Market Efficiency Under Differing Regulatory Frameworks

Evidence from a Swedish self-regulated exchange

Jacob Carlsson 22682 Erik Bergstrand 22668

Abstract

This study investigates empirical evidence for differences in terms of market efficiency between exchange-regulated (Multilateral Trading Facilities) and regulated marketplaces. The study explores the nature of the random walk of the marketplaces (i.e. the weak-form efficiency) and the rapidity and correctness of adjustments to new information (i.e. semi-strong form efficiency). The data sample consists of 14 indices spanning at least a decade back in time as well as 2,674 interim earnings announcements that occurred during the 2010 to 2017-time period, covering the Swedish Nasdaq Stockholm and Nasdaq First North exchanges. While evidence for difference in semi-strong form market efficiency is found between the exchanges, when segmenting based on size and considering the possible effect of transaction costs these differences can be considered rather small. The tests for weak-form efficiency rejects the random walk null hypothesis for weekly returns only for the smallest segment of Nasdaq Stockholm and for only part of the First North indices.

Acknowledgments: We would like to express gratitude to our tutor Håkan Thorsell., for his continual support and encouragement.

Table of Contents

1. Introduction

The question of the rationality and "efficiency" of the markets has been studied for decades, with the efficient market hypothesis (EMH), the idea that markets fully reflect all the available information, becoming the dominating paradigm after a series of papers during the 1960's, by now famous authors such as e.g. Eugene Fama (1965, 1970) and Paul Samuelson (1965). While this paradigm began to be challenged by behavioural economist during the 1990's, such as Thaler and Shiller arguing against the EMH based on a number of "anomalies", the issue is far from settled.

An opportunity to explore the parameters of the efficient market hypothesis is offered by the emergence of alternative, exchange-regulated marketplaces during the 90's and the 2000's, such as those implemented with the Markets in Financial Instruments Directive ("MiFID"), a EU directive implemented in 2007. This provides an opportunity to study how, or whether, regulatory frameworks for marketplaces impact market efficiency. The MiFID directive was a far-reaching legislative effort aimed towards harmonising the regulation in the different member countries of the European Union and increasing competition and consumer protection in the financial markets, setting a standard EU-wide template for exchange-regulated marketplaces, Multilateral Trading Facilities (MTF).

The presence of a two-tiered system of regulated versus exchange-regulated marketplaces presents an opportunity to conduct research on the differences in market efficiency that possibly could arise from different approaches to exchange regulation and structure. This is the primary motivation for this paper.

The hypothesis that there are noticeable differences in market efficiency between regulated and exchange-regulated marketplaces will be tested by two tests, one analysing the nature of the random walk of the marketplaces, and one analysing the price responsiveness to new information of the markets, between the exchanges.

2. Theoretical development

2.1 The Efficient Market Hypothesis

The notion of the markets as being "efficient" has a long history, with early work appearing as early as the early 1900's (see e.g. Bachelier (1900)). The hypothesis was popularised by Eugene Fama in his 1970 paper on the subject, *Efficient Capital Markets: A Review of Theory and Empirical Work,* and while the theory has been the subject of intense research since, the fundamental theory of the paper is still relevant.

As Fama describes in his 1970 paper, a market where prices of assets always "fully reflect" the available information is termed "efficient". The term "fully reflect" might demand some further explanation. Most conditions of market equilibrium can be stated in terms of expected returns, and these usually are functions of an asset's "risk". Such models can all be described notationally as depicted below.

$$\mathrm{E}(\tilde{\rho}_{j,t+1}|\Phi_t) = [1 + \mathrm{E}(\tilde{r}_{j,t+1}|\Phi_t)]\rho_{jt}$$

ρ_{tj} is the price of an asset j, at time t. $\rho_{j,t+1}$ is the price at time *t+1,* $r_{j,t+1}$is the one-period return. Φ_t denotes whatever information is available at the time. The expectation conditional on the full utilization of Φ_t implies that the price ρ_{jt} fully reflects the current available set of information.

Fama presents three models of efficient markets in his paper, with the base model being the martingale model. He additionally presents two variations of this, the sub-martingale and the random walk, specifically the random walk model which requires independent and identically distributed return increments.

In addition to the types laid out by Fama, there exists a number of different models, varieties and restrictions on random walk models of the markets, but for the sake of clarity four main varieties is presented in this section, in line with the classification laid out by Campbell et. al. (1997), which classifies the different models based on the dependence between returns at times *t* and *t+k* (RW1, RW2, RW3).

