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► To cite this version:

Nathalie Oriol, Iryna Veryzhenko. Market structure or traders' behavior? An assessment of flash crash phenomena and their regulation based on a multi-agent simulation. 2015. halshs-01254435

HAL Id: halshs-01254435

<https://shs.hal.science/halshs-01254435>

Preprint submitted on 12 Jan 2016

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MARKET STRUCTURE OR TRADERS' BEHAVIOUR? AN ASSESSMENT OF FLASH CRASH PHENOMENA AND THEIR REGULATION BASED ON A MULTI-AGENT SIMULATION

Documents de travail GREDEG
GREDEG Working Papers Series

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GREDEG WP No. 2015-16

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Market structure or traders' behaviour? An assessment of flash crash phenomena and their regulation based on a multi-agent simulation

Nathalie ORIOL * Iryna VERYZHENKO†

GREDEG Working Paper No. 2015–16

Abstract

This paper aims at studying the flash crash caused by an operational shock with different market participants. We reproduce this shock in artificial market framework to study market quality in different scenarios, with or without strategic traders. We show that traders' strategies influence the magnitude of the collapse. But, with the help of zero-intelligence traders framework, we show that despite the absence of market makers, the order-driven market is resilient and favors a price recovery. We find that a short-sales ban imposed by regulator reduces short-term volatility.

JEL Classification: G1, C63

Keywords: Agent-based modeling, zero-intelligence trader, limit order book, technical trading, flash crash

1 Introduction

In the first half of the 20th century, the technologies were poorly implemented in the trading process. Early historic episodes of market instability (like crashes in 1897 or 1929) were caused by wrong default risk estimation. A period after the Second World War is characterized by globalization and a significant development of direct finance. But the crashes during this period were still provoked by economic or geopolitics fundamental factors. Starting in 1980s, crashes began to change their nature with active use of technologies for trading. The crash of October 1987 on American stock market and the crash in 1994 on bond market demonstrated a new factor negatively affecting financial stability, algorithmic trading. This practice was not the main reason of crashes but it partially determined the magnitude of market collapse (Carlson, 2007). Nowadays, market participants increasingly rely on computers to make a trading decisions and order routing. At the same time,

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since the last decade, with the impulse of fragmentation of execution places, and decimalization of stock prices, short-term violent crashes (Flash Crashes) became a frequently observed phenomenon on stock markets. Algorithmic strategies, and specially high frequency trading strategies were most often quoted as the designated culprit, initiating regulatory debates about restricting those practices. In the first regulatory report of the most notable flash crash in the financial market history, May 6 2010, CFTC-SEC (2010) has described several contributing factors: fragmentation of order flows, systemic linkage between index futures and ETFs, liquidity gaps and algorithmic trading. The identified trigger was reported as a large institutional selling order generated by an algorithmic program of Wadell and Reed, unusually executed in few minutes. Other studies such as Menkveld and Yueshen (2013) has shown that "the crash cannot be attributed to a single agent but really is the product of agent interaction ". Although several years -and others similar phenomena-have passed since the first notable flash crash, uncertainty remains on the triggers for both prices collapse and market recovery.

Financial markets exhibit a complex structure with a large number of heterogeneous interacting microscopic parts -investors- as input, and macroscopic properties -price dynamics- as output. According to Sornette (2009), the complex system approach, which involves to reconnect the whole picture with its component parts in an agent-based setting, is a relevant way to explore the emergence process of extreme events. In light of mixed results about the responsibility of one group of users for extreme failures, it seems more reasonable to argue that extreme events are an intrinsic part of the system. We propose to build an artificial computer simulation to explore the link between market microstructure, agents' behavior and the appearance of major and intraday disruptions. Precisely, we artificially reproduce a flash crash in several simulation settings and show that either agents' behavior or microstructure and the order book state are part of the prices collapse and the market recovery.

Our paper is structured as follows: In the second section, we will present the nature and potential reasons of flash crash. We then provide the current state of research on this question, especially in the agent-based framework. In the third section, we question the role of agents' strategies by reproducing an artificial intraday crash. We specifically compare the statistical properties of prices in a purely fundamentalists populated market, and a mixed market with technical analysis traders. Section 4, a particular focus will be placed on the role of market microstructure in price recovery in a zero-intelligence traders framework. In both cases (smart agent-based, or purely microstructure), we show that our model is capable of reproducing the empirically observed extreme disruptions of order flows, such as in the 6th of 2010. We show that both traders' strategies and market microstructure are part of the collapse magnitude and the recovery. Section 6 reports the impact of short-sales restriction on market quality as a result of regulatory intervention such as the recent SEC Rule 201. Our paper also contributes to the debate on what generates large price failures in stock markets and the appropriate regulatory scheme to contain extreme events. Specifically, we find that a short-sales ban reduces short-term volatility but also the trading volume, depth and euro depth.

2 Exploring flash crashes

2.1 Facts

According to Nanex studies, there were 254 mini-crashes events (the stock had to tick down/up at least 10 times before ticking up/down with price variation of more than 0.8% within 1.5 seconds) in 2006, and 2576 in 2007. But sometimes, the collapse is more violent, initiating the so-called "flash crashes era" for financial markets. The most known flash crash of 6th May 2010 is the result of selling of 75000 "e-mini" futures, on the S&P 500 index, that provoked a 10% drop of price of American equities and index. A large institutional investor was alarmed by an exogenous information (crisis in Greece) that potentially would affect the stock prices, for that reason, he started executing a large volume selling program. To minimize the execution costs the algorithm broke down a big-volume order into smaller pieces. The volume of decomposition pieces was determined according to the past trading volume. Automated traders aggregated such sell pressure of institutional investor. At the same time they tried to minimize the volume of holding securities in order not to be beaten by better informed traders and to reduce an exposure to long-term market risks. For this reason, algorithms aggressively sold their holdings (Kirilenko2010). They actively traded inside their group increasing a general trading volume. It lead the algorithm settled by institutional investor to sell a higher volume. As result, the price significantly declined. This phenomenon ended as trading algorithm has been completely executed.

Next event of market instability because of automated trading systems was registered on August 1, 2012, when American market maker Knight Capital lost more than 460 million because of an error in its new order routers. During the deployment of the new code for the routing software, one of Knight's technicians did not copy a new code to one of eight servers. In 45 minutes, their computers sent millions of unintended orders (buying at best ask and then selling at best bid) to the market and provoked a significant disruption in the prices of 140 stocks listed on the NYSE. For example, China Cord Blood, which opened at 2.47, doubled its value to 6.20. Trinity Industries, opened at 28.32, jumped to 32.84. Molycorp, opened at 17.50, dropped to 14.35. The affected stocks were rapidly corrected. This perturbation is considered as mini flash crash. Finally, in the list of recent disruptive events, 23th of april 2013 is another textbook case with a 143 point fall of the DJIA because of a false tweet posted by hackers on Associated Press twitter, about a white-house bombing. The market recovered within a few minutes after Associated Press refutation.

All those events differ with respect to the main source of the shock. Changes in expectation about fundamentals combined to a large sell market order are possibly the main reason of the flash crash in 2010. In case of Knight Capital, a software malfunction (operational error) caused catastrophic consequences for the company, investors and marketplace. In the 2013 case, a false rumor of attack spread on Internet is responsible. But speed and magnitude of disruption remain a common characteristic of all these extreme market events.

2.2 Related literature

To our knowledge, only few papers deal with a flash crash phenomena analysis. Chakravarty *et al.* (2010), Kirilenko *et al.* (2011), Easley *et al.* (2011), J.Yu (2011), Madhavan (2011), Menkveld and Yueshen (2013) and Bou (2014) are the main academic studies using May 6, 2010 market datas. Most of them are focused only on one responsible party which is either a microstructure part or a strategical behaviour of one investors category. Chakravarty *et al.* (2010) show that there is a positive feedback effect between market conditions and Intermarket Sweep Orders use on May 6. As market conditions tend to be deteriorated, ISO uses increases leading to exacerbate market conditions. Kirilenko *et al.* (2010) conclude that HFTs did not trigger the Flash Crash, but their responses to the unusually large selling pressure on that day exacerbated market volatility. Easley *et al.* (2011) suggests that the crucial feature is a liquidity event arising from structural features of high-frequency traders. J.Yu (2011) show that contrarian traders helped to stabilize prices fluctuations. Madhavan (2011) highlights the role of microstructure, market fragmentation and the changing nature of liquidity provision in exacerbating the impact of an external liquidity shock. Menkveld and Yueshen (2013) show crash cannot be attributed to a single agent, as it happens the large initial seller. Bou (2014) show a specific market atmosphere this day, such as a decrease of shareholder wealth and market quality.

