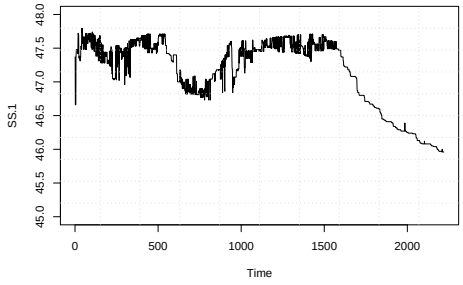
(b) $UZIT_U$



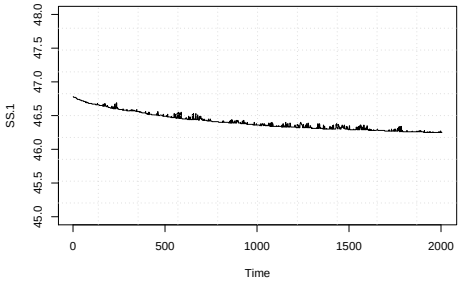
(c) $UZIT_N$



(d) $SZIT$



(e) $TZIT$



(f) $AZIT$

FIGURE 2 – Price dynamics, real vs. simulated

be matched by any of the various ZIT families. Only the interaction between agents with some adaptive abilities (like trend following) and market features is able to capture the higher moments of price and returns, and the correlation between volume and volatility.

Additionally, a sensitivity analysis of our model shows that the proportion of Big-to-Small fishes is one of the key elements affecting return and price features. Playing the role of liquidity providers, Big fishes "feed" Small fishes. Small fishes can easily buy or sell stocks with a price close to the current market price, as long as a large-volume order sent by a Big fish is available in the order book. Thus, increasing the proportion of Big fishes has a positive effect on the slope of the decay function for the autocorrelation coefficients of absolute returns.

To sum up, the above analysis shows the importance of limit order market structure in explaining the main qualitative stylized facts. Our model relying on ZITs highlights that beyond behaviors, market structure *does matter*. Qualitative stylized facts of returns are reproduced by the structure of the order book itself, while ignoring agents rationality. However, our basic ZIT models fail to generate quantitative statistics of prices in line with real market observations. For a good replication of real data, we may need to consider some kind of interaction between sophisticated behaviors for artificial agents, including trend-following, and market structure.

3.2 Institutional design and individual behavior

Modern stock exchanges are largely organized as continuous-trading limit order books, a type of market structure that significantly encourages high frequency trading (Budish *et al.*, 2015). The alternative to continuous-time market design is discrete-time trading where investors can send orders at any time during the day but prices are set at specific points in time.

There is an ongoing debate over the relative advantages of continous- and discrete-time trading mechanisms. In June 2014, the SEC declared that batch auction can be a *"more flexible, competitive"* exchange design. In November 2018, the European Securities and Market Authority (ESMA) launched a call for evidence about the effect of periodic and frequent batch auctions systems on the price determination process and market

transparency. According to Mary Jo White, who served as the 31st Chair of the Securities Exchange Commission (SEC), the topics of market structure policy are of particular importance and the advances in this field should help ensure that ..."*markets continue to operate openly, fairly, and efficiently to benefit investors and promote capital formation.*"

Inspired by the latter statements, we investigate in Biondi and Veryzhenko (2018) [11] the emergence of aggregate market properties (volatility, liquidity, efficiency) in various securities markets subject to a variety of institutional designs. We also allow these market structures to be populated with heterogeneous investors having specific sets of resources (budget, knowledge) and capabilities. Computational simulations allow us to compare how different market mechanisms behave in an all else equal setting of strictly similar initial conditions (number of trading rounds, number of market participants, number of held stocks,...).

The market structures we consider are both analyzed extensively in the literature and widely used in the industry and include: full matching, batch auction, Walrasian auction, discrete time market architecture called "share exchange" (initially presented in Biondi and Giannoccolo (2015)), quote driven architecture in presence of a market maker (specialist market), and order driven architecture (continuous-time central order book) with continuous trading. These market designs are summarized in Table 2.

The markets we simulate may be populated by one of four categories of traders. We start with simple atomistic zero intelligence agents called ZER. This type of trader randomly picks, from a given interval, an expected price (focal value) $E_{i,t}(p_{t+1})$, that determines the price limit of his orders. We assume that these traders buy or sell with equal probabilities. Since traders belonging to this category receive no information, have no learning capabilities and act randomly, the effects on price dynamics are the outcome of market design.

Similarly to $ZERs$, $ARTs$ determine their focal value $E_{i,t}(p_{t+1})$ randomly ; this value is uniformly drawn from a given interval. However, $ARTs$ buy if they expect that the price will continue to rise, i.e. $E_{i,t-1}(p_t) < E_{i,t}(p_{t+1})$ and sell otherwise. The next category of agents, called TRF, trade on fundamental and momentum information. They determine their focal value as $E_{i,t}(p_{t+1}) = p_t + \psi_i(p_t - p_{t-1}) + \phi_i(F_t - F_{t-1})$ where ψ_i and ϕ_i are parameters that capture their sensitivity to trend and to changes in fundamental informa-

tion, respectively. These investors sell (buy) when the last clearing price is higher (lower) than their focal price expectations, i.e. when $p_t > E_{i,t}(p_{t+1})$ ($p_t < E_{i,t}(p_{t+1})$). They rely on limit orders, and their price limits are equal to their estimated focal values. Agents with strategic order placement TRS follow the same rules as $TRFs$ to form their expectations but rely on completely different schemes for final order pricing. These investors check the best bid and the best ask available in the order book to optimize their final trade. TRS buyers quote a price that does not fully reflect their focal value, betting that a possible seller would accept this relatively low bid. Therefore, they submit their bids at $p_{t,i} \sim U[b_t, E_{i,t}(p_{t+1})]$, where $p_{t,i}$ denotes a bid quote submitted by agent i at moment t, b_t being the best bid at moment t. Similarly, TRS sellers propose a price that is higher than their reservation price, expecting that there will be a bidder willing to buy at such high price. TRS submit ask orders at $p_{t,i} \sim U[E_{i,t}(p_{t+1}), a_t]$, where $p_{t,i}$ denotes an ask quote submitted by agent i at moment t, a_t being the best ask at moment t. Hence, TRS agents determine the direction and price of their orders based on the last market price and the current status of the order book. These four trading strategies are summarized in Table 3.

The combination of four types of agent strategies and six types of institutional designs results in the 24 simulation protocols analyzed in depth in this paper. We investigate different dimensions of market quality: i) volatility measured by range, kurtosis and standard deviation of daily returns ii) informational efficiency measured by the deviation from fundamentals, and iii) allocative efficiency measured by the number of transactions and the number of waste (unexecuted) orders. [4]

We first focus on the volatility generated by each trading protocol. As mentioned above, if agents have zero-intelligence (ZER and ART), the statistical properties of returns are the sole outcome of the underlying market mechanism and do not stem from agents' strategies. In other words, it is the underlying market structure that drives the results. We find that the Full matching market structure displays the largest distribution of returns with amplified losses and gains. Markets with market makers feature smaller swings in returns. Moreover, returns in the dealership market are the least volatile, with standard deviations of returns twice lower compared to limit order central book, and insignificant kurtosis. The

4. This measure is introduced by LiCalzi and Pellizzari (2007).

Name	Description
Full matching	All orders are sorted with price and time priority. Satisfies all orders which can find a match. Matching is performed starting from the best prices on both sides.
Walrasian	A trading session is divided into discrete time intervals, and, at each round, all orders are treated as having the same time stamp. The auctioneer proposes a tentative price and adjusts it based on aggregate excess demand. An auction ends when the proposed price clears the market ($D = S$). Walrasian auction perfectly matches the supply and the demand.
Batch	The price is at the intersection point of supply and demand curves.
Share exchange	$\frac{\overline{P}_{D,t}(\overline{P}_{S,t}-\underline{P}_{S,t})+\underline{P}_{S,t}(\overline{P}_{D,t}-\underline{P}_{D,t})}{(\overline{P}_{D,t}-\underline{P}_{D,t})+(\overline{P}_{S,t}-\underline{P}_{S,t})}$ if $\overline{P}_{D,t} \geq \underline{P}_{S,t}$
Market maker	$P_{t+1} = \triangle \cdot median(E_{i,t}(p_{t+1})) + (1 - \triangle) \cdot P_t$, where $\triangle = \frac{\lvert \sum D - \sum S \rvert}{N}$.
Order book	Continuous market mechanism. A transaction occurs when the best bid $\geq$ best ask. Possibility of multiple transactions at each time step.

