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an der Universität Hohenheim

Arne Breuer

An Empirical Analysis of Order Dynamics in a High-Frequency Trading Environment

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Vorwort

Die vorliegende Arbeit entstand während meiner Tätigkeit als wissenschaftlicher Mitarbeiter und Doktorand am Lehrstuhl für Bankwirtschaft und Finanzdienstleistungen der Universität Hohenheim. Das Institut für Financial Management hat die im Dezember 2011 eingereichte Arbeit unter dem gleichen Titel als Dissertation zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaften (Dr. oec.) angenommen.

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Wustrow, im Oktober 2012

Arne Breuer

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List of Abbreviations

ASX	Australian Stock Exchange
ATF	Alternative Trading Facility
ATP	Automated Trading Program
BBO	Best Bid and Offer
CFTC	Commodities Futures Trading Commission
CIC	Constant Initial Cushion
EC	European Commission
ECN	Electronic Communication Network
ETF	Exchange-Traded Fund
FINRA	Financial Industry Regulatory Agency
GDP	Gross Domestic Product
HFT	High-Frequency Trading
IBEX	Iberian Exchange
MiFID	Markets in Financial Instruments Directive
MFT	Multilateral Trading Facility
ms	Millisecond(s) (i.e., 10^{-3} seconds)
μs	Microsecond(s) (i.e., 10^{-6} seconds)
NASDAQ	National Association of Securities Dealers Automated Quotations
NAV	Net Asset Value
ns	Nanosecond(s) (i.e., 10^{-9} seconds)
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares

RegNMS	Regulation National Market System
s	Second(s)
SEC	United States Securities and Exchanges Commission
SWX	Swiss Stock Exchange
TAQ	Trades And Quotes
TWAP	Time-Weighted Average Price
VSE	Vancouver Stock Exchange
VWAP	Volume-Weighted Average Price

List of Variables

α	Intercept parameter
β	Regression parameter
β_0	Scale parameter of Weibull distribution
δ	Dummy variable
d	Estimation result for jump dummy
ϵ	Error term
$f(\cdot)$	Limit order risk function
F	Probability that the last price of the trading window is equal to or below P_{lim} conditional on the arrival of a liquidity trader
$g(\cdot)$	Goodness-of-fit function
i	Probability of the arrival of an informed trader
I	Indicator for the arrival of an informed trader
j	Probability of the arrival of a liquidity trader
L_t	Order lifetime of t $\{$milli $-$ $\vert$micro $-$ $\vert$nano$-\}$ seconds
n	Some value $\in \mathbb{N}$
N	Size of dataset
p	Shape parameter of Weibull distribution
φ	Fit parameter for exponential distribution
P_{lim}	Limit price
P_0	Current price of the security
P_{last}	Last price of the security

R_t	Revision time of t {milli|micro|nano} seconds
$S(\cdot)$	Survival function
t	Time variable
t_0	Initial time
t_d	Time of order deletion
t_p	Time of order placement
t_{max}	Length of longest interval
T	Time variable
U	Indicator for the arrival of a liquidity trader
x	Some value $\in \mathbb{R}$
x_{60}	Some value $\in \{60, 120, 180, \ldots\}$

Chapter 0

Introduction

Over the last decades, financial markets have changed drastically, and not only once. In fact, there were two or three major changes that have radically altered the way how assets are traded. In their early days, many stock exchanges were Walrasian markets with more or less fixed points in time where the market-clearing price was determined in an auction. Trading was therefore sequential. Because market participants performed the price discovery in person at the stock exchange, this market structure is called a call market. It gave way to the dealer market, where appointed market-makers continuously quote prices for which they are willing to buy or sell stocks during the opening hours of the stock exchange. Some major stock exchanges changed again in the 1990s into order-driven markets. This means that individuals transmit their intention to trade by stating a price and a quantity for a specific stock. If no other trader executes the order, the stock exchange inserts it into its limit order book. The trader can then choose between deleting or waiting for execution.

In the late 1990s and early 2000s, electronic communication networks (ECNs) introduced high-speed open limit order books that promoted the increased use of a new market participant: algorithmic trading. Today, the various forms of algorithmic trading are important determinants of trading. Because algorithmic trading is a huge topic for today's stock exchanges and market participants, this thesis will help investigate this clandestine actor.

Algorithmic traders are computer programs with cash or assets that trade independent of human interaction. The first algorithmic trading engines appeared in the second half of the 1980s. These rather simple algorithms followed pairs of companies whose share prices developed similarly in the past. If the prices began to differ significantly, the algorithm bought (went long in) the relatively lower-priced stock and sold (went short in) the relatively higher-priced stock. With this strategy, it bet that the spread between the two stock prices would decrease to the usual level (Pole, 2007).

The range of sophistication of these algorithms is much greater in today's markets, there is a broad diversity of algorithmic trading strategies. For example, rather simple programs work off larger positions of shares with minimal market impact and base their trading strategy on benchmarks, for example the volume-weighted average price (VWAP). More advanced programs look for arbitrage opportunities or produce unmarketable limit orders to benefit from order-rebate programmes. Other algorithms try to extract other algorithmic trading strategies from the order flow to make a profit by front-running them.

To avoid becoming victims of front-running, creators of algorithms take great care to be as stealthy as possible. For other parties, the underlying models ought to remain in a black box. The algorithms absorb all kinds of market data, process it in an undisclosed way, and produce limit orders. This makes a direct measurement of the extent of algorithmic trading difficult if not impossible; algorithmic orders do not look any different from orders from humans in order book data. Estimations for algorithmic trading in the US range from 50 to 70 per cent of the total market activity. These figures are diverse because no hard numbers exist and sometimes mean different things altogether: there is a difference between total order flow, traded volume, number of trades, and other factors.

To summarise, it is doubtful that anyone fully understands what impact algorithmic trading has on market microstructures. However, algorithmic trading has obviously to be analysed, and it raises questions. Do algorithms make the market more stable or more volatile? What happens to market liquidity and other market factors? What happens to the price discovery? Do traditional measures still work in an environment where algorithms insert and delete limit orders within microseconds? A lot of research is necessary to answer these new questions.

Current empirical evidence suggests that algorithms improve liquidity and contribute to the market. Nonetheless, many market participants doubt that this counts for all market environments. Many blame algorithms for causing the famous flash crash of 6 May 2010, when the Dow-Jones Industrial Average lost and regained 1,000 points or around nine per cent within some 15 minutes. Another controversial strategy is the so-called quote-stuffing. Within a fraction of a second, algorithms pour thousands of non-marketable limit orders into the market. Their aim is to overload the stock exchange's matching or reporting algorithm or the computers of their competitors to gain a temporary advantage.

While researchers and regulators alike still struggle to draw definitive conclusions, human traders are often sceptical toward their electronic counterparts. One reason is the opaqueness of algorithmic trading. It is easy to make algorithmic trading the scapegoat for market irregularities. Some allegations may be debatable – for example, quote-stuffing or rebate-hunting. However, algorithms serve as a tool to relieve human traders of chores such as reducing a large position in a 'normal' market environment. Without algorithms, some tasks such as best execution, where the trader has to search for the best possible bid or offer, are only possible with great cost.

Thus, the interest of regulatory institutions in algorithmic trading and the number of scientific papers concerning algorithmic trading have increased in the last few years. However, it is not possible to tell human trading from algorithmic trading. To analyse algorithmic trading, researchers usually have to rely on special datasets to get a grip on it. I will per-