Considering the fact that flash crash phenomena cannot be easily neither empirically nor stochastically studied, an alternative way using agent-based model is actually explored. In light of mixed results about the responsibility of one group of users for extreme failures, it seems more reasonable to argue that extreme events are an intrinsic part of the system. Then, agent-based models, which involves to reconnect the whole picture with its component, is a relevant way to explore the emergence process of extreme events. Moreover, the flexible character of simulation program allow to test different regulatory hypothesis. A wide variety of traders are designed in the paper of Vuorenmaa and Wang (2014) to simulate the key aspects of the flash crash of May 6, 2010. The authors define stylized traders (fundamentalists, noise and opportunistic traders), institutional algorithmic trader and high-frequency traders (HFT). It is reported that HFT agents provide higher liquidity in normal trading conditions, but they become aggressive liquidity takers during the crash. As the number of HFT agents increase, so does the probability of flash crash. Paddrik *et al.* (2012), propose a similar agent-based model of the E-Mini S&P 500 futures market including fundamental traders, market makers, HFT, small traders and opportunistic traders. They conclude that a "hot potatoe" effect was generated by HFT. These results are in line with Leal *et al.* (2014), who also simulate the interactions between high and low frequency traders to study their impact on price dynamic. Authors show that presence of high frequency traders generate moment of high illiquidity represented by large bid/ask spread, that exacerbates price volatility and causes crashes. They also conclude that HF traders' order cancellations speed up post-crash recovery. Alternatively, LEE *et al.* (2011) or Brewer *et al.* (2013) distinguish themselves from previous papers by their conclusions. LEE *et al.* (2011) claim that extreme event problem might be less about HFT but rather about a dominant population of traders that are responding to a given set of market variables in similar ways. They conclude that any regulatory attempt to "slow down" trading may cause more problems than it solves. Brewer

et al. (2013) focus on the effect of large-volume order and change in fundamentals on the market quality. In this paper, market is populated only by zero-intelligence agents. They conclude that the nature and impact of liquidity erosion is sensitive to the market structure and that the exact nature of crash and book erosion depends on the structure of the order flow. Authors test different mechanisms to reduce the negative effect of flash crashes: introducing minimum resting time; shutting off trading for a certain period; switching to call auction market session, that is particularly effective. Our paper is most closely related to those two last. We assert that both microstructure and agents'behaviour are part of the collapse and the market recovery. Moreover, our study complements the regulatory debate by looking at the role of market microstructure and the effectiveness of specific extreme events rules such as the alternative uptick rule.

3 Flash crash in artificial multi-agent market

Researchers actively study this question with agent-based artificial market, as this approach allows to reproduce main features of flash crash phenomenon and to test trading rules not applied by regulator in the real market. Agent-based models (ABM) are computational models which simulate the actions and interactions of autonomous agents in order to study dynamic of global system. An agent is a microscopic element of the model. A representation of agent varies from simple equation to complex software components with artificial intelligence. Agent-based models reproducing stock market often refer to *Artificial Stock Markets*. Artificial stock markets represent a program or application geared at reproducing some features of a real stock market (price formation, liquidity dynamic,...)

To study flash crash phenomenon we use ArTificial Open Market (ATOM) (Brandouy *et al.*, 2013), which is highly flexible simulations platform and allows different parametrization of microstructure and traders behavior for different scenarios. This platform contains three main modules: *market microstructure*, that provides a mechanism for orders routing; *economic world* provides exogenous information about corporate development, dividends and coupons changes; *agents* component encompasses multiple types of agents with different utility functions, beliefs and strategies. Trading strategies take into account exogenous information, functionality and rules of market microstructure, and endogenous information (post transaction information, generated by agents interaction).

3.1 Traders' strategies

The ATOM platform allows us to settle two scenarios. First one is the market populated by fundamentalists only. This case is considered as a benchmark. The second scenario proposes a market populated by fundamentalists and chartists. Flash crash can be initiated by events and practices destroying liquidity. In two scenarios we cause a flash crash by introducing a big size market order.

Fundamentalists are driven by the true (fundamental) asset's value. The true value is estimated based on fundamental information like financial reports, information about a firm's management, earning announcements, dividends payments, and analysts opinions. The fundamental value of each stock evolves according to a jump process $V_t = V_{t-1} + \delta_t$, where $\delta_t \sim N(0, \sigma)$.

As the agents are bounded rational (or noisily informed), the fundamental value is biased by ϵ_i , which determines the accuracy of the agent i to interpret the fundamental information.

$$W_t = V_t + \epsilon_i$$

$$\epsilon_i \sim N(0, \sigma_W)$$

Agents are heterogeneous with respect to their parameter ϵ_i . To make a buy/sell decision an agent compares the stock's current price P_t with fundamental value W_t . If $P_t > W_t$ stock is overvalued and agent send a sell (Ask) order. If $P_t < W_t$ stock is undervalued and agent send a buy (Bid) order.

Technical traders rely on algorithms to generate trading signals using historical price series as a main source of information. The basic hypothesis of technical trading are as follows: 1) market is not efficient, price is impacted not only by a fundamental information, past price trend impact the actual price 2) price series follows the trends 3) history is repeating itself 4) price reflects predictions and a common mood of traders. A graphic is considered as a synthesis of market behavior. There exist upward and downward trends. Upward and downward confirmed trends determine buy and sell trades. Technical traders use the algorithms to determine a trend and to estimate whether the stock is underpriced or overprice comparing to this trend. In other terms, they identify tradings signals based on past price movements (Murphy, 1999). Technical analysts focus on generating trading signals that provide a higher investment return. For these simulations we use three strategies of technical analysis, widely used by practitioners and largely studied in theoretical and empirical literature (??)

Momentum indicator compares the current price with the price in the past $D(t, n) = \frac{P_t}{P_{t-n}} \times 100$, where n is a historical window length, wich is uniformly driven from an interval $[50, 500]$. If $D > 100$, an agent sends a Bid order, and if $D < 100$ the agent sends a Ask order.

Simple Moving Average strategy determines a general tendency on the market. A price series is replaced by $Y_t = \frac{1}{n} \sum_{i=t-n}^t P_t \forall t = n, \bar{N}$

Relative Strength Index strategy measures the strength of a trend.

$$RSI = \frac{U}{U + D} \times 100$$

U – an upward change, D – a downward change. The RSI indicator is plotted on a scale of 0 to 100. 0 represents the most oversold conditions and 100 the most overbought.

3.2 Simulations and results

To match supply and demand stock exchanges use trading rules and mechanisms. These rules vary over different markets and evolve following technological progress (Schauer, 2006). Here we describe the model of market mechanism and agents interaction parameters we use in our experiments.

- As in real markets, trading occur asynchronously at discrete-time interval $t = 1, 2, \dots, 200$
- A trader can have only one open position at the time and, therefore, before issuing a new order he should cancel and old one pending in the order book.

The agents send limit, market and cancel orders. They also have a possibility to send a null order. In such a way we model different trading frequencies, and hence model realistic patterns of activity throughout the day.

- The identity of active trader is driven uniformly from the interval [1;200]
- Short selling is allowed

Another important issue is how the limit price is determined, as it impacts market liquidity. We propose the procedure inspired by price setting rules described in Jacobs *et al.* (2004).

1. Bid price

$$P_{Bid_t} = P_{Bid_{t-1}} + \beta_t$$

where $P_{Bid_{t-1}}$ is the best bid price in the order book in $t - 1$; β_t is a random value in the range [2; 10]: it means that best bid price at the moment t will be increased by value from 2 to 10 cents. P_{Bid_0} is equal to the previous day closing price.

