Research Report

# The Cost of Being Slow in Times of High Frequency Trading

THIS PROJECT PROVIDES A PERFORMANCE MEASURE ON THE EFFECT OF LATENCY IN THE CONTEXT OF THE COMPETITIVE ADVANTAGE OF IT. BASED ON A DATASET OF DEUTSCHE BÖRSE'S ELECTRONIC TRADING SYSTEM XETRA, AN EMPIRICAL ANALYSIS IS APPLIED. THAT WAY, WE QUANTIFY THE IMPACT OF LATENCY FROM A CUSTOMER'S POINT OF VIEW.

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## Introduction

In Q1/2009 Deutsche Börse reported 45% of all transactions on Xetra to originate from algorithms with increasing tendency (Deutsche Börse, 2009). The rationales for the success of algorithmic trading – with high-frequency trading (HFT) as a specific subgroup primarily focusing on proprietary trading with highest latency requirements – are plentiful: First, algorithms allow overall cost savings in comparison to human brokers (Domowitz and Yegerman, 2005). Second, they do not have human limitations and thus allow permanent surveillance of outstanding orders. This capability allows algorithms to readjust their trading decisions "immediately" to changing market conditions – e.g., by retaining unexecuted orders at best market prices (i.e. at the top of the order book) (Gsell and Gomber, 2009). Besides, algorithms have been proven to substantially enhance market liquidity, though the effects of HFT on welfare are ambiguous (Hendershott et al., 2011). Latency in trading has become a key competitive factor among marketplaces. They compete with ever faster access to their trading systems. From an IT business evaluation perspective, the following research questions arise: what are the effects of latency and do they require market participants to employ low latency technology? To provide market participants guidance in answering these questions, we develop a performance metric to measure the impact of latency on the risk of adverse order book changes consistently among different combinations of markets and instruments.

Every trader, human or algorithmic, has to cope with latency effects. When submitting an order at $t_1$, a decision must be made about limit and order size based on information generated at time $t_0$ (usually the order book, describing current bids and offers at the market). When the order reaches the market at time $t_2$, the situation at the market might have changed (cf. Figure 1). Our concept estimates the inherent risk of possible changes. Looking only at latency figures one can hardly derive the directly associated costs.

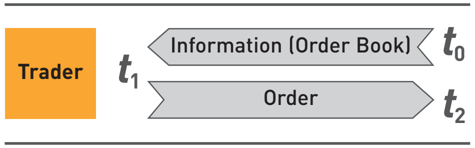


Figure 1: General dependence of a trader on latency

Since the future amount of order book changes and the impact on one's trading strategy are unknown, traders require a quantitative input to estimate the potential order book changes within the latency lag.

## Order Book Fluctuations

For the estimation, we introduce the notion of order book fluctuations, which we define as the probability of an order book change within x milliseconds. In case no information about trading intentions is available, we cannot distinguish whether the fluctuations are favorable or unfavorable for the trader. Therefore, we define relevant changes for four basic strategies, buy active, buy passive, sell active and sell passive. These cases are chosen rather for demonstration purposes of the methodology than to simulate a real application on a complex algorithm. However, every strategy is a combination of these four basic strategies.
The difference between active and passive strategies refers to the application of marketable and non-marketable orders.
Finding estimators for the probability of order book changes is straightforward due to the model's simple structure. We use the relative frequency in which order book changes occurred in the past. Estimators for limit and volume changes can be derived by calculating the mean of the quoted volume and limit changes in the time span for which the probability is estimated.

## Dataset

We choose Deutsche Börse's Xetra trading system for our analysis. Typically, algorithms are employed for instruments with high liquidity. Market capitalization is used as a proxy for liquidity. The 30 largest-capitalized instruments in Germany are represented in the DAX, and are thus used for the analysis at hand. The dataset comprises a two week sample of orderbook snapshots from 2009 and is taken from Thomson Reuters Data Scope Tick History.

## Day Pattern in Order Book Fluctuations

A trading day is separated into 15 min intervals. The probability of order book changes shows a significant day pattern. The trend of the average probability for our four basic strategies and the overall measure of limit and volume changes for a latency of 10 ms is depicted in Figure 2. All five lines exhibit the same form, which is only shifted upwards or downwards. As the top line in Figure 2 aggregates all unfavorable order book changes, it shows the highest probabilities. The next two lines represent the passive (buy/sell) strategies and the two last graphs with the lowest probabilities correspond to the active (buy/sell) strategies. Obviously, there are no striking differences among the buy/sell pairs of active or passive strategies as the corresponding best-bid/ask limits are symmetric around the instruments' mid-