TABLE 2 – Summary of market designs. $E_{i,t}(p_{t+1})$ is the expectation of agent i at moment t about the price at next time step. $\sum D$ is the total demand volume, $\sum S$ is the total supply volume, and N is the number of traders. $\overline{P}_{S,t}$, $\underline{P}_{S,t}$ are the minimum and maximum ask prices submitted by agents at moment t. $\overline{P}_{D,t}$, $\underline{P}_{D,t}$ are the minimum and maximum bid prices submitted by agents at moment t.

Acronym	Name	Description
ZER	Null intelligence behavior	Quotes of limits of orders are uniformly drawn from the interval $U[100; 300]$, Bids and Asks are sent with the same probability
ART	Auto-regressive traders	Focal value is randomly drawn from the interval $U[100; 300]$. Autoregressive process in price discovery. If expectations on future price $>$ previous focal value $\Rightarrow$ Bid. If expectations on future price $\leq$ previous focal value $\Rightarrow$ Ask
TRF	Agents trading on fundamental and momentum	Sensitive to momentum and fundamental signals. Define their focal value based on previous market price, trend dynamics and fundamental information. If last market clearing price $\leq$ focal price expectation $\Rightarrow$ Bid. If last market clearing price $>$ focal price expectation $\Rightarrow$ Ask.
TRS	Agent with strategic order placement	Form focal values similar to TRF. Do not submit at their expectations. Check current state of the order book to optimize their final trade. Submit bids at $p_{t,i} \sim U[b_t, E_{i,t}(p_{t+1})]$. Submit their at $p_{t,i} \sim U[E_{i,t}(p_{t+1}), a_t]$, where b_t and a_t are the best bid and the best ask at moment t.

TABLE 3 – Summary of agents' strategies

latter can be explained by the fact that market makers set their quotes based on the total bid/ask volume imbalance at the previous round and the last trading price. This reduces the impact of individual orders, which results in less dispersed prices compared to other market mechanisms where pricing results directly from individual quotes of thousands of market participants (as in a continuous trading central order book). We thus conclude that, without strategic agents, the order-driven market mechanism is the one that features the largest swings in both profits and losses.

To check the robustness of these results in presence of intelligent agents, we consider markets populated by investors with some cognitive abilities like TRFs and TRSs. This allows us to study the dynamics produced by non-trivial interactions between investors' strategic behavior and market structure. Additionally, the synchronization between profit-oriented traders can be an endogenous source of bubbles and crashes. In this framework, we try to figure out which market structure prevents the occurrence of such extreme price movements. Our findings reveal that speculative bubble seeking seems especially material for the order-driven market, where positive swings of excess return reach considerable peaks. On the contrary, we observe that volatility is significantly reduced on dealership markets, share exchanges, Walrasian, and batch auction protocols.

We then turn to the analysis of informational efficiency by comparing the distributions of generated price series to those of fundamental signals. With agents having zero-intelligence (ZER and ATR), we get that a full-matching market design produces chaotic pricing with considerably large price distribution. Obviously, it does not fit the distribution of fundamentals. We find that batch auctions perform slightly better than a dealership market with regard to deviations from fundamentals. We also find that a continuous trading limit order book tends to disperse prices more than the distribution of fundamentals, with an average price deviation from fundamentals that is twice larger than under Walrasian or batch auction.

Finally, we study allocative efficiency, which we proxy by the percentage of excess volume (total volume of trades divided by the total volume submitted at the bid or the ask side of the order book). In each round, all agents try to make a transaction. A protocol should minimize the number of waste orders or efficiently set aside orders with extreme pricing which potentially could produce extreme price movements. The batch

auction and the specialist dealership market designs generate minimal excess volume. In contrast, the continuous double auction is seriously wasteful. Only around 8% of all orders are executed under this market architecture if it is populated by zero-intelligence agents. Moreover, increasing trading intelligence tends to increase the number of waste orders, most notably in the continuous order-driven market, where only 5% of orders submitted by rational profit-oriented agents result in a trade.

The large positive and negative return swings and significant deviations from fundamentals produced under the continuous central order book mechanism show that this type of market does not perform relatively well regarding informational efficiency and volatility. The strong positive asymmetry of return distributions produced by strategic TRS agents interacting in the limit order book also suggests that this mechanism can foster the development of speculative bubbles. Overall, we find that the immediacy offered by the continuous-time market design comes at the expense of other dimensions of market quality. We also show that discrete time batch auction features better informational and allocative efficiency and reduced volatility. These results are of particular interest for market regulators, as the frequent discrete-time batch auction (lasting only several milliseconds) has rapidly gained a significant market share since the application of MiFID II.

4 High frequency trading: strategic competition between heterogeneous traders

Algorithmic and high-frequency trading constitute a recent field of study, however no precise and universal definition has yet been agreed on (ESMA, 2014; Megarbane *et al.*, 2017). Generally speaking, the algorithmic trading is *"the use of mathematical models, computers, and telecommunications networks to automate the buying and selling of financial securities"* (Kirilenko and Lo, 2013).

The SEC (2011) in Concept release on equity market structure lists the characteristics of HFTs: 1) professional traders acting in a proprietary capacity 2) the use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders 3) use of co-location services 4) very short time-frames for establishing and liquidating positions 5) submission of numerous orders that are cancelled shortly after

submission 6) ending the trading day in as close to a flat position as possible.

The AMF (2017) adds quantitative characteristics of HFTs based on the lifetime of canceled orders. The AMF defines HFTs as market participants that cancel at least 100,000 orders in a year, and whose canceled orders have a lifetime shorter than the average lifetime of orders in the order book. The AMF also defines HFTs as the market participants that cancel at least 500,000 orders per year, whose orders lifetime is shorter than 0.1 s (meaning that such investors quickly update their orders in the order book) and whose a canceled order 1% lifetime percentile is less than 500 microseconds.

The next subsection presents the elements of HFT modeling in our artificial market framework that are common to the papers presented below. Heterogeneous HFT traders are used in a series of papers: in Veryzhenko *et al.* (2017a) [4], Veryzhenko *et al.* (2017b) [5] to investigate the effect of heterogeneous HFT on market quality in normal conditions, and in Arena *et al.* (2018) [3] and Oriol and Veryzhenko (2018a) [2] to investigate their effect on market quality under extreme market events. A particular attention is dedicated to the order book high speed manipulations in the paper Oriol and Veryzhenko (2018b) [13]. In all these papers, we study different regulatory tools which affect HFT's behavior and market quality.

4.1 HFT Modeling in an Artificial Market Framework

We mainly focus on six groups of traders in different studies: slow fundamentalists, high-frequency news traders, high-frequency trend followers, high-frequency contrarians, high-frequency order book pressure followers, spoofers. Their behavior is summarized in Table 4.