2.1.1 The "Fair-game" Martingale Model

The simple model of randomness in the financial markets known as the Martingale model is one of the earliest models in the field. It was developed from concepts of games of chance, where a "fair game" represents a game where neither of the players are favoured in any way. Thus, the rational expectations of the players of the winnings in future time periods should equal zero, or equivalently, that the expectation, i.e. the best prediction, of the future price (P_t) of an asset is that it is unchanged, $E[P_t - P_{t+1}] = 0$. This necessarily also results in that the price changes of non-overlapping periods of an asset are uncorrelated.

The Martingale theory was initially considered a necessary condition for a weak-form efficient market. In an efficient market, there should be no possibility of profiting from information contained in the assets price history. Note that the Martingale model does not incorporate risk in any way, which is a central focus of modern financial and economic research. For the Martingale model to be expected to hold, asset returns need to be risk-adjusted.

2.1.2 RW1 - IID increments

RW1 is the independent and identically distributed version, and the simplest. Define the price-log process $X_t = \ln P_t$, where P_t is the price of e.g. a security at time t.

$$X_t = \mu + X_{t-1} + \epsilon_t \qquad \epsilon_t \; i.i.d. N(0, \sigma_0^2)$$

Above is the recursive price formation formula, where μ is a drift parameter, while ϵ_t represents an error term, with the distributional property $\epsilon_t \; i.i.d. N(0, \sigma_0^2)$, a condition characteristic of the RW1 variation of the random walk.

2.1.3 RW2 - Independent increments

The RW2 model expands on the more restrictive RW1 model by departing from the identical distribution of the increments. This is a more realistic assumption, as changes to economic, technological, regulatory conditions etc. likely impacts the volatility of asset prices, as noted by Campbell et. al. (1997). This allows for heteroskedasticity, varying volatility, of the increments (ϵ_t), but also makes it more difficult to reliably test for.

2.1.4 RW3 - Uncorrelated increments

The weakest form of the random walk variations in the classification used by Campbell et. al. is the third variation, RW3; in this model, the increments are dependent but uncorrelated. This is the most general version and the one most commonly tested for.

2.1.5 Forms of efficiency

In his 1970 review, Fama classifies the research into efficient markets according to the particular subset of available information that is tested for. Three types of tests are described; weak-form tests, semi-strong form tests, and strong form tests.

The weak-form tests, which was the main concern of early research into the subject, primarily tests whether the historical price information subset is fully reflected and incorporated into the current price. The main topic of research into this subject tends to be whether there exists some form of forecastability of returns based on historical information, which might include historical price movements (as in the case of technical trading analysis) or fundamental security information (as in the case of fundamental analysis, e.g. price-to-book, industry data etc.).

Semi-strong form tests concern the rapidity of price adjustment to new information, which by necessity of the model needs to be immediate. The last type, the strong form tests, concerns research into whether there are investors that possess monopolistic access to subsets of information with price impact (public versus private information), which tends to be generalized as tests concerning whether insider information is reflected in current prices, despite being private information.

Testing for semi-strong form efficiency

Fama's (1970) definition of the semi-strong form of market efficiency, which concerns the rapidity of price adjustment to new information, is usually tested by a so-called event study. Event studies usually starts with defining the type of event; this can include a wide variety of events, including but not limited to stock splits, dividend announcements, earnings announcements, layoffs, etc. These studies usually aim to analyse the release of previously private information to the public; the aim being to test the rapidity and correctness of price adjustment, seeing how the market reacts to new information being added to the information set (Φ_t) that should be "fully reflected" in the asset price. The overall aim of such studies is to see whether there is a sizeable unexplainable abnormal return in the price; if there is no new information provided in the aftermath of an information event, but drifts unexplainable by expected normal return are detected in the price of the asset, a potential explanation is that the markets has to "digest" the information, which would not be in line with the semi-strong form of market efficiency.

2.1.6 Market conditions

Optimal market conditions for a frictionless and efficient market, where prices "fully reflects" all available information is worth commenting on. Fama lists three conditions;

1. Absence of transactions costs
2. All available information is costlessly available to all market participants
3. Consensus on the implication of the available information on asset prices

Fama makes the argument that while these conditions are sufficient, they are not necessary for an efficient market to exist. Significant transaction costs can exist without implying that prices do not reflect all available information. Only a "sufficient" number of investors need to have access to available information in order to enable an efficient market. A corollary can be made here to Benjamin Graham's description of the markets as a voting machine in the short term. Disunity among investors on the implications of the available information only implies inefficiency if there are certain investors who consistently can use superior analysis to make better evaluations. While all three of these deviations certainly can be claimed to exist in the markets, the question posed to research on market efficiency is whether these potential sources of inefficiency have a sizeable impact on the price formation of the markets.