2. Ask price

$$P_{Ask_t} = P_{Ask_{t-1}} - \alpha_t$$

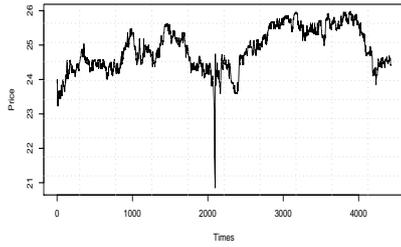
where $P_{Ask_{t-1}}$ is the best ask price in the order book in $t - 1$; α_t is a random value with the range [1; 10]: it means that best ask price at the time t will be decreased by value from 1 to 10 cents. P_{Ask_0} is previous day closing price.

This rule provides liquidity and reduce the *bid-ask spread* (difference between buy/sell prices).

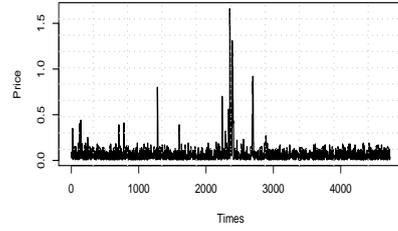
In the condition of double auction market, a profit-oriented buyer sets up the price lower his limit price because there would be a seller willing to accept this low bid price. Similarly, a seller sets a price higher his limit price, expecting that there would be a bidder ready to accept a high ask price. In condition of competitive market, the price comes closer to the market equilibrium price. As long as the buyer can undercut a competitor and still make a profit, he will add some insignificant amount to the last best bid price, similarly, seller will decrease the last best ask price by insignificant value, if it does not exceed his limit price.

To address the question of market quality we study its statistical properties. In this research we use order driven artificial market, where buy and sell orders are brought together to guarantee a continuous trading, so the market dynamic and market liquidity are results of traders' strategies and their interactions.

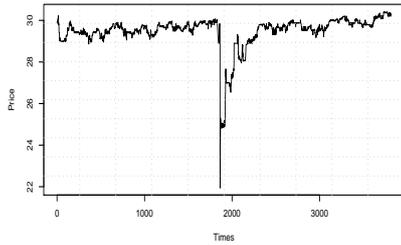
In the first experiment we run two scenarios: i) operation shock (without fundamental reasons) in the market populated by 250 fundamentalists only (these simulation results serve as a benchmark to study an impact of technical traders) ii) operation shock in the market populated by 100 fundamentalists, 50 momentum agents, 50 RSI agents, and 50 SMA agents. Flash crash is produced by submitting a 20-time higher volume market order compering to average order size. We study the impact of this operational shock on the market liquidity and price dynamic. In both scenarios, Ask market order destroys Bid side liquidity and price falls rapidly. Just after this crash, bid side contains few orders, hence the market is at its most vulnerable and sensitive stage. High volatility period follows the crash. Figures 1(b) and 1(d) report an increasing of bid/ask spread, and consequently, a high volatility.



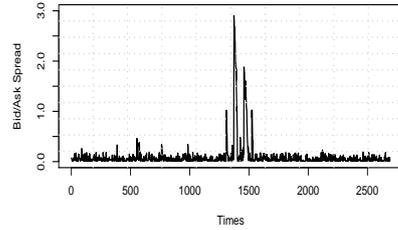
(a) Price. Market of fundamentalists



(b) Bid/ask spread. Market of fundamentalists



(c) Price. Mixed market



(d) Bid/ask spread. Mixed market

Figure 1: Simulations with 250 agents.

In the presence of intraday technical traders, which ignore the true value of the stock, the market crash is deeper (for the same shock, the speculative market loses on average 26.5%, while fundamentalists market declines on 12.3%) because speculative strategies bring down the prices. As far as downward trend is registered, some part of speculative traders cancel their old bid orders to submit the new ones with lower limit price, the other part takes short position on this stock. In the market of fundamentalists the big-size market ask order generates 27 transactions and 12.3% price cut. In the presence of chartists, the big-size market ask order generates 18 transaction and 8.11% decreasing in price. Downward trend is quickly explored by chartist, which exacerbate the already declining prices.

In the market of fundamentalists, the crash depth is determined by the initial state of the order book. The crash is finished as far as market order is over. If a large majority of agents (60%) follows speculative strategy bid side of order book is negatively impacted by orders canceling and short sales. It provokes liquidity problems and makes the correction more complicated. As far as fundamentalists start actively buying the stocks (as it is undervalued) the stock price goes back up but high volatility is registered due to high bid/ask spread.

Bid-ask spread is an important characteristic of a flash crash simulation. Figure 1(b) shows that in the fundamentalist market the spread increases about six times compared to the level before, while in presence of technical traders the spread is about ten times higher than the average level before the crash (see figure 1(d))

After simulating a sample path, we compute the time series of returns $r_t = \ln(P_t/P_{t-1}), t = 1 \dots T$. Their histogram, the sample autocorrelation function and

the sample autocorrelation function of absolute returns are presented in Figure 2 and 3 for fundamentalist market and mixed market respectively.

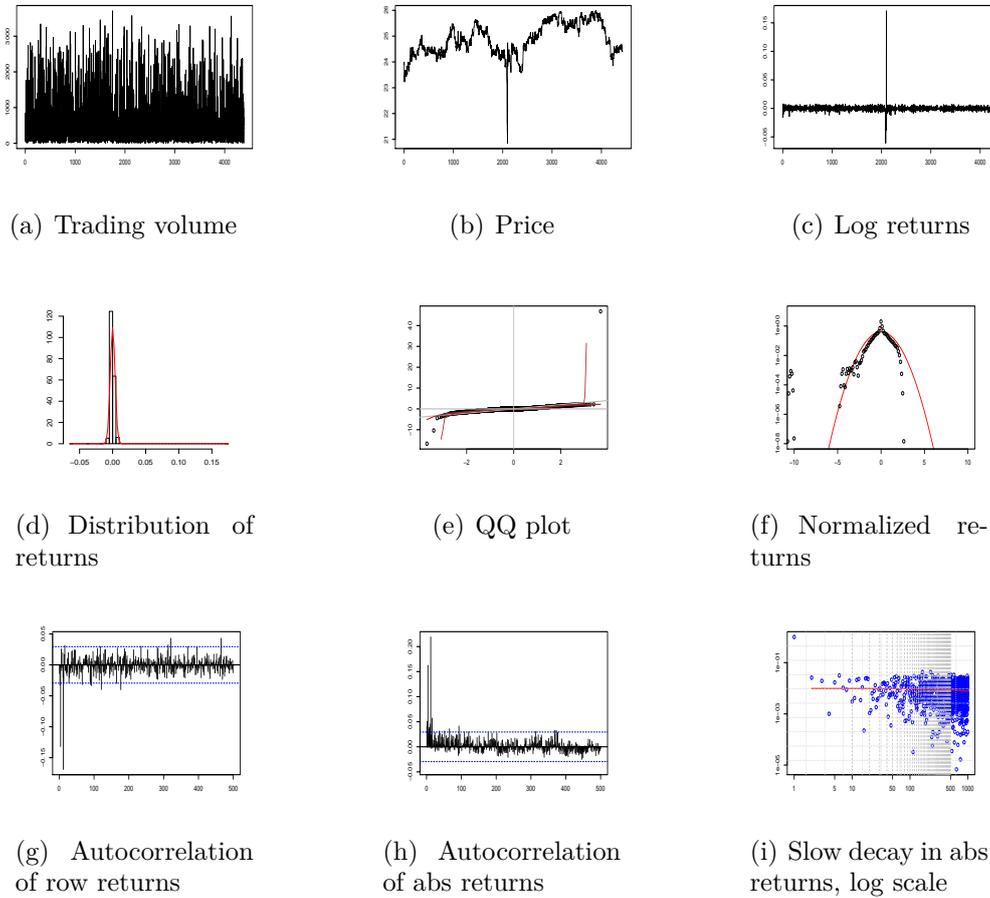


Figure 2: Stylized facts. Simulations with 250 fundamentalists.

