High Frequency Trading

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1. INTRODUCTION

High Frequency Trading (HFT) became prominent after the "Flash Crash" in the U.S. on the 6th of May, 2010. During the "Flash Crash" the Dow Jones Industrial Average plunged about 9% within 20 minutes, drawing attention of the public, regulators, and academia towards HFT (SEC, 2010). Furthermore, the recent financial crisis leads to the fundamental question of whether financial markets in general, and HFT in specific, are serving the real economy. Unfortunately, much of the public discussion referred more to generalizations instead of profound academic results, drawing a blurred image onto HFT. This also resulted in the undistinguished usage of key terminologies commonly used in the field of electronic trading. In our article, we help to lessen these deficits by drawing a distinct picture of how HFT is designed both from a trading strategy perspective and a technological perspective and how it operates in today's financial markets.

In the first section we will give an overview of the terms Algorithmic Trading and HFT and the business model behind HFT by outlining strategies employed by High Frequency Traders (HFTs) on financial markets. By presenting recent research findings, the third section discusses whether HFT is beneficial to market quality and the section gives an overview on recent regulatory initiatives concerning this concept. Thereafter, technological aspects of this highly demanding business model will be elaborated by discussing three important technological factors in the HFT context: latency, protocols and text mining. Concluding remarks are given in the last section.

2. BACKGROUND

2.1 Definitions, Delineations and Market Relevance

Academic literature mostly defines HFT as a subset of Algorithmic Trading (AT). Thus, Algorithmic Trading is described first, serving as a basis for the definition and specification of HFT.

In the broadest sense, AT describes the submission and transmission of buy and sell orders by a software algorithm to an exchange (Prix, Loistl, & Huetl, 2007). In this context, an algorithm is defined as a set of instructions that are able to observe financial data in real-time and send orders to one or several markets without any human intervention. Stricter definitions require the IT system to have a direct market access, which allows the algorithm to get instant price updates. An automated order management and the usage by professional market participants are further core elements of the strict definition. While AT aims at placing orders to minimize the market impact of large customers' positions in the first place (Gomber & Gsell, 2009), HFTs engage mostly in proprietary trading, i.e. in their own name and on their own account, by applying corresponding trading strategies.

HFT is a trading technology that is characterized by very short holding periods, high trading volumes, frequent order updates and is mostly performed by proprietary traders. As a prerequisite to persist in this high frequency environment, their algorithms have to react instantaneously on changing market conditions, e.g., changing order book situations in order to be the

DOI: 10.4018/978-1-4666-5888-2.ch001

first trader who is able to execute orders in case of a profitable market situation. Therefore, HFTs seek to minimize the latency between the exchange back-end and their trading servers/systems. Consequently, they locate their trading system servers physically close to the backend servers of the trading venues/stock exchanges by co-location or usage of proximity services. In this context, co-location refers to services that are provided by a market operator and offer a setup where a market participant's hardware is located directly next to a market's matching engine. Proximity services refer to a facility space that is made available by specialized network providers to market participants for the purpose of locating their network and computing hardware closer to the matching engines specifically in order to optimize the location with respect to multiple venues and to maximize flexibility. HFTs mainly focus on high liquid instruments, which allow the HFTs, on the one hand, to achieve many transactions (extracting very small margins per trade) and, on the other hand, to liquidate open positions quickly at lowest costs and risks. To avoid over-night risks, positions are typically liquidated at the end of the trading day. HFT is mainly used by highly specialized, technologically leading trading firms and investment banks (Gomber & Haferkorn, 2013).

The market share of HFT in securities trading is related to the development status and technology advancement of the respective market. Due to the lack of a common definition and delineation of HFT as well as different methodologies of the respective studies, market shares diverge across the different studies. In the U.S. equity markets, 40% to 70% of executed trades take place involving HFT. In Europe, stock exchanges quantify the share of HFT within a range of 13% and 40%, while HFTs estimate the share between 30% and over 40% (AFM, 2010).

2.2 HFT Based Strategies

A lot of media reports in the last years suggest that HFT is a monolithic structure and discuss HFT mainly in an undifferentiated way. However, most market observers and academics today agree that HFT is a trading technology to support a multitude of strategies rather than a single strategy. Therefore, the discussions about HFT should be based on the different algorithms and strategies and the individual effects of the respective strategies on market quality. Many strategies used by HFTs are similar to already established trading concepts, even though they profit from short latencies (Fabozzi, Focardi, & Jonas 2011). While the general strategies are well-known and are described in academic, regulatory and industry papers, HFTs do not publish their algorithms' details and implementation as this represents their intellectual property and the basis of their business model. Basically, trading strategies can be classified into four categories (Gomber & Haferkorn, 2013): arbitrage-strategies, electronic market making-strategies, liquidity-detection-strategies and others.

Arbitrage-strategies are built upon the price differences of at least two financial instruments with similar payoff structures. These can be further subdivided into market neutral- (e.g. pairs trading that uses current deviations from the historical price correlations of stock pairs), cross market- (e.g. simultaneous purchase and sell of the same financial instrument in different markets) and cross asset-strategies (e.g. purchase of an exchange traded fund and shorting the underlying stocks) (Aldridge, 2010).

Electronic market making-strategies, i.e. the simultaneous submission of buy and sell orders are also often conducted by HFTs (ASIC, 2010). These strategies can be further distinguished into liquidity provision strategies at the top of the order book (spread-capturing) and rebate driven strategies. Using the first strategy, HFTs profit from the spread between bid and ask prices by continuously buying and selling securities and adjusting their quotes according to the respective order book situation. Rebate driven strategies are based on the maker-taker-pricing models that are mainly used in alternative trading venues like multilateral trading facilities. There, traders who submit liquidity to the market in the form of limit orders (maker) are provided a rebate per executed order, while members removing liquidity from the market (taker) are charged a fee. Applying electronic market making-strategies therefore enables HFTs to earn the spread by providing liquidity and in parallel realizing fee rebates in markets with respective fee structures.

The third class of HFT strategies are liquidity-detection-strategies. These strategies try to dissect the trading patterns, and thus the hidden liquidity of other market participants and adjust their actions accordingly. HFTs try to identify hidden liquidity by systematically looking for hidden large volume orders (e.g. hidden

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