2.1.7 The joint hypothesis problem

Concurrently with the development of the original hypothesis, and since then, economists which have studied whether markets reflect all available information or not have noted the difficulty in testing for efficient markets. The issue in question is regarding asset pricing; Tests of whether a market is efficient or not are done on the assumption that returns are expected to follow an expected market return, but since the expected market return is a model in itself, a rejection of efficient markets in a test could either be because of a non-efficient market or because of an inaccurate model of normal market returns. This was called the joint hypothesis problem by Fama (1991). Fama (2014) notes that the reverse of this problem is also true, i.e. that most tests involving a model of market equilibrium, such as asset pricing models, assume that all information is costlessly available to all market participants, and thus simultaneously tests for market efficiency. Fama is quite pessimistic in his view of this problem, stating that it is unlikely that accurate inferences about the degree of market efficiency are possible as long as the perfect model of normal asset returns is unavailable.

2.1.8 Empirical evidence and critiques

The empirical body consists of a vast number of studies and while it is not feasible to survey or recount them all this section attempts to provide an overview of the findings. A vast literature of empirical evidence exists in favour of the efficient market hypothesis, but the last few decades has seen the growth of academical scepticism.

The most significant movement of critics of the classical notion of efficient markets is the behavioural economic school of thought. It evolved from empirical observations of phenomena that could not, according to them, be explained by the classical model of efficient markets, and gained popularity throughout the turn of the millennium. It challenged the governing theory of rationality and argued that markets are instead driven by psychological, social and cognitive factors as well, drawing on sociobiological theoretical perspectives and bounded rationality to frame market efficiency.

The empirical evidence that contradicts the efficient market hypothesis mainly consists of observed anomalies and trading strategies which give indications of abnormal returns. Examples include e.g. DeBondt and Thaler (1985) where they observed a momentum effect in that stocks with low returns in previous periods tend to outperform stocks with high returns. In contrast to this, Jagadeesh and Titman (1993) found that a portfolio of past high return stocks outperformed low performing stocks, contradicting DeBondt and Thaler but still producing evidence against the efficient market hypothesis. This would mean that investors could potentially gain superior returns by trading on past performance, which would not be in accordance with the efficient market hypothesis. Another example is calendar related anomalies, which refer to trading strategies which seeks to exploit observed movements in stock prices related to specific dates. These include the “January Effect” as a seasonal increase in stock prices during the month of January. Studies by Keim et. al. (1983) and Reinganum (1983) found that the abnormal return for smaller stocks was larger in January, particularly during the first trading days. Later studies such as Booth (2000) were unable to find significant non-zero anomalies and argue that illiquidity related to smaller equities plays a part. Other examples of anomalies include e.g. technical trading strategies, fundamental valuation etc. These are just a few examples of the number of studies which claims to have found deviations from the efficient market hypothesis.

The proponents of EMH maintains that any anomalies in the market is either priced out quickly or can be explained by market microstructure impediments to efficiency, such as transactions costs, which are extensively referenced in Malkiel’s (2003) rebuttal of identified anomalies.

In an extension of the behavioural-EMH debate, Andrew Lo proposed the Adaptive Market Hypothesis (AMH) in his paper *Adaptive Market Hypothesis* (2004), where he sought to create a bridge between the EMH and behavioural economics, based on an evolutionary approach to market efficiency, where market efficiency is not seen as a static variable.

2.1.9 The role of transaction costs

Malkiel (2003), in his literature review of market efficiency anomalies, notes that there are several anomalies, such as calendar effects and some forms of technical analysis, which potentially could have minor predictive power. However, since the effects of these anomalies are small in comparison to the transaction costs involved in trying to exploit them, they do not necessarily break the underlying principle of market efficiency. Malkiel presents an alternative definition of the efficient markets, more akin to early studies which characterised the markets as a “fair game”. His alternative definition is that efficient markets do not allow investors to earn above average returns without accepting above average risks, i.e. there are no “short-cuts”, such as predictable patterns or superior analysis, to above average returns without also taking on above average risks. The presence of some minor predictable patterns can thus be explained by the fact that there is no way to exploit these patterns reliably because of e.g. transaction costs. An alternative and similar definition of efficient markets to Malkiel’s is Jensen’s (1978), who defines efficient markets such that it reflects prices to the point where the marginal benefits of acting on the information do not exceed the marginal costs.