Next, we study the statistical properties of stock market before and after flash crash in two scenarios, we particularly focus on volatility as risk measure (Grouard *et al.*, 2003). A price series is divided in two subsequences before and after the crash. The first series is represented by P_1, P_2, \dots, P_k , where k is a moment of big-volume Ask order arrival. We calculate returns based on this price series r_1, r_2, \dots, r_{k-1} , where $r_i = \ln(P_{i+1}) - \ln(P_i)$. This series represents a period before the crash. The second series is based on the prices P_{k+m+1}, \dots, P_n , where $P_{k+1} > P_{k+2} > \dots > P_{k+m}$ and $P_{k+m} < P_{k+m+1}$, m is the time length of the flash crash. Next we calculate the series $r_{k+m+1}, r_{k+m+2}, \dots, r_{n-1}$ which represents a series after the flash crash.

In table 1, we show the mean and standard deviation of each subsets along with higher order statistics such as skewness and kurtosis for historical intraday returns. We report increased volatility just after the crash: in the market populated by fundamentalists increases from 0.003777883 to 0.004609726, in the mixed market

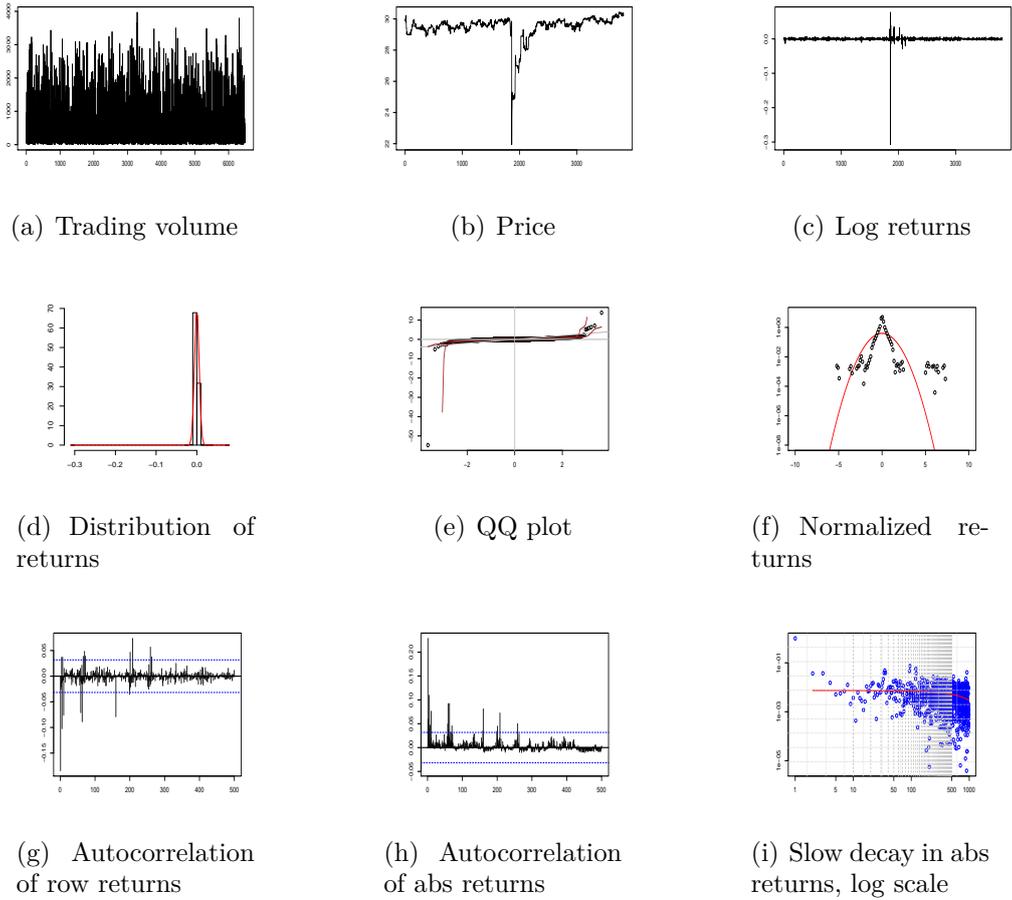


Figure 3: Stylized facts. Simulations with 100 fundamentalists and 150 chartists.

standard deviation jumps from 0.003969339 to 0.005433639. Next, we estimate skewness and kurtosis as well. In the market populated by fundamentalists only, the coefficient of asymmetry is negative (from -6.138734 to -2.496489, that indicates a high probability of extreme loss, which decreases after crash), this coefficient is positive in the mixed market (it varies from 1.807211 to 3.125376, that means a high probability for extreme loss, which increases after crash).

The results provide the evidence that in presence of chartists the operational shock affects a price dynamic in a more significant manner. In addition, this practice reduces resiliency properties of market and makes the price rapid convergence towards its fair value more difficult.

In the next section we focus on the market microstructure mechanisms and their effect on the price dynamic during an operational shock.

	Market of fundamentalists		Mixed market	
	Before	After	Before	After
Mean	-0.0001045985	4.542041e-05	-1.909056e-06	0.0002301199
Sd	0.003777883	0.004609726	0.003969339	0.005433639
Skewness	-6.138734	-2.496489	1.807211	3.125376
Kurtosis	131.1714	38.6699	38.76373	77.49765

Table 1: Summary statistics of log returns before and after flash crash

4 The role of market microstructure in post flash crash recovery

The literature indicates that many stylized facts and price patterns are due to the market microstructure and not to the sophisticated traders strategies. Gode and Sunder (1993, 1997) report that good market performance should not be automatically attributed to traders rationality and intelligence, it can be also explained by market mechanisms (auction). Zero-intelligence agents are able to reproduce main qualitative stylized facts of real market intraday and daily returns.

In this section we study the role of market micro-structure in market recovery after flash crash. To address this question formally, we use artificial market framework populated by zero-intelligence agents.

Traders' strategies. For traceability reasons, the market is populated only by 15 zero-intelligence traders, who negotiate only one asset. The fixed price is a result of orders submitted to the order book by traders. The price of an order is randomly selected from the interval $[P_{min}, P_{max}]$. This interval initially communicated to all agents and stay constant over simulations. We define two subgroups of agents which differ with respect to their traded volume: "Small fishes" and "Big fishes" (send 10-times higher volume orders). "Small fishes" and "big fishes" represent 33% (1/3) and 67% (2/3) of the total population respectively. This proportion is explained in Brandouy *et al.* (2012). Small fishes determine the trading volume arbitrary from the interval $[V_{min}, V_{max}]$. The order's volume of big fishes is uniformly driven from the interval $[V_{max}, 10 \times V_{max}]$

There are two possible order types: Limit, Market. Market order is used only once by an agent to generate a market crash and to get an immediate effect on the market dynamic. Rest of the agents submit only Limit orders, with no expiry.

Each agent can buy or sell the asset with the same probability. The short selling is allowed, so the agents can conclude the transaction even if they don't enough cash to do so.

Simulations and Results. Zero-intelligence agents may provide some insight and intuition of the role of market microstructure in market dynamic, especially we focus on the role of order execution mechanism in market recovery after operation flash crash.