4.2 The effect of heterogeneous HFTs on market quality

The behavior of HFT is a hot topic in current research. So far, no consensus has emerged regarding their impact on market quality. Chordia *et al.* (2008), Brogaard (2011),Hendershott and Moulton (2011), and Brogaard *et al.* (2018) argue that HFTs can be beneficial as they contribute to increase liquidity, reduce volatility and improve price discovery. However, other studies highlight undesirable effects, especially during periods of significant market turmoil. Kirilenko *et al.* (2017) report that the liquidity provided by HFTs tends

Name	Description
Fundamentalist	The fundamental value of each stock evolves according to a jump process $V_t = V_{t-1} + \delta_t$, where $\delta_t \sim N(0, \sigma^\delta)$ is a normal random variable with zero mean and constant standard deviation. Agents are boundedly rational (or noisily informed), the fundamental value is biased by ϵ_i, which determines the accuracy with which the agent i interprets the fundamental information and determines his expectation on fundamental value $E(W_{i,t}) = V_t + \epsilon_i$, $\epsilon_i \sim N(0, \sigma^\epsilon)$. Fundamentalists buy if $E(W_{i,t}) > P_{t-1}$, and vice versa.
High frequency news trader	HFTs obtain information faster than other market participants (Biais and Foucault, 2014a). This type of HFT tries to predict price movements just before V_t becomes public information, that is, before it is communicated to slow agents.
High frequency trend follower	Tries to make profit by anticipating price variations based on knowledge about historical prices (Aloud *et al.*, 2012; SEC, 2011). This HFT computes the price variation $\lvert\frac{P_t - P_{t-n}}{P_{t-n}}\rvert > \Delta_i$, where P_t is the last market price and P_{t-n} is the price at point $t-n$. Such agents are heterogeneous with respect to parameter Δ_i that denotes the minimal price variation. Trend followers buy (sell) when stock value has been increasing $P_t - P_{t-n} > 0$ (declining $P_t - P_{t-n} < 0$) over the last n time stamps.
High frequency contrarian	According to Brogaard (2011), one part of the HFT population acts as liquidity providers: they buy (sell) stocks whose prices have been declining $P_t - P_{t-n} < 0$ (increasing $P_t - P_{t-n} > 0$) over the preceding n time stamps.
Order book pressure follower	These traders use order book imbalance to predict the next price movement. The bid-ask spread imbalance measure is $I = \frac{\sum_{i=1}^{n} Q_i^{bid} - \sum_{i=1}^{n} Q_i^{ask}}{\sum_{i=1}^{n} Q_i^{bid} + \sum_{i=1}^{n} Q_i^{ask}}$ where Q_i^{bid} and Q_i^{ask} are the bid and ask volumes posted at n positions of the order book. Such HFTs explore the positive relation between this indicator and future stock returns. The index I lies between -1 and +1. Agents buy when I is high and sell when I is low.
Spoofer	An HFT spoofer trader initially follows a simple trend following strategy. The agent submits a large-volume limit order to the book without a real intention to make a transaction in order to mislead other investors who follow institutional investors or who analyze order book pressure.

TABLE 4 – Summary of agents' behavior

to vanish very quickly during periods of high market stress. Moreover, Bellia *et al.* (2018) find that HFTs are also responsible for initiating flash crashes.

One of the major problems of empirical research on this subject is the identification of HFT operators [5]. Even those who are able to develop proxies to identify HFT accounts only report the aggregate impact of heterogeneous high-frequency strategies on market quality (Brogaard *et al.*, 2018, 2015). Therefore, their results are driven by the dominating strategy on a given platform [6]. The lack of an exact measure for HFT activity is potentially one of the causes of the high heterogeneity in the results reported in the empirical literature.

To circumvent these issues, we analyze in Arena *et al.* (2018) and Oriol and Veryzhenko (2018a) [3, 2] an agent-based model which allows us to observe the liquidity provision and consumption of different categories of traders. As HFT activities may vary with market conditions, we focus on their behavior in normal market conditions, as well as during extreme market events such as a sudden significant liquidity dislocation. The later is of particular importance as even small liquidity dislocations combined with a high speed and massive data flows may lead to systemic flash crashes or bubbles in a matter of minutes (Kirilenko *et al.*, 2017). A flash crash is a period of large and temporary selling pressure followed by a price reversal. In our study, we address the following questions: (i) to which extent HFTs and non-HFTs trigger a significant price variation ? (ii) Do HFTs improve or hamper liquidity in normal market conditions ? (iii) How much liquidity is supplied and consumed by HFTs and fundamentalists at different stages of a flash crashes ? (iv) Who gains and who loses from a flash crash ?

To answer these questions we compare two protocols. One corresponds to a market populated only by slow fundamentalists (non-HFT), while the other corresponds to a market populated by slow fundamentalists and high frequency traders. Most known high

5. Empirical studies employ either direct or indirect approaches. The first method directly identifies as HFT those market participants whose primary business is the HFT carried out on proprietary basis. Usually, this information is provided by trading venues. For instance, this type of data is used in Degryse *et al.* (2018). The second method identifies HFTs according to their operational features, such as cancel-to-trade ratio or order-to-trade ratio. These proxies are developed in Boehmer *et al.* (2012); Hendershott and Moulton (2011).

6. For instance, one platform can be dominated by a high-frequency market makers, so that researchers report overall positive effect of HFTs on market liquidity. On other platforms high frequency trend following can be the dominant practice, and researchers would report an aggressive liquidity consumption by the HFTs that operate on that platform.

frequency trading strategies (Biais and Foucault, 2014a) are included in our model: high frequency news traders (news-HFT), high frequency trend followers (trend-HFT), and high frequency liquidity providers (liquidity-HFT)[7]. The first protocol mimics the period when orders were sent by slow human traders and matched by platforms. The second protocol presents the current situation where most orders are sent and matched by trading automates. The first protocol is a benchmark case that allows us to identify the effect of different high frequency strategies on market quality. These two scenarios help us isolate the effect of HFTs. Each scenario is repeated 1,000 times with the same initial settings, and all statistics are computed based on 1,000 runs.

First of all, we focus on price volatility in normal market conditions. *Extreme price movements* (EPMs), which we define as 10-second intervals with the largest absolute returns, can be a good proxy for price volatility (Brogaard *et al.*, 2018). We compare return series generated by protocols with and without HFTs to understand the effect of HFTs on EPM amplification. We also try to figure out whether HFTs trigger EPMs in normal market conditions. Next, we pay a particular attention to the role of different trader categories in triggering flash crashes and in exacerbating price shocks. Analyzing the flash crash of May 6, 2010, Menkveld and Yueshen (2016) argue that it was caused by a large investor, without including any detail about the nature of its primary activity. We simulate a flash crash by introducing an aggressive market order with a volume 20-times higher than the average order size. This large-volume order depletes about twenty best limits. As a result, it produces on average a -2% downward trend, which corresponds to the size of a typical flash crash (Bellia *et al.*, 2018). In our simulations, this very large order is submitted by non-HFT.

Our findings show that the presence of HFTs does not increase the number of EPMs and does not amplify a typical EPM in normal market conditions. Moreover, we report a significant decrease in the mean and median absolute returns during EPMs if HFTs are present in the market. To understand the contribution of HFTs in the emergence of such large price variations, we analyze liquidity provision and consumption over 10 seconds prior to an average EPM episode. For each EPM, we identify the trading category with

7. High frequency arbitrageurs are excluded from the analysis as we focus on the case where a stock is listed only on one market.

the largest volume pressure in the direction of the EPM, and we consider this category as the one responsible for the price movement. We find that non-HFTs initiate most of the transactions (53%) in the direction of an EPM. HFTs also actively consume liquidity during a typical positive or negative EPM. On average, trend-HFTs and liquidity-HFTs consume about 40% of the liquidity (in the direction of the EPM) most of which is provided by non-HFTs. However, all categories of HFTs also continue to initiate transactions in the opposite direction of the EPM. Trend-HFTs, liquidity-HFTs, and news-HFTs initiate respectively 14%, 18%, and 15% of all transactions against the direction of a typical EPM. This suggests that HFTs may speed up the reversal process. Our results show that high frequency trading practice is not the unique cause of EPMs in normal market conditions. Some of these extreme price variations are linked to the changes in fundamentals incorporated into prices by non-HFTs, and others can result from the synchronization of high-frequency trend-followers.