2.2 Exchange-regulated market places

Before moving on to the methodological procedure of the study some background information on the development and differences in regard to the studied exchanges is necessary.

2.2.1 Development

Variations in the types of regulatory frameworks available to exchanges has existed for a long time. Variations existed throughout Europe, and in e.g. Sweden the pre-MiFiD regulatory framework allowed for three different types of exchanges, regulated exchange, self-regulated exchange, and "licensed marketplace". The introduction of MiFID, the Market in Financial Instruments Directive, which took effect in November of 2007, harmonized the rules across the European Union, with exchanges now offered either a regulated exchange status or a status as a self-regulated "Multilateral Trading Facility"[1]. The U.S. and Canadian equivalent is the "Alternative Trading System" framework. The stated aim of MiFID was to make trading more transparent, foster increased competition and provide a greater level of investor protection.

Since the adoption of the common regulatory framework a multitude of such multilateral trading platforms has emerged. As of the time of the writing of this paper, more than 600 active licenses have been issued, though the vast majority of these are so-called *dark pools*. The impact of the introduction of the MiFID framework on the overall market is difficult to gauge, and not the aim of this paper. However, e.g. Riordan et. al. (2011) found results which suggested that multilateral trading facilities contribute positively to market quality and that there were benefits from the increased competition.

2.2.2 Differences

In the case of equities, the practical implications for choosing to be traded on a multilateral trading facility is that there are less stringent requirements for listing and reporting, as the regulatory status of the company does not change. Multilateral trading facilities has no standard listing process, and as such the requirements on the traded securities can vary greatly. There are however four regulatory requirements made; (1) Pre-trade price transparency of existing orders, (2) Post-trade transparency, with trades having to be published in real-time, (3) Publicity and transparency in prices and charges, (4) A common rulebook for how the exchange works and ways of applying for membership.

An exemption from the pre-trade transparency rules is available to multilateral trading facilities when orders are large in scale compared with normal market size for the share or

[1] A third category was also present, "Systematic Internaliser", which were meant to apply to investment firms that on a frequent, systematic, and substantial basis executes client orders on own account, outside of the other legally defined trading venues.

type of share in question. This waiving of pre-trade transparency makes the exchange in question a so-called *dark pool,* which are commonly used to trade in blocks of shares, in order to avoid market impacts of large trades.

In Sweden, the principal active multilateral trading facility for equities is the Nasdaq First North MTF, which is operated by the same company which also operates the main Swedish regulated exchange, Nasdaq. Besides listing requirements being considerably lower, less requirements are being made on the participating companies in regard to company administration (e.g. board composition) and reporting, as well as legal counsel. An example of lesser requirements is the frequency of information disclosure, with e.g. quarterly earnings reports not being a requirement, which contrasts in comparison with the regulated exchange ("main market").

This relaxed demand for transparency and administration can be related to the concept of market efficiency; with less frequent access to public information, the question becomes whether this can have a noticeable impact on the efficiency of the marketplaces in question. It is also relevant to note that the two different exchanges attract different types of investors; the First North market, due to its status as a non-regulated marketplace, is in many cases a restricted exchange for many large institutional investors, such as pension funds, which are limited to, when it comes to equity investments, publicly traded companies on regulated exchanges.

It is also worth noting that the First North exchange also has a subsection called First North Premier, which is a middle ground between the main market and First North, with higher requirements being made on the participating companies overall. Table 1 is a comparative table of the requirements for the dominant equity MTF in the Nordic region (First North) and the largest regulated exchange (Nasdaq Stockholm). Note that these regulations only serve as an example, as MTF's by virtue of their status as self-regulated can vary widely in terms of regulation.