Figure 4(b) reports a typical picture of the price series generated by the population of zero-intelligence agents. The significant crash is followed by the high-volatility regime over 200 ticks. The upward trend comes just after the high-volatility period. We also report a significant reduction of volatility. The market

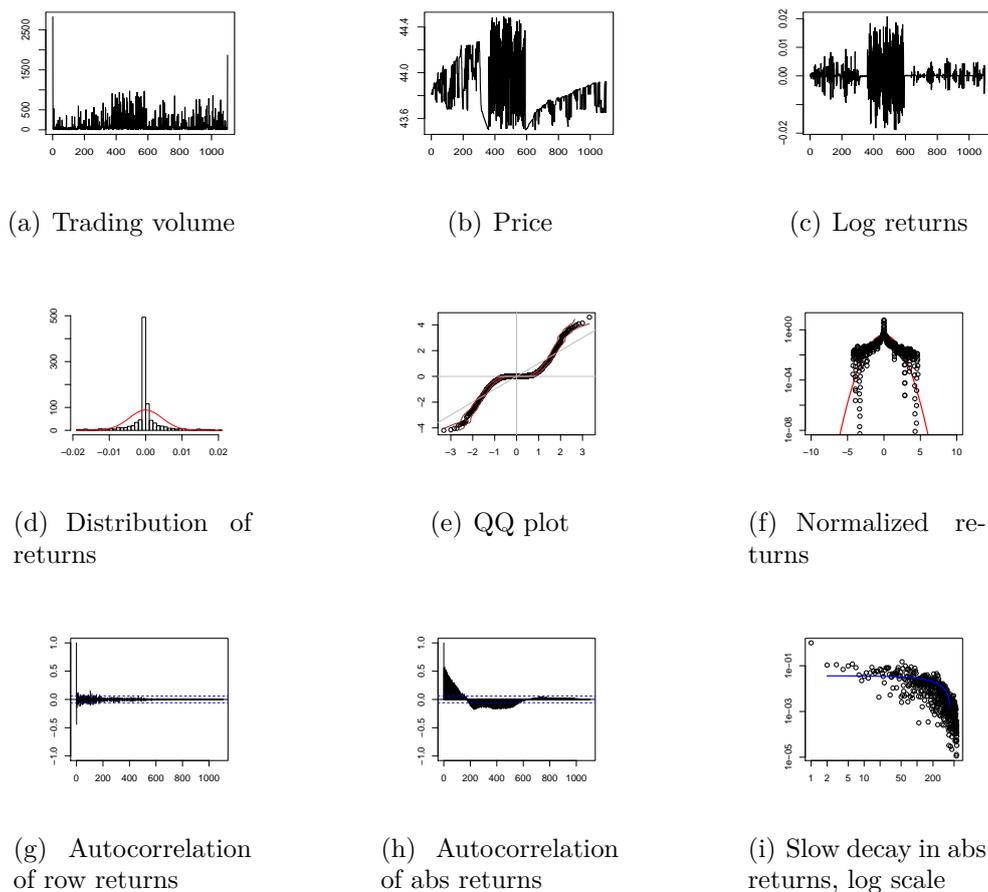


Figure 4: Simulations with 15 zero-intelligence agents.

mechanism explains this phenomenon. Over first 200 ticks big fishes provide liquidity and permit the market to stay quite stable. Due to operational error a new big-size market order appears in the ASK side. This order immediately matches all Bid orders pending in the order book as well as new incoming orders. While the big-size Ask order is not totally fulfilled we observe the high-volatility regime. As Bid/Ask orders arrive with the same probability and only "ex-market" order takes part in transaction, Ask side becomes deep and dense. As far as market order is completed, other Ask orders pending in the order book can be proceed. According to the timestamp priority, the concluded transaction price corresponds to the Ask order which generates a transaction. As a result, market goes up that can be considered as the market autocorrection.

Next, we discuss the statistical properties of market returns during the market crash. Denote P_t as the price at time t . $r_t = \ln P_t - \ln P_{t-1}$ is the log-returns at time t . We focus on one trading day. There are 1100 observations. We split the whole series into sub-periods (subsets): opening $t = \overline{1, 303}$, crash $t = \overline{304, 363}$, high volatility regime $t = \overline{364, 592}$, and finally the recovery subperiod $t = \overline{593, 1100}$. These subperiods differ with respect to realized volatility. Table 2 gives the summary statistics for r_t $t = \overline{1, 1100}$.

	Opening [1:303]	Crash [304:363]	High Volatility [364:592]	Recovery [593:1100]	Total
Sd	0.002407484	0.001454453	0.009262715	0.001289769	0.004502408
Skewness	-0.07323768	4.118557	0.0924176	0.1421421	0.1367247
Kurtosis	3.921369	24.32296	-0.7998684	6.834737	5.39807

Table 2: Summary Statistics. Return series produced in the market populated by 15 zero-intelligence agents

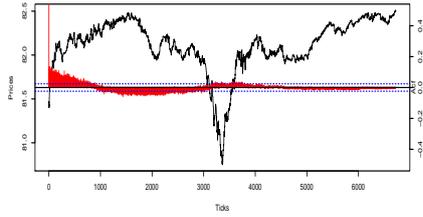
The sample statistics as well as Figures 4(d), 4(e), 4(f) indicate that the returns distribution generated by zero-intelligence traders is far from being normal. The sample skewness is 0.1367247 while the sample kurtosis is 5.39807. The most significant deviation from normality is observed during the Crash time interval. The skewness of the Crash sample is 4.118557, and its' kurtosis is 24.32296, implying several extreme returns relative to the standard normal distribution. Notice, that High Volatility sample has negative kurtosis. It means that the return distribution is flatter and cover a wider range, it occurs when the market is trending.

We next examine the autocorrelation properties in the return series. The absence of autocorrelation in row returns is a well known stylized facts in intra-day/daily data (Cont, 2001). This fact is also reported in the figure 4(g). The reported average stock autocorrelation ranges between -0.09 and 0.05. At short horizons equity returns exhibit negative autocorrelation, possibly due to microstructure, such as bid/ask bounce. We run Box-Ljung test to study independence in the absolute return series. The p-value is very small ($p - value < 2.2e - 16$), so the null hypothesis on the independence in the returns can be rejected.

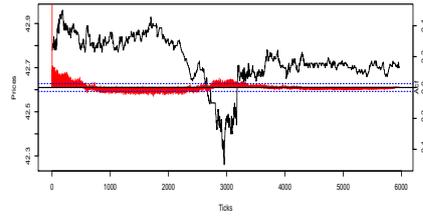
Figure 4(h) and 4(i) report slow decay of autocorrelation in absolute returns $|r_t|$ over 174 lags that is followed by a cluster of negative correlations. As one can see from the figure 4(h), the coefficients are significant over long period which supports the so called mean-reversion behaviour of stock market returns. These results are in agreement with the observations reported in (Cont, 2007). This non trivial behavior of autocorrelation is also reported in the absolute returns of the real individual stocks during the flash crash on April 23, 2013. This observation is remarkably stable across S& P 500 stocks (see Figure 6). This phenomenon can be explained by the fact that positive effects of past order flows on current prices are reinforced during the periods of high stress (Cohen and Shin, 2002).

We run Kwiatkowski-Phillips-Schmidt-Shin (KPSS) to study stationarity in row return series. p-value is 0.1 so the null hypothesis of trend stationarity is not rejected at the usual 5% level. The p-value of KPSS test with absolute returns is 0.01 below 0.05 so there is an evidence that it may be trend stationary. During the call regime stocks are suspending in the order book, and they are executed at the opening procedure. This mechanism of price fixing produces predictability in stock returns.

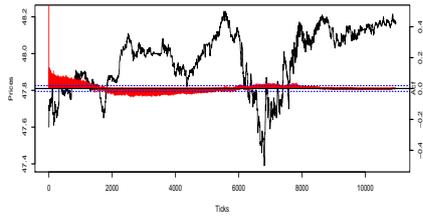
Robustness check with respect to the size of operational error In this subsection we test the robustness of the phenomenon with respect to the volume of market order which provokes a crash. We run the simulations with settings described above, we only modify the volume of market order. It takes the values



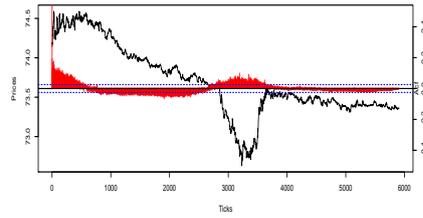
(a) The Procter & Gamble Company (PG)



(b) Coca-Cola (KO)



(c) JP Morgan (JPM)



(d) Helmerich & Payne, Inc. (HP)

Figure 5: Tick-size data on April 23, 2013. Price series is plotted in black, and coefficient of autocorrelation of absolute returns in plotted in red.