Our analysis of individual behavior during flash crashes shows that at the early stage of a price drop HFTs may act as liquidity providers. One second (1,000 milliseconds or 1,000 rounds in our simulations) after the introduction of an aggressive order (early crash), about 90% of the total volume of sell transactions is initiated by non-HFTs. The aggressive market order sent by a slow fundamentalist is mainly executed against the orders of HFTs resting in the book book. On average, 37% is provided by high-frequency trend followers, 47% by high-frequency liquidity providers, and 5% by high-frequency news traders. These observations can be explained by the fact that HFTs heavily rely on limit orders located at the top of the order book, as reported in Kirilenko *et al.* (2017) and as modeled in our simulations. This available liquidity is consumed at the first moments of the crash by aggressive market orders. However, ten seconds (or 10,000 simulation rounds) after the introduction of an aggressive sell market order (late crash) HFTs do not act any more as liquidity providers. HFTs create a "hot potato effect", i.e. repeated buying and selling of contracts within the group of HFTs (Kirilenko *et al.*, 2017). In the late crash period, positive feedback trend-HFTs consume as much liquidity as they provide. News-HFTs actively consume liquidity offered by liquidity-HFTs. Non-HFTs provide 57% of the total volume for buying transactions pushing the price up, which favors the market recovery. A comparison of the two protocols, i.e. with and without HFTs shows that, in presence

of HFTs, the average duration of a crash[8] is twice longer and a crash is on average three times deeper. Thus we see a two-fold effect of HFTs on market liquidity during a crash event: first, HFTs provide liquidity during the first stage of the price drop as their liquidity available at top of bids is consumed by the aggressive market order. Then, multiple transactions within the group of HFTs make the price correction more difficult.

We also explore the profitability of a flash crash for different traders. To do so, we compute the revenue from trades at the moment of the flash crash and over the 10-second period following it. The results show that high-frequency trend followers realize profitable short sales and end up with a positive final revenue. Fast news traders (news-HFTs) also make small profits out of flash crashes on average. This is due to the fact that the price shock is caused not by the release of "news" but by the execution of a single large order sent by mistake. As a consequence, news-HFTs do not actively react to the changes in price. They supply little liquidity to the order book at the early stages of the crash. Only 4% of the liquidity provided by news-HFTs is consumed by the aggressive sell market order. Hight-frequency news traders start buying when their activation threshold is reached as a result of the significant deviation of the market price from the fundamentals. So, news-HFTs are able to cumulate several profitable trades, "buy low and sell high", during a price drop and its recovery. High-frequency liquidity providers and fundamentalists respectively lose on average -0.4% and -0.8% from a flash crash. Therefore, extreme market events such as flash crashes can be profitable for some categories of HFTs. These findings are in line with the observations of Brogaard *et al.* (2018).

Our results deliver important insights for market participants and policy makers. We show that no particular trading category amplifies market volatility in normal market conditions. However, there are some categories of traders which, by coincidence, combine their actions in a manner that deepens a price crash. Finally, our results show that flash crashes can be profitable for some categories of high frequency traders. To the best of our knowledge, we are the first to describe the role of different categories of HFTs, i.e trend-HFTS, liquidity-HFTs, and news-HFTs in the creation and development of flash crashes. The perfect traceability of market participants' activities in our model allows us to contribute to the understanding of the mechanism at the root of these extreme market

8. We assume that a crash is over when at least two-thirds of a price drop is recovered

events.

5 Regulatory policy and traders' behavior

A series of disruptive events caused (or amplified) by algorithms – like the flash crashes of 2010 or 2014, the loss of $440 million in 30 minutes by Knight Capital Group, the crash of Facebook initial public offering – showed a necessity to find a particular regulation to impose certain limits and restrictions on HFT practices. In this section we present a series of studies on the effect of financial regulation (introduced without or with the intention to restrict HFTs) on market quality and traders' activities.

5.1 Cancelled order tax

The Financial Transaction Tax (FTT) implemented on August 1, 2012 by the French government comprises three different taxes: i) a tax on the acquisition of equity securities ii) a tax on naked sovereign Credit Default Swaps (CDS) and iii) a tax on HFT. In Veryzhenko *et al.* (2017a) [4] and Veryzhenko *et al.* (2017b) [5] we focus on the latter. The tax on HFT is a 0.01% tax on the amount of cancelled or modified orders within a half-second time span, on a given trading day, which exceeds a threshold of 80% of the total trading amount. This tax applies only to French actors, who in fact are minimally affected because an exemption applies to market-making activities, and because of the very high 80% threshold. The French government estimates that the tax on HFT generated no revenue in 2012 (Capelle-Blancard, 2017).

Our objective is to analyze the effectiveness of a modified cancelled order tax, that is one where no agent benefits from an exemption. In particular, we attempt to figure out first whether this regulatory policy is likely to discourage speculative activity, and second whether it would impact market quality. To answer these questions, we construct a simulation-based algorithmic model.

We simulate a market populated by players whose strategies are those described in Table 3. Moreover, to make the model more realistic, we consider that the agents feature learning mechanisms, that is they account for the new market rule in their order submissions and canceling. The model is calibrated based on parameter estimations (proportion of different categories of traders, average trading volume, initial cash) as found in the

empirical studies by Kirilenko *et al.* (2017) and Colliard and Hoffmann (2017).

We run two scenarios: a benchmark scenario without any tax and a second scenario where HFTs' orders cancelled within a half second time span are taxed. We vary the tax level from 0.01% to 0.1%. To estimate the impact of this new regulation on market quality metrics, we use a difference-in-differences technique.

We find that the order-to-trade ratio decreases dramatically with the introduction of this new regulation, and at the same time, the dollar volume divided by the message traffic increases tenfold (from $1,603 to $11,184 per electronic message). A higher tax thus removes the fastest HFTs which are those that are characterized by a high number of small volume orders. Therefore, a higher tax leads to less HFT activity.

The number of cancelled orders decreases progressively with the tax increase, as does the message traffic. The intuition for this result is that HFTs are both searching for trades even with small potential profit (based on short-lived momentum or fundamental information) and are all competing on the market, so that profitable trading opportunities disappear quickly. Once these opportunities are gone, HFTs cancel their orders, which gives rise to excessive levels of order cancellation and resubmission. For example, in our simulations, we find that 30% of all orders are cancelled before 0.5 seconds with the 0.1% tax regime, whereas 45% of their orders are cancelled before 0.5 seconds with the 0.01% tax regime.

We also study the consequences of this reduced HFTs' activity on market quality. Our results show a reduction of market liquidity in the form of a smaller number of traded shares (-20%) and euro depth (-5%) with the 0.01% tax. We find no evidence of a positive/negative effect of reduced HFT activities on market volatility. This can be explained by the fact that the bid/ask spread remains almost unchanged. As reported in the empirical literature (Biais and Foucault, 2014b; Subrahmanyam and Zheng, 2015), and as modelled in our artificial market, HF traders tend to submit their limit orders near the best limits without necessarily improving the bid/ask spread. Hence, their reduced activity does not deteriorate bid/ask spreads and does not significantly increase market volatility in normal market conditions.

5.2 Short-selling ban

With no direct link to the activity of high frequency algorithmic traders, in February 2010 (effective on May 10, 2010) the SEC adopted a short selling restriction, referred to as the "alternative uptick rule" (*Rule 201*). During the 2007/2008 global financial crisis, more than 30 countries had already implemented short-selling bans to prevent further declines in stock prices. A particular feature of Rule 201 is that it deals with intraday extreme market events. Short-sales bans are occasionally implemented during financial panics when market volatility is particularly high in order to protect market quality and avoid any financial manipulation. It prohibits short selling to avoid further decline of stock prices when those have already significantly dropped in one day. As such, it aims at preventing speculators from placing excessive downward pressure on troubled financial firms.