Requirements	**Nasdaq First North (MTF)**	**Nasdaq Stockholm (MM)**
Reporting	At least semi-annual reporting	Quarterly reporting
Accounting standard	GAAP or IFRS	IFRS only
Administration	None	Compliance with a corporate governance code
Board	Assistance from certified advisor	Experience and composition requirements
Free float requirement	10%	25%
History prior to IPO	No requirements	Three annual accounts and documented profitability
Market value	1 MEUR	No minimum value

Table 1 – Comparison between a regulated exchange (NASDAQ OMX) and an MTF (First North)

3. Method

In exploring the differences in market efficiency between the two exchanges, two forms of efficiency will be explored. On one hand, the weak-form efficiency will be analysed with a random walk analysis, based on the assumptions of uncorrelated but not identically distributed increments, as laid out by Campbell et. al (1997) in their RW3 model of random walk. The non-IID but uncorrelated assumption of the random walk model is deemed to be the most realistic, especially as the time period studied will cover the 2008 global financial crisis, which is likely to have caused significant volatility.

Additionally, a test of the semi-strong form efficiency of the markets will be pursued through an event study of the interim earnings announcement of the firms on the different exchanges.

3.1 Random walk analysis

The overlapping variance ratio test is laid out in Lo and MacKinlay's 1988 article, and while not the first to make use of the variance ratio, they popularised the concept in efficient market testing. The following test methodology is in line with their proposed test.

The variance ratio test analyses the predictability of a time series by comparing the variances of the differences of (in case of securities data) the returns over a number of time intervals. If a time series follows a random walk, the variance of a *q*-period should equate *q* times the variances of the subperiods. As an example, the variance of returns on a weekly basis should be a quarter of the monthly variance of returns.

3.1.1 Variance ratio

Below is a brief overview of the variance ratio method, as laid out by Lo and MacKinlay (1988).

Define $X_t = ln\ P_t$, where P_t is the price of e.g a security at time t.

$$X_t = \mu + X_{t-1} + \epsilon_t$$

Above is a model of the recursive price relation, where X_t is the log-price of a security at time *t*, μ is an arbitrary drift parameter, $X_{t-1}$is the log-price of the security at time *t-1*, and ϵ_t is a random "disturbance" term which according to the classical random walk hypothesis is constrained to be independent and identically distributed (IIID).

However, an important consideration when analysing the data is the possible presence of heteroskedasticity, i.e. that the volatility changes over time. Assuming homoscedasticity and rejecting the random walk due to the presence of heteroscedasticity would not yield an interesting result, due to the likelihood of varying volatility in market returns over time. This is in line with the RW1 versus the RW3 model touched upon earlier. Lo and MacKinlay therefore proposed the use of a test statistic that was initially developed by White (1980) and White and Horowitz (1984), which allows for a general form of heteroscedasticity, where ϵ_t is allowed to deviate from normality and vary over time. The heteroscedasticity-robust test statistic is presented on the next page.

Suppose that $nq + 1$ observations are contained in a sample, with observations numbering $X_0, X_1, X_2, \ldots, X_{nq}$. *q* can be any integer greater than 1.

$$\hat{\mu} = \frac{1}{nq}\sum_{k=1}^{nq}(X_k - X_{k-1}) = \frac{1}{nq}(X_{nq} - X_0)$$

$\hat{\mu}$ is the maximum-likelihood estimator of the mean drift parameter of the time series (μ).

$$\bar{\sigma}_a^2 = \frac{1}{nq - 1}\sum_{k=1}^{nq}(X_k - X_{k-1} - \underline{\mu})^2$$

$\bar{\sigma}_a^2$is the maximum-likelihood estimator of σ_0^2.

$$\bar{\sigma}_c^2(q) = \frac{1}{q(nq - q + 1)\left(1 - \frac{q}{nq}\right)}\sum_{k=q}^{nq}(X_k - X_{k-q} - q\hat{\mu})^2$$

$\bar{\sigma}_c^2(q)$is just like $\bar{\sigma}_a^2$ the maximum-likelihood estimator of σ_0^2 but only utilises a subset of the observations, containing *nq-q+1* terms. Lo and MacKinlay also presents a simpler estimator which uses *n* observations in their paper but prefers the overlapping $\bar{\sigma}_c^2$(q) estimator due to the additional number of observations that can be included, thus making it a more efficient estimator, creating a more powerful test.

$$\bar{\mathrm{M}}_r(q) = \frac{\bar{\sigma}_c^2(q)}{\bar{\sigma}_a^2} - 1$$

Under the random walk hypothesis, the values of the variance ratios of 1+$\bar{\mathrm{M}}_r(q)$ will be one or close to one, due to the linearity of the variance of the increments that is present under a random walk.

$\bar{\mathrm{M}}_r(q)$ is an estimate of the q-order autocorrelation coefficient of the return increments. For e.g. weekly returns, this would, in the case of $\bar{\mathrm{M}}_r(2)$, correlate to an approximation of the first-order autocorrelation of weekly returns.