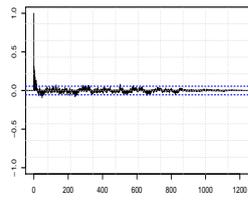
	Mean	MSE	Sd	MSE	Skewness	MSE	Kurtosis	MSE
Opening	-1.872087e-05	2.478729e-10	0.002191085	1.261521e-07	0.02963037	0.1029354	4.720417	3.280026
Crash	6.052193e-05	2.236242e-08	0.004594409	7.914096e-06	0.3241042	2.906865	6.717337	106.1191
High Volatility	-2.513175e-05	1.54881e-09	0.008555825	4.759363e-07	-0.004618635	0.0114655	-0.1669818	0.1832083
Recovery	1.205051e-05	1.027123e-10	0.001560661	1.501283e-07	0.0519157	0.4286335	9.808747	100.2467

Table 3: Means of Statistics of 500 simulations. MSE - mean squared error.

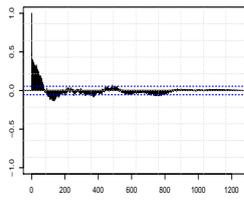
10-, 30-, 50-times higher than the average order size. The goal in agent-based modeling of financial market is to gain insight into its behavior. We try to determine the factors that may produce autocorrection of the market, hence a non-trivial autocorrelation behavior in absolute returns. In all these cases we report that slow decay in autocorrelation of absolute returns is followed by a cluster on negative autocorrelation. A size of the market order determines a magnitude of negative autocorrelation cluster. As soon as the market order volume decreases, a period of negative autocorrelation is significantly reduced to become really narrow.

Extensive analysis Next, we run more extensive simulations and present the statistics (mean of 500 return series) in the table 3

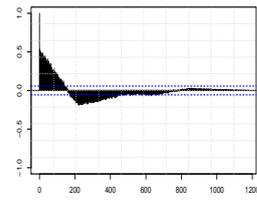
In all these scenarios, liquidity drops after the market crash during the high-volatility regime. Liquidity is rapidly deteriorated as a sole provision of liquidity comes from limit orders. Limit orders are marched according to the price and time priority rules. Market order is executed against a best price on the opposite side. As



(a) 10-times higher volume market order



(b) 30-times higher volume market order



(c) 50-times higher volume market order

Figure 6: Autocorrelation of absolute returns generated by zero-intelligence agents in red.

The flash crash is provoked by very aggressive market order. 95 percent confidence intervals are plotted as dashed lines.

its volume significantly overcomes a volume of simple limit orders, the market order cannot be completely executed so the remaining part of the order is transformed into a limit order at the best price. We show that, despite the absence of market makers, the order-driven market is resilient and favors a price recovery.

These results are useful for market authorities as we highlight the role of market microstructure in a market recovery.

5 Restriction on short sales

After the May 6, and in response to the recommendations of the CFTC-SEC Advisory Committee on Emerging Regulatory Issues, several rules were finalized by the market authority. Those rules include the implementation of risk management controls for direct trading access users, a consolidated audit trail in order to allow regulators to accurately monitor all activity throughout the National Market System (NMS) securities, and technology standards adhesion for all the entities that are core to the securities markets structure. They include also market wide circuit breakers, and a limit up-limit down mechanism which is enable to prevent trades in individual securities from occurring outside of a specified price band. Brewer et al. (2013) and Subrahmanyam (2013) dedicated part of their works to the impact of circuit breakers and trading halts. But Subrahmanyam concludes that there is no evidence that breakers reduce volatility after trade restarts, and no evidence that they reduce panic-driven selling.

At the same time and with no direct link with flash crashes, the Security and Exchange Commission adopted short sale restriction, referred as "alternative uptick rule" in February 2010. During the global financial crisis in 2007/2008 more than 30 countries implemented short-sales bans to prevent further declines in stock prices, but Rule 201 is specially dedicated to intraday extreme events. This rule prohibits a short selling to avoid further driving down price of a stock that has dropped more that 10% in one day. Regulators occasionally implement short-sales ban in financial panics when the market volatility is particularly high to protect a market quality and avoid any financial manipulations by preventing speculators from placing excessive downward pressure on troubled financial firms.

	Before	After
Mean	-2.426143e-06	4.919492e-05
Sd	0.00323083	0.004925981
Skewness	-0.8106371	2.940718
Kurtosis	28.13067	94.22967

Table 4: Summary statistics of log returns before and after flash crash in the market with short sales ban

While regulators associate short sellers with speculative trading, excessive risk-taking, and reinforcing of stock market instability, the financial literature reports that restriction of short selling can limit market liquidity and destroy market efficiency, as stock prices can't move in line with underlying fundamentals (Abreu and Brunnermeier, 2003; Bohl *et al.*, 2012; Kolasinski *et al.*, 2013). Boehmer *et al.* (2008) show that that short sellers are relatively better informed, thus restricting their activities limits market efficiency. But on the other hand, focusing on extreme market movements, Brunnermeier and Pederson (2005) showed that short sellers exacerbate intraday price declines with aggressive trading strategies

In this section we test the effectiveness of alternative uptick rule during flash crash in the agent-based framework. In other terms, the purpose of this study is to examine whether short-sale bans achieve their desired outcome. We introduce the portfolio constraints in the simulations: $\varpi_s \in [0, 1]$ and $\varpi_c \in [0, 1]$, where ϖ_s and ϖ_c are respectively stock and cash weights in total portfolio. In such market, the big-size market ask order generates immediately 13 transactions and 7% price cut. As far as this downward trend is detected, some part of chartists, like RSI traders which identify that the market is oversold, update their orders with lower bid prices. Others, like Moving Average and Momentum agents can't really get benefice from price decreasing as short selling is not allowed. Fundamentalists realize that the stock is undervalued and start buying it as result, they provoke price increasing. We report that the downward abnormal market movement is faster than the upward correction. Our observations are in line with those of Yen and Chen (2014).

We analyze also statistical properties of produced series of returns before and after crash (Table 4). Our paper introduces an artificial market framework to measure the effect of regulatory reforms. We find that a short-sales ban reduces short-term volatility. This result is in accordance with conclusions of Lensberg *et al.* (2014).

5.1 Market quality measures

Our paper examines the impact of short-sales regulations on market quality. We compute a wide range of measures of liquidity and volatility to account for different dimensions of market quality.

Liquidity measures can be classified in three main categories: volume-based measures and transaction cost measures.

Volume-based measures

Measuring liquidity by volume is the most intuitive way, as by definition, liquidity