Empirically Boehmer *et al.* (2013), Beber and Pagano (2013), Brogaard *et al.* (2017) address the issues related to recent short sale bans. However, these studies face a series of limitations. The first is related to their "approximative" identification of different categories of traders. Most empirical studies develop their own proxies to classify orders issued by HFTs and non-HFTs. Usually, there proxies rely on operational features of HFTs, such as cancel-to-trade ratio or order-to-trade ratio (Boehmer *et al.*, 2012; Hendershott and Moulton, 2011). The second limitation relates to the choice of banned stocks and the definition of the control group. The timing of the ban and the stocks included into the ban are not random. Therefore, the changes in market quality could be caused by factors which led to the short selling ban and not by the restriction itself.

Artificial markets allow to overcome some drawbacks of the empirical approaches and can provide complementary results, focusing on different aspects of shorting restrictions. In Oriol and Veryzhenko (2018a) [2], we question the effectiveness of short sale bans at dampening the effect of a liquidity shock on market liquidity and at reducing the magnitude of intraday price movemets. First, we focus on the reaction of the market without any ban after an aggressive selling order which can be considered as an operational error ("fat finger" event). Heterogeneous HFTs and slow fundamentalists also called non-HFTs (see Table 3) participate in trading. All traders can take long or short positions. In line with the empirical literature (Battalio *et al.*, 2012) our setup considers that high-

frequency traders do not maintain short positions for long periods. More precisely, HFTs close their positions when a potential profit reaches a level Δ, where Δ is uniformly distributed over the interval $[0.01\%, 0.5\%]$. As a result, HFTs close short positions within minutes or even seconds after opening them. This first scenario generates a series of returns which serves as our unrestricted control group. Second, we repeat the experiment with the same initial settings and with the following modification: if an executed aggressive order produces a minimum 2% downward trend, short sales are no longer allowed for the rest of the trading session. We focus on the impact of this rule on both market quality and the activity of different market participants. We distinguish two different periods (before and during the ban), which allows us to apply the Difference in Differences (DiD) technique to study the changes produced by the new policy.

We find that the ban largely eliminates HFTs' shorting activity as they seem to be less active at different stages of the crash. First, a short sale restriction prevents any "hot potato" effect (repeated short-selling and buy back) within the group of positive-feedback HFTs during a decline in a stock price. Second, this defensive regulation reduces HFTs' trading activity in the recovery phase and during the post-crash period. We observe the latter since, without the ban, traders who hold short positions with a return that exceeds the level Δ buy back shares and bring liquidity on the bid side of the order book. Hence, the short-sale ban leads to a 70% decrease in HFT's average number daily trades. Overall, HFTs act as liquidity consumers rather than liquidity providers in both buy and sell transactions in an automatically triggered short-sale ban scenario. They consume half the volume available on the bid and ask sides. In this context, non-HFTs appear to be main liquidity providers as they supply about 70% on the ask side, and 80% of the depth of the bid side. Thus, a short-selling ban pushes non-HFTs to become the main liquidity providers in the market during periods of financial turmoil.

We next focus on the consequences of a short sale ban on market quality. The results of the DiD test point out a significant reduction in volatility which results from the fall in the activity of directional traders. Volatility, as measured by the absolute return, is reduced by 30% relative to the unrestricted control group, and the squared return is reduced by 60%. Moreover, our results also show a deterioration of liquidity in the market subject of a ban. Our analysis shows a significant reduction in the log dollar volume and an increase in the

relative bid/ask spread. Differences in liquidity measures under short-selling restrictions stem from the shrink in order size and trading frequency. This is mainly explained by the fact that high-frequency positive feedback traders is not the only trading category affected by this defensive policy. The short selling ban also leads to a reduced number of active news-HFTs and slow fundamentalists who usually detect underpriced stocks and bring liquidity to the market. Slow fundamentalist's activity is also reduced because their activation threshold is not reached.

As shown by our results, a short-selling ban can be a good device to reduce positive-feedback trading activities in a highly volatile market. It can be also an effective tool to reduce post-crash volatility. However, the bans have the unwanted effect of lowering market liquidity. Our findings are important to better understand the effectiveness of short-selling bans not only as a defensive policy during a financial crisis, but also as a short-term mechanism to prevent price declines during a flash-crash episode. However, regulators should be aware that the imposed short selling ban can be considered as a negative fundamental signal itself. Traders will sell in response to this negative information in order to reduce their risk exposure. We plan to analyze this issue in future research.

5.3 Circuit breakers

In response to the May 2010 flash crash, regulators have taken proactive steps to avoid crashes and to deal with periodic illiquidity in markets. The SEC proposed several measures, in particular updated circuit breakers and limit up/limit down mechanisms also known as ex-ante circuit breakers (SEC, 2011).

According to the ESMA (2020), circuit breakers are *"mechanisms that monitor the market continuously and trigger a trading halt as soon as the price (or its variation) of an individual security or an index falls below or rises above a predetermined level"*. On Euronext, a trading halt is automatically triggered in case of a +/-8% deviation from the static reference price for Blue Chips constituents, and a +/-10% for other stocks. The static reference price is taken from the opening price of the security if it has trades on the same day, or the last reference price from the previous trading day. Continuous trading can be also interrupted if the execution price lies outside the dynamic price range compared to the dynamic reference price, e.g. the last traded price. The dynamic reference price

changes throughout the trading day after each trade, with the last traded price becoming the new reference. On Euronext, the dynamic threshold is set to +/-3% for Blue Chips and to +/-5% for other stocks.

On Euronext, a circuit breaker is recorded as a particular event with a series of states and their exact timing. The "Halted instrument" state means that the static or dynamic price range is reached or breached and trading is interrupted. Different to former trading halts, a circuit breaker does not completely suspend all trading activities but triggers an unscheduled call auction stage titled "Delayed opening". During a call phase, orders can be submitted, updated or canceled, and indicative prices and volumes are displayed. The purpose of this temporary trading suspension is to give market participants a few minutes to evaluate any new piece of information, reconsider their interests and remove any erroneous orders. The minimum trading halt duration is 3 minutes. If the potential execution price still remains outside the predetermined acceptable range the auction can be extended. The "Go to open state" corresponds to the moment when the opening price is determined. "Start continuous trading" defines the moment when trading shall take place on a continuous basis.

The existing empirical research (Ackert *et al.*, 2001; Subrahmanyam, 1994, 1995) on circuit breakers has primarily focused on the effects of trading halts (a former control mechanism) on overall market quality. Former trading halts suspended all order book activity during a long period (sometimes for hours). The effects of recent circuit breakers, which automatically interrupt trading for short periods of time and allow order revision, are widely unexplored. In Ligot and Veryzhenko (2019) [10], we study the ability of a circuit breaker to limit large price swings and to reduce panic trading. Our focus is on the strategic decisions made by market participants and how these vary with market conditions. To do so, we compare liquidity provision and consumption by market participants over relatively calm periods and see how their behavior is altered during particular turbulent periods which lead to trading halts. This analysis helps us detecting the trading categories which contribute to the amplified volatility. We also focus on the impact of the traders' quotations during the circuit breaker on post-pause market dynamics. It allows us to analyze the extent to which this mechanism helps controlling price fluctuations and stabilizing the market.

To conduct our analysis, we use the Eurofidai Base Européenne de Données Financières à Haute Fréquence (BEDOFIH). Our sample covers trades and orders (all messages) on the most liquid stocks that are included in the SBF120 index from January 4, 2016 to December 28, 2016. All messages are labeled by the category of its owner. The Autorité des Marchés Financiers (AMF) identifies three categories of market participants: pure-HFTs, investment banks with HFT activities (MIX) and all remaining traders (Non-HFTs). [9]

To study the reaction of different categories of traders in a stressful situation and their reaction during trading halts, we focus on a sample of 125 circuit breaker trigger events. In this sample, 42 circuit breakers occurred as the outcome of significant price drops against 83 for significant price rises.