Test statistic

Lo and MacKinlay proposes both a non-heteroskedastic robust and a heteroskedastic robust test statistic in their paper. Presented below is the heteroskedastic-robust version of that test statistic.

$$\hat{\delta}(j) = \frac{\sum_{k=j+1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2(X_{k-j} - X_{k-j-1} - \hat{\mu})^2}{[\sum_{k=1}^{nq}(X_k - X_{k-1} - \hat{\mu}]^2}$$

$\hat{\delta}(j)$ is a heteroscedasticity-consistent estimator of the asymptotic variance of $\hat{\rho}(j)$, i.e. the autocorrelation coefficient estimator.

$$z^*(q) \ = \frac{\sqrt{nq}\overline{\mathrm{M}}_r(q)}{\sqrt{\sum_{j=1}^{q-1}[\frac{2(q-j)}{q}]^2\ \hat{\delta}(j)}}$$

$z^*(q)$ is the heteroscedastic-robust standardized test statistic that is used by Lo and MacKinlay, and it is asymptotically standard normal.

Infrequent trading analysis

Spurious autocorrelation patterns could hypothetically be induced due to low liquidity and a delayed price response in comparison to more well-traded stocks. The hypothesis is that smaller stocks incorporate new information slower than larger, more well-traded stocks, which could lead to a situation in which a market-wide information event impacts asset prices of more liquid stocks before their smaller counterparts, which would look like positive serial correlation. This is most noticeable in equal-weighted stock indices, and less pronounced in value-weighted.

Testing for this is difficult, but an estimation can be made of the impact of such non-trading, providing an estimation of whether the detected correlation is possibly due to the non-trading effect. Lo and MacKinlay (1988) calculates the impact of non-trading and show that if there is a ten-percent chance of non-trading for any given period, the induced autocorrelation on a weekly basis is 2.1 percent, which is quite low.

3.1.2 Daily versus weekly increments

While daily increments of return provide a large number of observations, certain issues have been highlighted by e.g. Campbell et. al. (1997) and Lo and MacKinlay (1988) in regard to the use of daily increments. The effects of biases such as asynchronous trading, where public information impacts low liquidity securities later than highly traded securities (which looks like correlation), non-trading etc. leads to the preference of many researchers in using weekly returns data instead. The obvious drawback of this is the smaller amount of observations that can be included for a certain time-period, but the results are generally less susceptible to biases and thus it is preferred. In this study both daily and weekly returns data will be analysed for the sake of completeness. In the case of weekly returns, midweek prices (the Wednesday closing price) was chosen as the basis for weekly returns calculations.

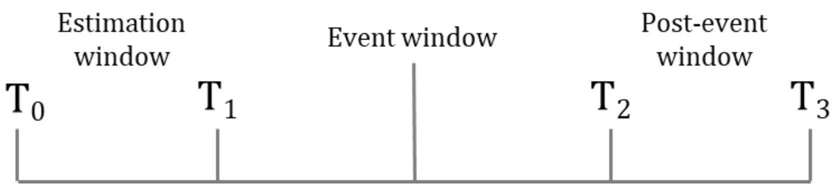
3.2 Event analysis

In order to add additional empirical evidence for the difference in market efficiency between the different exchanges, a test of the semi-strong efficiency is performed in addition to the test of the randomness of the markets.

The markets will be tested for the investors rapidity of response and information incorporation into the asset price. This will be done through an event study focusing on earnings announcement among firms on the relevant exchanges and the corresponding effect on their listed equity price. This will be performed by measuring the cumulative abnormal return (CAR) of earnings announcements. CAR is an extensively used type of semi-strong form test.

A prototypical event study also categorizes events into a good-, bad-, no-news classification, with the aim to study the relative impact of these types of events. Regardless of type of event, the null hypothesis of an efficient market is that there should be no drift in the absence of new information which could impact the price of the asset. In the case of this study, the lack of a good estimator of market expectations on the announced earnings of the companies in both First North and of the smaller main market companies restricts the study from categorizing events in such a way.

The start of any event study is the choice of event window length, as illustrated below.



$$L_1 = T_1 - T_0$$

$$L_1 = T_3 - T_2$$

L_1 and L_2 represents the pre-event and post-event window, respectively.