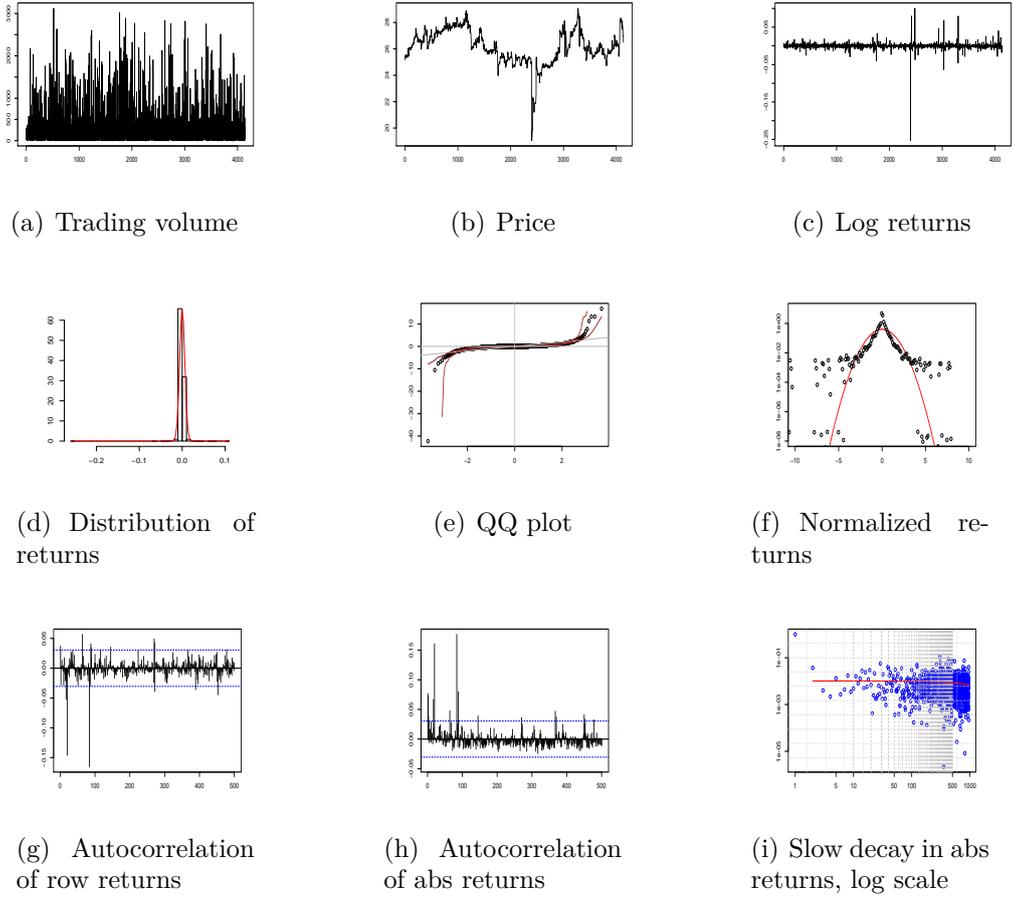


Figure 7: Simulations with 100 fundamentalists and 150 chartist under budget constraints.

is the ability to trade large volume order without affecting a price in a significant manner. First, we compute log volume.

$$\ln(\text{Volume}_t) = \ln(Q_t \times P_t)$$

where P_t is the transaction price at the moment t , and Q_t is traded volume at the moment t .

We include also *depth* into our study. Depth is the average number of shares that can be traded at the best bid and ask quotes. *Depth* is measured as the average number of shares that can be traded at the best bid and ask quotes (Heflin and Shaw, 2005)

$$\text{Depth} = \frac{Q_t^{\text{bid}} + Q_t^{\text{ask}}}{2}$$

where Q_t^{bid} is the best bid size, Q_t^{ask} is the best ask size.

Euro depth is calculated as the average of the sum of the number of shares quoted at the ask price plus the number of shares quoted at the bid price, times their respective quoted prices (Heflin and Shaw, 2005)

$$\text{Euro depth} = \frac{Q_t^{bid} \times P_t^{bid} + Q_t^{ask} \times P_t^{ask}}{2}$$

Transaction cost measures

Another widely used measure of liquidity is bid-ask spread. The spread is defined based on the lowest price at which someone is willing to sell (best ask) and the higher price at which someone is willing to buy (best bid).

$$\% \text{ Quoted half - spread} = \frac{1}{2} \times \left(\frac{Ask_{it} - Bid_{it}}{M_{it}} \right) \times 100$$

$M_{it} = \frac{Ask_{it} + Bid_{it}}{2}$, Ask_{it} and Bid_{it} are the posted ask price and bid price.

Volatility measures

In this paper we consider following market volatility measures: squared return R_t^2 and absolute return $|R_t|$, where $R_t = \log(P_t/P_{t-1})$ is the log return. These measures are very similar, but their means are differently impacted by extreme variations. We choose this selection of volatility measures, as we can generate a series of squared returns and absolute returns applicable for a final regression test.

Table A.1 provides pairwise correlation coefficients for the measures of liquidity and volatility. Among the liquidity measures, the highest correlation is observed between depth and euro depth in both scenarios. Among the liquidity and volatility measures, the highest correlation is between bid/ask spread and squared and absolute returns.

5.2 A difference-in-difference approach

A difference-in-difference (Ashenfelter and Card, 1985) is a widely used technique to estimate the impact of a policy change or some other shock on population. We consider two groups and two periods case. After the flash crash one population is exposed to short sales ban.

$$Y_i = \beta_0 + \beta_1 \cdot G_i + \beta_2 \cdot T_i + \tau \cdot \overbrace{G_i \cdot T_i}^{Ban_i} + \epsilon_i$$

where Y_i is a measure of market liquidity or volatility, G_i is a group dummy variable, T_i is a time dummy variable. $G_i \in 0, 1$, this variable is equal to 1 for scenario exposed to short-selling ban, and 0 for others. $T_i \in 0, 1$ is equal to 0 before flash crash (2000 first ticks), and 1 after the crash (2000 last ticks). τ is a parameter of interest.

The test of short-sales ban is well suited for DiD methodology, because there are pre- and post ban period. The quality of DiD is foremost determined by the quality of the control group. For this reason, we run two simulation scenarios with identical initial settings (number of traders, their initial wealth, trading frequency...), but with different post-shock policies. This methodology is easily extended to a panel data, where multiple treatment and control series are registered for pre- and post-event, and thus allows for additional robustness within time.

In this paper, we will refer to the simulation results from the market without any restrictions on short-sales as *unrestricted* sample, and to the simulation results from the market with short-sales restriction as *short-sales ban* sample.

We estimate the impact of the introduction of short-selling restriction on the market quality and present the results of difference-in-difference test in Table A.2.

The estimation is done for two different control groups. In column 1, we present results for completely unrestricted mixed market as a control group. In column 2, the scenario of unrestricted market of fundamentalists is considered as a control group.

The results show that the introduction of short sales restriction is efficient in volatility reduction (relatively to unrestricted control groups), even if this effect is associated with reduction of the trading volume, depth and euro depth. According to coefficients in Table A.2, column 1, the absolute return, as a measure of volatility, is reduced by 26.83% relatively to the unrestricted control group, and squared return is reduced by 59.21%. This result is in line with conclusions of Lensberg *et al.* (2014), and empirical findings of Chang *et al.* (2007).

6 Conclusion

This paper aims at studying the flash crash caused by an operational shock with different market participants. We reproduce this shock in artificial market framework to study market quality in different scenarios, with or without strategic traders. Trading interactions within a group of technical traders make a shock reflected in the price dynamic deeper comparing to the similar shock in the market populated only by fundamentalists. Our evidence sheds some new light on the hypothesis that if traders relying only on algorithmic decision making dominate the market, intraday prices tend to deviate significantly from their true fundamental value. Moreover, chartists make more difficult market recovery by fundamentalists. Technical traders create an additional volatility just after market recovery. Additionally, we study the role of market microstructure on the prices collapse and recovery. In all ZIT scenarios, liquidity is rapidly deteriorated as a sole provision of liquidity comes from limit orders. As the volume of the big market order significantly overcomes a volume of simple limit orders, the aggressive order cannot be completely executed so the remaining part of the order is transformed into a limit order at the best price. We show that, despite the absence of market makers, the order-driven market is resilient and favors a price recovery.

There are some potential solutions explored by regulator to limit an effect of trend following during extreme market events. According to Artus (2012), it is necessary to increase a number of fundamentalists in order to stabilize market. But it is not an easy task as traders change their strategies from fundamentalist to chartist and backward according to their profitability. Our paper examines the impact of short-sales regulations on market quality and specifically the SEC Rule 201. We compute a wide range of measures of liquidity and volatility to account for different dimensions of market quality. The results show that the short-sales ban reduce in significant manner the market volatility comparing to the unrestricted cases.