We find that HFTs and non-HFTs significantly increase their trading aggressiveness by heavily relying on market orders 5 minutes prior to- and during the first stage of a typical breaking episode. The market-to-limit ratio of pure-HFTs is three times higher during the halt compared to normal market periods. The market-to-limit ratio of non-HFTs jumps from 6% under normal market conditions to 10% under extreme market events. Our findings also show that non-HFTs increase liquidity consumption measured by monetary net trade imbalance [10] and create the strongest liquidity pressure into the direction of the underlying trend observed over the 5 minutes preceding a typical automatically triggered halt. In contrast, non-HFTs are the biggest liquidity providers in the opposite direction of the underlying trend at the time of delayed opening. Hence, non-HFTs start playing the role of liquidity suppliers and efficiently use trading pauses to dampen price movements. The trading pause protects from adverse selection market participants (for instance non-HFTs and mix-HFTs) willing to trade against the price movement. These protected categories of traders initiate a trend reversal.

During the "Delayed opening" stage, the behavior of pure-HFTs differs depending on the direction of the trend. They contribute to market correction during a typical positive circuit breakers triggered by a strong upward trend. However, pure-HFTs tend to be

9. According to the AMF, there are 10 to 20 pure-HFT, 10 to 20 IB-HFT and 100 to 150 non-HFT operating on Euronext Paris.

10. To measure liquidity consumption/provision we use monetary net trade imbalance (Brogaard *et al.*, 2018), i.e. the difference between the funds invested to buying trades and funds gained as a result of selling trades. A negative net imbalance for a trader category during a crash indicates that this category contributes to the price drop, whereas positive net imbalance during a crash indicates that this category contributes to market stabilization and price recovery.

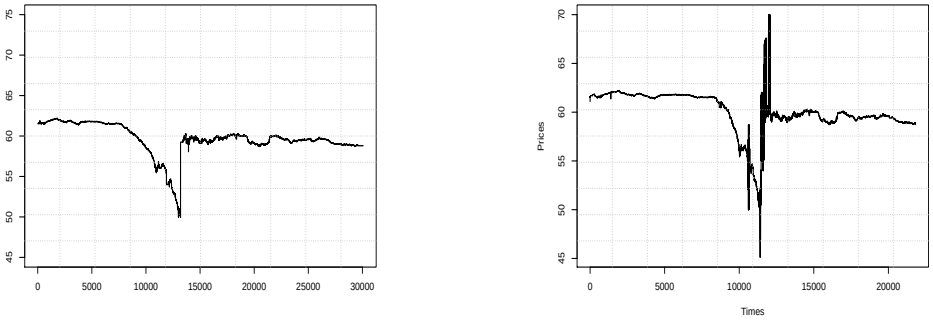
substantial sellers during the price fall and after the trading pause has been triggered. Even 5 minutes after reopening, the average monetary net position of pure-HFTs is negative. This implies that pure-HFTs tend to initiate more trades into the direction of an average crash rather than to stabilize prices. Overall, our findings suggest that a circuit breaker can be an insufficient tool to deter all traders from following a trend and to prevent the amplification of a crash.

We also analyze the effectiveness of a circuit breaker mechanism in reducing traders' panic and in managing extreme price swings. To establish the would-be outcome of a selling pressure coming from pure-HFTs in the absence of a circuit breaker mechanism, we conduct an in-depth analysis of the trading session of Vinci shares on November 22, 2016. On that day, due to the diffusion of a false press release, an extremely large price move and reversal of Vinci share price occurred over just a few minutes.[11] This flash crash is of particular interest as it likely resulted from the first cyber-attack of Bloomberg and it triggered a series of three trading halts on the Euronext stock exchange. In our study, we compare two price paths. The first one corresponds to the real price series of Vinci stock with the circuit breaker in place on November 22, 2016. The second one is a simulated price series resulting from the replication of all real messages on Vinci share submitted to the Euronext Trading Platform on that day with one modification: there is not any trading halt and all orders are executed on a continuous basis. Using ATOM, we accurately replicate Euronext limit order book and the resulting trades from the historical message stream provided by BEDOFIH. We keep track of the various order book states by recording order information at each price level with all updates, cancellations, executions and partial-executions.[12] Figure 3 shows the real price dynamics of Vinci shares on that day against our simulated data. We find that the flash crash would have been deeper and that the price would have dropped to 45 euros in the absence of a circuit breaker mechanism compared to a realized market price of 50 euros at its lowest level. Therefore,

11. A false press release on the revision of accounts has appeared on Bloomberg at 04:05 pm. At 04:10 pm, Vinci's price fell by 18%, which represents a 6 billions euro loss in market value. See Berthier (2017) for a detailed chronological recap of Vinci Flash Crash on November 22, 2016.

12. At any time the limit order book reflects the orders remaining after the order placement prior to the time in question and is netted with all prior execution and cancellation records. We start by entering the orders with the arrival dates prior to the period in question. After the prebook is constructed, new orders are added to the prebook. The order book is continuously scanned to check trade conditions. A transaction is possible if best ask is smaller than the best bid. Completely executed and canceled orders are eliminated from the order book.

our findings suggest that circuit breakers can moderate partially price swings, but that they are not able to limit selling pressure.



(a) Real market data (b) Simulated data

FIGURE 3 – Vinci equity on November 22, 2016. Left panel presents the actual price dynamics, right panel presents the would-be price dynamics without circuit breaker as simulated using ATOM.

5.4 Delayed market order execution

Market manipulation is widely studied in the existing financial literature and is a major issue for financial regulation (Egginton *et al.*, 2016; Lee *et al.*, 2013; Luo and Zhdanov, 2016). For example, the Autorité des Marchés Financiers (AMF) handed down a 5 million euros penalty to Virtu Financial Europe for its role in market manipulation and for circumventing Euronext's market rules. Virtu, a well known high-frequency trading company, sent large amounts of orders to five trading European venues and cancelled them in less than five milliseconds before others were able to trade on their offers, giving misleading volume information to investors. Such algorithmic market manipulation is called *spoofing* (Tse *et al.*, 2012). Oriol and Veryzhenko (2018b) [13] focuses on such trading practice and suggests regulatory policies to prevent it.

In this paper, we study the feedback loop created between spoofing strategies and market dynamics. First, we try to figure out how a spoofing practice impacts market quality. Second, we examine the profitability of this practice under different market conditions. Our work also contributes to the regulatory debate by testing a random delay of market orders execution to reduce the profitability of spoofing episodes proposed by Foucault *et al.* (2016). Foucault *et al.* (2016) suggest that this tool would reduce HFT's ability to quickly pick a demand or supply, and would leave time to other traders to revise their limit order quotes.

To address this issue, we build a simulation-based model, where an order-driven market architecture matches orders sent by a heterogeneous population of investors, including simple slow fundamentalists, high-speed volume pressure analysts, and slow uninformed traders who tend to mimic institutional investors by following large volume orders. Traders' strategies are detailed in Table 4. This population is misled by a spoofer. The spoofer randomly enters the market to buy stocks he intends to sell at a higher price. Hence, he submits a large limit-buy order with a bid well below the current market price without the intention of filling it, making the buy side of the order book seemingly large. A spoofer hopes that other traders will react to this fake demand, and will push the price up. Once the stock price increases, the spoofer submits his real market sell order on the same stock. In our setup, we assume that traders discover that they are manipulated after the first spoofing episode. As a result, only a small fraction (one third) of traders continues

to respond to the order imbalance produced by the spoofer. We also assume that agents optimize their decisions to reduce adverse selection risk and opportunity cost. Therefore, they submit their bids below the large volume order price. By doing so, they potentially produce an unprofitable price trend for the spoofer.