3.2.1 Cumulative Abnormal Return

As noted in the theoretical review section, a pervasive problem in the study of abnormal returns and market efficiency is the question of the joint hypothesis problem. In terms of the event study methodology, the question is relevant for the estimation of normal return, where a number of different approaches are possible. Campbell et. al. (1997) summarizes the different approaches available, which can be loosely divided into two categories; statistical models and economic models. Statistical models, in contrast to economic models, does not require assumptions about investors behaviour, which can be seen as an advantage.

The model which has been chosen to conduct the study under is the market model, which is a statistical model which relates the return of a security to a market portfolio and is a commonly used model for performing event studies. Examples include De Bondt, W.F.M. and Thaler, R. (1985) and Brown (1984).

The market model is presented as an improvement on the Capital Asset Pricing Model and the constant mean return model due to its removal of the share of the return that is related to market return variation. The model is a linear statistical model that presents the relation between market returns and individual security returns, with an assumed joint normality. This approach uses the Ordinary Least Square (OLS) method to obtain consistent estimators of the parameters of the market model.

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

$$E(\varepsilon_{it} = 0) \qquad var(\varepsilon_{it}) = \sigma^2_{\varepsilon_i}$$

R_{it} and R_{mt} are the returns of the security and the market. ε_{it} is the disturbance term, with an assumed zero mean. $\sigma^2_{\varepsilon_i}$,α_i,β_i, represents the disturbance variation, abnormal return and beta (market return covariance), respectively.

$$\hat{\beta}_i = \frac{\sum_{\tau=T_0+1}^{T_1}(R_{i\tau} - \hat{\mu}_i)(R_{m\tau} - \hat{\mu}_m)}{\sum_{\tau=T_0+1}^{T_1}(R_{m\tau} - \hat{\mu}_m)^2}$$

Beta for security i

$$\hat{\sigma}^2_{\varepsilon_i} = \frac{1}{L_1}\sum_{\tau=T_0+1}^{T_1}(R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau})^2$$

Variance for disturbance term of security i

$$\hat{\mu}_i = \frac{1}{L_1}\sum_{\tau=T_0+1}^{T_1} R_{i\tau}$$

Mean return of security i

$$\hat{\mu}_m = \frac{1}{L_1}\sum_{\tau=T_0+1}^{T_1} R_{m\tau}$$

Mean market return

$$\widehat{AR}_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau}$$

One-period abnormal return for security i

Under a null hypothesis of efficient markets the disturbance term, and therefore the abnormal return, has a (conditional on the event window market returns) conditional zero mean and a conditional variance $\sigma^2(\widehat{AR}_{it})$.

$$\sigma^2(\widehat{AR}_{i\tau}) = \sigma^2_{\varepsilon_i} + \frac{1}{L_1}[1 + \frac{(R_{m\tau} - \hat{\mu}_m)^2}{\hat{\sigma}^2_m}]$$

Conditional variance of the abnormal return

The conditional variance has two components; the $\sigma^2_{\varepsilon_i}$ is related to the original market model, while the second term is additional variance due to sampling errors. As L_1 increases, the additional variance approaches zero as the sampling error vanishes.

$\widehat{CAR}$ is defined as the cumulative abnormal return for a given event, which aggregates the abnormal return measure across time for the event.

$$\widehat{AR}_{it} \sim N(0, \sigma^2(\widehat{AR}_{it}))$$

$$\widehat{CAR}_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \widehat{AR}_{i\tau}$$

An aggregation of results, $\overline{CAR}$, can then be produced either from the mean of the individual securities $\widehat{CAR}$ or, as below, from the summation of mean $\overline{AR}$.

$$\overline{AR}_\tau = \frac{1}{N}\sum_{i=1}^{N} \widehat{AR}_{i\tau}$$

$$\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_\tau$$

$$\overline{CAR}(\tau_1, \tau_2) \quad \sim \quad N(0, \bar{\sigma}^2(\tau_1, \tau_2))$$

3.2.2 Test statistic

The method for conducting a statistical inference of the results from the event study follows the guidelines set out by Campbell et. al. (1997) and MacKinlay (1997). The average CAR is calculated, but in order to test whether this number is statistically significantly different from zero an estimator of $\bar{\sigma}^2$ is needed, since it is unknown. In practice, with large samples of events, $\hat{\bar{\sigma}}^2(\tau_1, \tau_2) = \frac{1}{N^2}\sum_{i=1}^{N} \hat{\sigma}^2_i(\tau_1, \tau_2)$

$$\theta_1 = \frac{\overline{CAR}(\tau_1, \tau_2)}{[\hat{\bar{\sigma}}^2(\tau_1, \tau_2)]^{1/2}} \sim N(0,1)$$

The distribution of the test statistic θ_1 is asymptotically convergent with a normal distribution of mean 0 with respect to large numbers of events and the length of the estimation windows.