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A Appendix

Unrestricted fundamentalists market						
	ln(Volume)	Bid/ask spread	Depth	Euro Depth	R_t^2	$ R_t $
ln(Volume)	1.0000	-7e-04	0.0546*	0.0592*	-0.0034	0.0143
Bid/ask spread		1.0000	-0.0394*	-0.0433*	0.2065*	0.2264*
Depth			1.0000	0.9989*	-0.0272	-0.0237
Euro Depth				1.0000	-0.0272	-0.023
R_t^2					1.0000	0.8258*
$ R_t $						1.0000
Unrestricted mixed market						
	ln(Volume)	Bid/ask spread	Depth	Euro Depth	R_t^2	$ R_t $
ln(Volume)	1.0000	-0.0041	0.0288	0.0638*	0.0064	0.0151
Bid/ask spread		1.0000	-0.0322*	-0.0463*	0.0314*	0.0667*
Depth			1.0000	0.987*	0.0191	0.0185
Euro Depth				1.0000	0.0073	0.0059
R_t^2					1.0000	0.8441*
$ R_t $						1.0000
Short sales ban in the mixed market						
	ln(Volume)	Bid/ask spread	Depth	Euro Depth	R_t^2	$ R_t $
ln(Volume)	1.0000	0.0771*	0.1227*	0.1055*	0.003	0.0309
Bid/ask spread		1.0000	0.0204	-0.0054	0.0722*	0.1247*
Depth			1.0000	0.9906*	0.0184	0.0502*
Euro depth				1.0000	0.0051	0.0289
R_t^2					1.0000	0.8438*
$ R_t $						1.0000

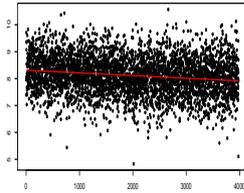
Table A.1: Correlation Matrix.

This table provides pairwise correlation coefficients for liquidity and volatility measures. The sample is a simple average for 100 samples generated with different scenarios. $\ln(\text{Volume}) = \ln(\text{Number of traded shares} \times \text{Price})$. $\% \text{ Bid-Ask spread} = \frac{1}{2} \times \left(\frac{\text{Ask}_{it} - \text{Bid}_{it}}{M_{it}} \right) \times 100$, $M_{it} = \frac{\text{Ask}_{it} + \text{Bid}_{it}}{2}$, where Ask_{it} and Bid_{it} are the posted ask price and bid price. $\text{Depth} = \frac{Q_t^{bid} + Q_t^{ask}}{2}$ where Q_t^{bid} is the best bid size, Q_t^{ask} is the best ask size. $\text{Euro depth} = \frac{Q_t^{bid} \times \text{Bid}_{it} + Q_t^{ask} \times \text{Ask}_{it}}{2}$. $R_t = \log(P_t/P_{t-1})$ is the log return. R_t^2 and $|R_t|$ are respectively squared and absolute returns.

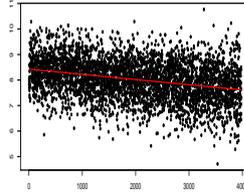
*indicates a correlation statistically different from zero at 5% level

	Mixed market	Fundamentalist market
% Bid-ask spread _{<i>i</i>}		
Ban	-1.179e-05***	-5.964e-06***
(s.e.)	(3.953e-07)	(2.370e-07)
adj. R^2	0.003499	0.008202
p-value	< 2.2e - 16	< 2.2e - 16
ln(Volume) _{<i>i</i>}		
Ban	-0.056240***	-0.324805***
(s.e.)	(0.007230)	(0.007249)
adj. R^2	0.02706	0.02393
p-value	< 2.2e - 16	< 2.2e - 16
Depth _{<i>i</i>}		
Ban	-165.582***	-161.525***
(s.e.)	(3.058)	(3.001)
adj. R^2	0.01564	0.02303
p-value	< 2.2e - 16	< 2.2e - 16
Euro Depth _{<i>i</i>}		
Ban	-87452***	-136771***
(s.e.)	(5035)	(5228)
adj. R^2	0.01046	0.01986
p-value	< 2.2e - 16	< 2.2e - 16
Squared return _{<i>i</i>}		
Ban	-2.081e-04***	-1.325e-04***
(s.e.)	(1.633e-05)	(7.089e-06)
adj. R^2	0.0006827	0.003495
p-value	< 2.2e - 16	< 2.2e - 16
Absolute return _{<i>i</i>}		
Ban	-2.516e-03***	-2.457e-03***
(s.e.)	(6.480e-05)	(4.535e-05)
adj. R^2	0.008285	0.04115
p-value	< 2.2e - 16	< 2.2e - 16

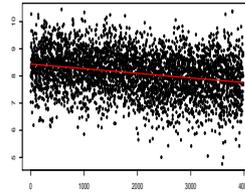
Table A.2: The impact of the short-selling ban on stock market liquidity and volatility



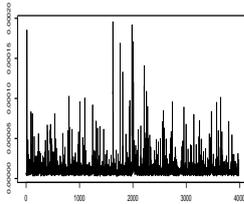
(a) $\ln(\text{Volume})$. Fundamentalists market. Short selling allowed



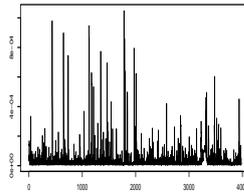
(b) $\ln(\text{Volume})$. Mixed market. Short selling allowed



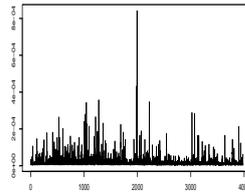
(c) $\ln(\text{Volume})$. Mixed market. Short selling ban



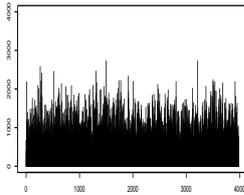
(d) % Bid/Ask Spread. Fundamentalists market. Short selling allowed



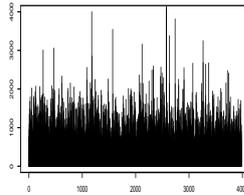
(e) % Bid/Ask Spread. Mixed market. Short selling allowed



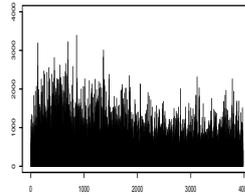
(f) % Bid/Ask Spread. Mixed market. Short selling ban



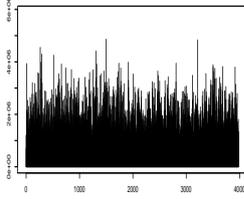
(g) Depth. Fundamentalists market. Short selling allowed



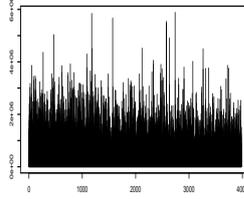
(h) Depth. Mixed market. Short selling allowed



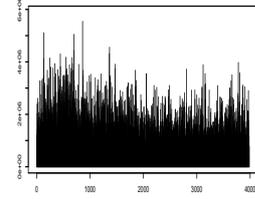
(i) Depth. Mixed market. Short selling ban



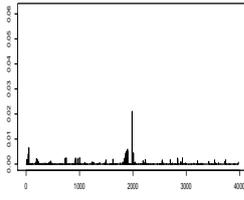
(j) Euro Depth. Fundamentalists market. Short selling allowed



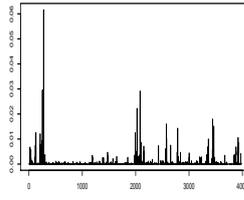
(k) Euro Depth. Mixed market. Short selling allowed



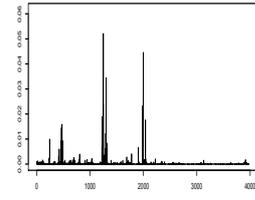
(l) Euro Depth. Mixed market. Short selling ban



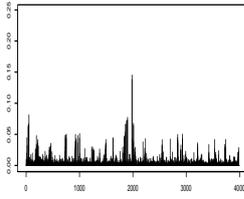
(m) R_t^2 . Fundamentalists market. Short selling allowed



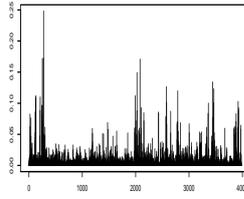
(n) R_t^2 . Mixed market. Short selling allowed



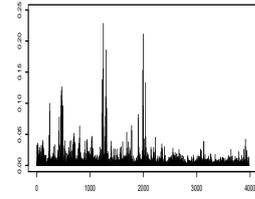
(o) R_t^2 . Mixed market. Short selling ban



(p) $|R_t|$. Fundamentalists market. Short selling allowed



(q) $|R_t|$. Mixed market. Short selling allowed



(r) $|R_t|$. Mixed market. Short selling ban

Figure 8: Dynamic of the market activity

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