Our findings document a relatively small effect of spoofers on market volatility measured as absolute return. This result can be explained by the fact that a spoofer reacts to very small price changes and removes a large-volume-spoofing-order within a few minutes following its submission. Overall, a spoofer intends to catch very small price movements and to take small profits several times a day without waiting for large price swings. The resulting absence of amplified volatility in the presence of a spoofer illustrates why it is difficult to detect such a practice.

Moreover, our findings shed light on the losers and winners of spoofing events. Our results show that a spoofer accumulates on average around a 47 bps net profit per day. However, the key consideration of a regulator is not really the profitability of spoofing but rather the losses other participants incur as a result of this kind of manipulation. Most fundamentalist traders are not concerned about spoofing orders, which are canceled before the slow fundamentalists react. Those who react to bid/ask imbalance and buy "high", can incur losses when prices revert to their fundamental value. The biggest losers are uninformed volume pressure followers. These results reveal that spoofers seek profit-making at the expense of other market participants.

We then question the profitability drivers of a spoofing strategy and how this profitability is affected by market design and market conditions. We focus on the relationship between the profitability of spoofing and the average trading volume, the fundamental value volatility, and the tick size of the market. To do this, we vary these parameters in the model, run 100 simulations for each parameter value and keep track of the profitability of spoofing episodes. [13] We use the following empirical model for the regression analysis:

$$\pi = \alpha + \beta V + \epsilon \tag{1}$$

13. A spoofing episode is a time period between the spoofing order submission and a moment when spoofer realizes a real sale.

where the dependent variable π is the average profitability of spoofing episodes and V is the independent variable (average volume, fundamental value or tick size).

Our results suggest that a large average trading volume increases the likelihood of profitable spoofing trades. A spoofer would prefer stocks with higher market capitalization and liquidity, not only because of the higher number of participants to manipulate, but also because of the higher number of traded contracts. We also find a positive effect of volatility in fundamentals on the profitability of the spoofing strategy. This suggests that spoofers would prefer stocks with a higher sensitivity to micro- and macro-economic announcements. Also, spoofing is more profitable in periods of uncertainty in fundamental value. Finally, we show that the modification of the tick size should have an insignificant effect on manipulative strategies making tick size an ineffective regulation device. Our study also has important implications for HFT regulation as we recommend market rules that have not been implemented yet. Actually, we analyze the impact of setting a 1 to 5 milliseconds random delay in order execution. This execution rule does not deteriorate market quality, does not amplify market volatility, and does not reduce market liquidity either. At the same time, we find that delaying the execution of market orders leads to general losses from all strategies relying on market orders, and involving a quick and aggressive consumption of liquidity.

Our results should help market regulators better understand spoofing strategies and develop effective tools to prevent this practice. Our findings are of particular interest for financial market operators and authorities aiming at protecting investors from losses due to price manipulations and at promoting ethical behavior in financial markets.

6 Ongoing research projects

Non-Value-Added Tax to Improve Market Fairness. In July 2015, Mary Jo White, who served as the 31st Chair of the SEC, called for market reforms to curb unfair advantages of HFT. Yet, she clearly stated that "the SEC should not roll back the technology clock or prohibit algorithmic trading, but should assess the extent to which computer-driven trading may be working against investors rather than for them". Ladely (2020) reveals that existing regulations such as financial transaction taxes, make/take fees, minimum rest time, and increasing the tick size are "ineffective in either improving social

welfare, market quality or reducing the profits of HFTs".

In our article *"Non-Value-Added Tax to Improve Market Fairness"* co-written with Arthur Jonath and Etienne Harb, we advance an absolutely new regulatory tool which we call a Non-Value-Added Tax (Jonath and Goldwater, 2018). The objective of this tax is to promote market fairness by encouraging value-added trading and reducing the negative effects of high frequency traders, without losing the benefits these agents bring to the market.

Our paper brings attention to the fact that there are "value-added" and "non-value-added" activities, which have quite different effects on the financial system and the economy as a whole. We identify a value-added trade as one that improves financial market quality, in the sense that it contributes to informational efficiency and price discovery, and supplies market liquidity while reducing market volatility. We implemented a graduated Non-Value-Added-Tax in a simulation-based model where the profit generated by an agent initiating a transaction that is not supported by fundamentals but driven by trend-following strategies is taxed at graduated rates under the NVAT regime.

Unlike existing or traditional Financial Transaction Taxes, the NVAT we advance is levied on profit, and not on price. We show that NVAT significantly reduces the profitability of traders relying heavily on momentum signals, considerably reduces volatility, and slightly decreases trading volume. More interestingly, NVAT reduces the size of extreme price movements resulting from exogenous liquidity shocks (like "fat finger" events). Hence, it reduces bubble-formation dynamics, and staves off dangerous financial fluctuations from "tipping points". As NVAT is levied on profit and not on price, investors solve a profit/value/tax equation to achieve their best result and not purely maximize profit.

Currently, we try to extend the concept of non-value-added tax to other dimensions of market quality, such as market liquidity that is easy to measure in practice.

Detection and prevention of market manipulations. The paper *"Spotting manipulation in the tape : the good igniter, the bad painter and the wily spoofer"* is extended in an ongoing study where we apply machine learning tools for spoofing detection (essentially, the Support Vector Machine – SVM – Zhang (2010) and supervised Classification And Regression Tree (CART) algorithm). As already mentioned, the main advantage of

agent-based methodology is the perfect traceability of results and observations. This methodology characteristic is important in the training stage of machine learning algorithms. We analyze the sets of data generated by 1,000 fundamentalists, 100 liquidity pressure followers and 1 spoofer, who randomly manipulates the market (on average 5 times daily). Market participants are classified based on the following features: price, volume, type timing and lifetime of each order, volume and price of the best bid and best ask at the moment of order submission. Additionally, each trader is characterized by a vector of the timing of his transactions.

Our SVM is able to detect 75% of spoofing events. The misclassification can be explained by the fact that a large volume of orders is not a distinguished feature of a spoofer. Therefore, it should be excluded from analysis and we should rather consider variables like bid/ask pressure and price variation during the lifetime of each order (until it is executed, canceled or modified).

The CART algorithm significantly improves the accuracy of detection of spoofing orders. Around 96% of them are correctly classified as manipulative. We get 2.3% of false positive and 3.9% of false negative classifications.

The next step is to test our SVM and CART algorithms trained on artificial market on real market data.

In the ongoing project **"Circuit breaker coordination between trading venues"** carried with Stephanie Ligot, we focus on traders' activity in a fragmented market environment, when a circuit breaker is triggered on one of the trading venues. Existing circuit-breaker mechanisms are parameterized to be triggered for individual stocks on a given platform but not on satellite markets. However, circuit breaking mechanisms could be coordinated between several trading venues or within the same platform between several securities in case of strongly correlated instruments.

The proponents of circuit breakers' coordination between trading venues argue that such coordination would lead to calmer trading conditions (Gomber *et al.*, 2012), avoid sudden capital movement between exchanges and prevent liquidity dry-ups. Non-coordinated circuit breakers, on the contrary, increase liquidity demand and market volatility on the non-halting markets. Critics of coordinated circuit breakers (Morris, 1990; Subrahmanyam, 1994), in contrast, claim that there would be technical difficulties to coordinate

delayed opening on several platforms.

We try to figure out how trading activity changes on alternative platforms when the halting occurs on Euronext. Should circuit breakers be coordinated across venues or are there potential benefits to continue trading on alternative platforms during halts ? To address these questions, we use the BEDOFIH database to conduct an empirical analysis of order-flow and trades from Euronext, BATS and Chi-X over 2016. To the best of our knowledge, there are no previous empirical studies on circuit breakers with a European cross-market perspective.