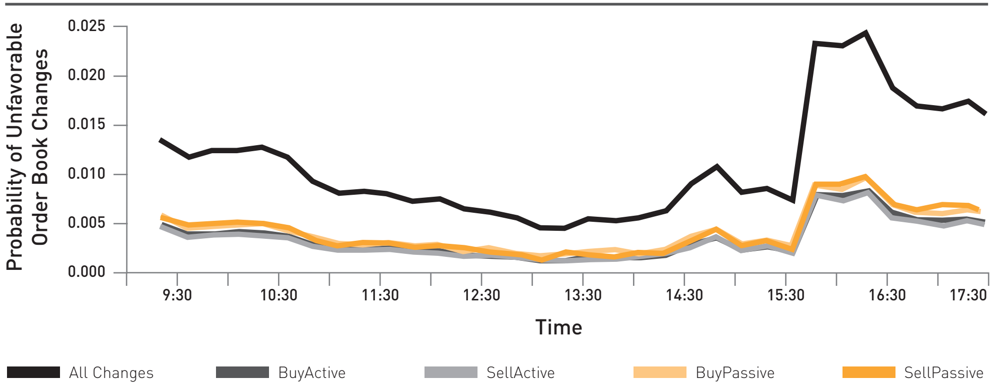


**Figure 2: Order book alterations in the course of the trading day for Siemens and 10 ms latency**

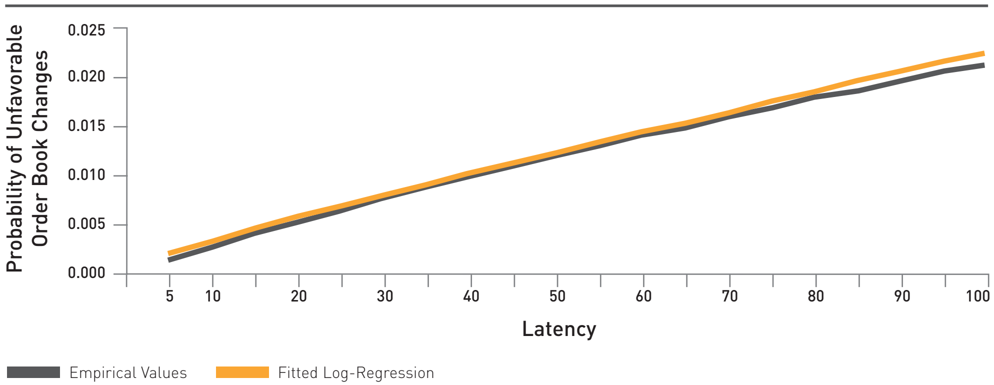


**Figure 3: Scaling of probability of order book changes due to latency**

point. As passive strategies have a slightly more complex setup, the probability to face unfavorable order book situations is somewhat higher.

In terms of an overall trend, all five graphs share a modified U-shape – as do trading volumes. Thus, in the morning the probability of order book alteration is high and decreases continuously. It reaches its minimum just after the midday-auction, then it increases again. Different from typical volume U-shapes, it falls sharply again at 14:30h, following a strikingly large increase at approximately 15:30h. This is congruent with the opening time of US markets.

## Latency Impact

Latency impact is examined for every 15 min interval separately. In every interval, the effect of latency on the probability of unfavorable order book changes typically shows a slightly concave relation. This concave effect on the probability can be found in any interval across all stocks and for all strategies in our sample. The graph in Figure 3 depicts the average increase of possible order book changes for a buy active strategy in E.ON shares. The empiric values can be fitted with a log-linear regression.

From the slope of this regression, we can deduct the following simple rule of thumb: a 1% increase in latency leads to a 0.9% increase in the probability of unfavorable order book changes.

## Conclusion

To answer the question whether latency effects require market participants to employ low latency technology, we investigated four fundamental trading strategies. The calculation of directly associated costs is only applicable for active strategies, passive strategies cannot be associated with direct costs without further assumptions regarding the true underlying trading strategy. In this case, we present average latency effects regarding the limit and volume effects market participants face. That way, buy and sell strategies do not exhibit significant deviations.

From the perspective of market participants, the following conclusions can be drawn: for retail investors, who cannot make use of low latency technologies, price effects are negligible. Volume effects also seem irrelevant as retail trade sizes are typically low compared to quoted best bid/ask volumes. For institutional investors, the answer depends on their business model: for algorithmic traders, latency effects yield low increases of error rates (i.e., realizations of possible adverse order book changes within the latency lag). For investors whose business follows long-term profits, these latency effects are less relevant, as they only rely on few infrequent but large trades. The situation is different the more frequently investors trade and the smaller their trading profits for each trade are. For strategies based on extremly small profits associated to each trade – like it is the case for HFT – the negative effects of latency become more relevant.

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