7 Other activities

7.1 Scientific Communication

— The papers presented in this manuscript benefited from the fundings of the Laboratory of Excellence on Financial Regulation (Labex ReFi) supported by PRES heSam under the reference ANR-10-LABX-0095. It benefitted from a French government support managed by the National Research Agency (ANR) within the project Investissements d'Avenir Paris Nouveaux Mondes (investments for the future Paris-New Worlds) under the reference ANR-11-IDEX-0006-02. My membership at the Laboratory of Excellence on Financial Regulation helped me to stay in contact with the members of the Advisory Board of French and European regulators, the primary target audience of my policy oriented research. I am a member of the executive committee and I am in charge of the policy papers at Labex Refi.

— I am a member of the research team (7 researchers of LABEX and 26 universities world-wide) that has applied to Call H2020-ICT-2018-2020, Fin-Tech (A FINancial supervision and TECHnology compliance training programme). The FIN-TECH project, under the EU's Horizon2020 funding scheme, aims to create a European training program, whose objective is to provide shared risk management solutions that automate the compliance of Fintech companies (RegTech) and, at the same time, increase the efficiency of supervisory activities (SupTech). The European Commission has selected our proposal in September 2018.

— From 2015 to 2018, I was a Member of the executive committee of research labo-

ratory LIRSA CNAM research laboratory.

— I am an associate member of the Pôle de recherche interdiciplinaire en sciences du management Université Paris 1 Panthéon-Sorbonne(PRISM, UR06 Recherche 06, EA 4101) and research laboratory LIFL Lille 1. This allows to be in contact with experts in different research fields.

— I am also a member of the research group Dynamic Systems Analysis for Economic Theory and Society (DYNAMETS) at Paris Dauphine. DYNAMETS is an interdisciplinary research group devoted to develop and apply innovative quantitative research approaches (including agent-based modelling and dynamic systems analysis) to socio-economic phenomena.

— I am regularly invited to review manuscripts for Economic Modeling, Intelligent Systems in Accounting, Finance and Management, Quarterly Review of Economics and Finance, and the International Journal of Emerging Markets.

7.2 Teaching related to my research topics

I deliver a series of courses related to my research topics: GFN113 Market microstructure and market participats (45 hours, L3, CNAM) ; FIN417 Financial Markets (42 hours, Master program, ESSCA), UE05 Financial Markets (30 hours, Master IAE de Paris). I am in charge of the AMF certificate at CNAM. I am a member of the group on the strategic evolution of the AMF certificate (Le groupe de travail 3 AMF, "Contenu et Utilisation de la base") chaired by Jézabel Couprey-Soubeyran and Xavier de La Maisonneuve.

7.3 Master thesis

I have supervised a series of master thesis on different topics related to my research at CNAM, ENSAM, IAE de Paris, ESSCA. I supervise on average 12 master thesis annually. This type of work allows me to acquaint my students to research activities and prepare them for potential PhD studies. Here is only some selected latest examples of thesis related to my research interests and defended under my supervision:

- Mohamed Mahmoud SIDI YOUSSEF, "Supervised based approach for spoofing detection", CNAM (2020)
- Paula SANCHEZ, "Impact de la taxe francaise sur les transactions financieres

realisees par les investisseurs institutionnels: le cas d'AXA IM", IAE de Paris (2017)

- Guillaume LATORRE, "Détection et Régulation des Stratégies Manipulatrices sur les Marchés Financiers Cas du Trading Haute Fréquence", ENSAM (2018)
- Louis TRONGNEUX, "High-Frequency Trading Strategies: An Heterogeneity and Profitability Review", ENSAM (2018)
- Sébastien VACHER-COPONAT "The Blockchain Technology", ENSAM (2018)
- Oussama SALHI, "Trading algorithmique Utilisation des réseaux de neurones dans la prédiction des cours", CNAM (2017)
- Cécile MIGLIORE, "La règlementation du Trading Haute Fréquence", CMAM (2016)
- Xiaoyuan FAN, "The impact of algorithmic trading on market quality", CNAM (2016)
- Mahdi Abdeljaouad ZOUKH, "Stratégie de scalping basée sur la modélisation des ordres limites par le processus de Hawkes", CNAM (2016)

List of publications

1. I. Veryzhenko (2020), *"Who gains and who loses in stock markets ? Risk preferences and timing matter"*, Intelligent Systems in Accounting, Finance and Management, forthcoming
2. N. Oriol and I. Veryzhenko (2019), *"Market structure or traders' behavior ? An assessment of flash crash phenomena and their regulation based on a multi-agent simulation"*, Quantitative Finance, 19 (7), 1075-1092
3. L. Arena, N. Oriol, I. Veryzhenko (2018), *"Too Fast, Too Furious ? Trading algorithmique et instabilité des marchés financiers"*, Systèmes d'Information et Management, vol.23, n2.
4. I. Veryzhenko, L. Arena, E. Harb, and N. Oriol (2017), *"Time to slow down for high-frequency trading ? Lessons from artificial markets"*, Intelligent Systems in Accounting, Finance and Management, vol. 24, pp. 73-79
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6. O. Brandouy, P. Mathieu, I. Veryzhenko (2013), *"On the Design of Agent-Based Artificial Stock Markets"*, Communications in Computer and Information Science, vol. 271, pp.350-364

7. O. Brandouy, P. Mathieu, I. Veryzhenko (2013), *"Algorithmic determination of the maximum possible earnings for investment strategies"*. Decision Support Systems, vol. 54, p. 816-825

8. O. Brandouy, A. Corelli, I. Veryzhenko, R. Waldeck (2012),*"Why Zero Intelligence Traders are not smart enough for Quantitative Finance"*, Journal of Economic Interaction and Coordination.7(2), pp. 223-248

Working papers

9. R. Gillet, S. Ligot, I. Veryzhenko (2020), *"Cross-Border Trading and Price Discovery: Evidence from French Stocks"*

10. S. Ligot and I. Veryzhenko (2019), *"The Vinci HoaxCrash: The High Frequency Trading and Circuit Breakers in an Electronic Market"*, YFS'2019 best paper award.

11. Y. Biondi and I. Veryzhenko (2019), *"Where does security market pricing quality come from ? Combined analysis of institutional design and individual rationality."* CEF'2019

12. I. Veryzhenko and A. Jonath (2019), *"Can we design an NVA-Tax to prevent bubble-building-bursting events and to improve market fairness ?"*, FMND'2019, SEM'2019

13. N. Oriol and I. Veryzhenko (2018), *"Spotting manipulation in the tape : the good igniter, the bad painter and the wily spoofer"*, presented at ISCEF'2018, AFFI'2018.

14. N. Oriol and I. Veryzhenko (2018), *"Trading disruptif et systèmes de traitement transactionnel : une illustration des techniques de spoofing au sein d'un carnet d'ordre électronique"*, presented at AIM'2018

Proceedings and Chapters

15. L. Arena, N. Orio, and I. Veryzhenko (2020), *"From the Pit to millions of bits: Exploring Stock market Crashes as Socio-technical Failures through a History-Friendly Agent Based Model"*, ECIS Proceedings, Association for Information Systems, 2020.

16. O.Bradouy, P.Mathieu, I.Veryzhenko (2012), *"Risk Aversion Impact on Investment Strategy Performance: A Multi Agent-Based Analysis"*, Managing Market Complexity. The approach of Artificial Economics, Springer (ISBN: 978-3-642-31300-4), vol.662, pp. 91-103.

17. O.Bradouy, P.Mathieu, I.Veryzhenko (2012), *"Optimal Portfolio Diversification ? A multi-agent Ecological Competition Analysis"*, Highlights on Practical Applications of Agents and Multi-Agent Systems, Springer (ISBN 978-3-642-28761-9), vol.156, pp. 323-332.

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