3.2.3 Infrequent trading during events

Since a substantial amount of companies listed on the First North exchange are small in terms of market capitalization, some in the order of a few tens of millions in market capitalization, (i.e. “micro-cap”), and thus often have low liquidity, the issue of thinly traded stocks, alternatively called infrequent trading, must be accounted for. Bartholdy et. al. (2006) provides guidelines for conducting studies on smaller stock exchanges, of which some has been incorporated into this study. In the event of a non-trading day, the return is calculated as the average between the last trading day and the next trading day, and the results of the event study has been grouped according to the (in the case of First North) corresponding tercile in terms of market capitalization of the company at the time of the event in relation to the other companies in the event data set.

4. Data analysis

4.1 Descriptive statistics

4.1.1 Variance ratio data

The test will be made under the null hypothesis of a random walk with drift. The data used consists of ten indices from the First North marketplace, as well as four indices from the Nasdaq Stockholm exchange. Indices are used in place of individual securities as the returns of individual securities contains idiosyncratic noise which adds difficulty in identifying possible correlation patterns. While it is possible to construct proprietary total return indices or perform tests on individual securities, the risk of error or idiosyncratic noise makes existent commercial indices attractive as a data source.

The First North indices are represented by a general all-share index, as well as a number of sectoral indices. As the selection of indices available to study for the market were limited in terms of age, these were chosen to provide an adequate cross section of the First North market. The main market indices consist of an all-share index, and three segmented indices meant to represent the three different size classes that the companies listed on the main market belong to. The intent with this choice is to be able to compare the results from the smaller index with the results from the First North indices, as liquidity should be more comparable for this index. While it would have been preferable to have used size-segmented indices also for the First North exchange, no such total return indices of suitable age exist as of yet. Data has been retrieved through Thomson Reuters Eikon service, as well as from Nasdaq's online price history repository directly. Table 2 below presents an overview of the included indices and data.

Index	Nr. of observations (daily)	Nr. of observations (weekly)	Date span
Stockholm All-Share	2481	491	2/01/2008-30/11/2017
Stockholm Small Cap	2794	554	2/10/2006-30/11/2017
Stockholm Mid Cap	2794	554	2/10/2006-30/11/2017
Stockholm Large Cap	2794	554	2/10/2006-30/11/2017
FN All-share	1998	391	2/10/2009-30/11/2017
FN Oil & Gas	2981	594	2/01/2006-30/11/2017
FN Basic Materials	2985	595	2/01/2006-30/11/2017
FN Industrials	2987	596	2/01/2006-30/11/2017
FN Consumer Goods	2987	596	2/01/2006-30/11/2017
FN Healthcare	2987	596	2/01/2006-30/11/2017
FN Consumer Services	2987	596	2/01/2006-30/11/2017
FN Utilities	2486	494	28/12/2006-30/11/2017
FN Financials	2986	596	2/01/2006-30/11/2017
FN Technology	2987	596	2/01/2006-30/11/2017

Table 2 – Overview of the studied variance ratio data points

4.1.2 Event study data

The sample which makes up the event study consists of 2,674 company earnings announcements, of which 1,658 events relate to companies listed on the Nasdaq OMX Stockholm exchange and 1,016 are events relate to companies from the self-regulated First North exchange. The events are sampled from the start of 2010 to October 2017.

Data on share price and earnings announcements, such as the date and company name, has been retrieved through Thomson Reuters Eikon service as well as from Nasdaq's online news repository directly. The date and company identifier for each earnings announcement was matched with the retrieved price history in order to create an event window.

Window length

A 30 trading days pre- and post-event window is studied for each event. However, the 20-day window is likely to be of more interest in the analysis, as it is less likely that alternative information is released during the shorter time period. 20 trading days roughly corresponds to one real-time month.

An estimation window of 250 trading days, roughly corresponding to a full year in total trading and non-trading days, has been chosen to provide an adequate length of time to provide parameters to the market return estimation.

Estimating market return through indices

In order to accommodate for industry-specific risks and news events, the abnormal return of each security has been built based on the performance of the security versus its respective industry index. The classification, industries, and indices used is the Industry Classification Benchmark ("ICB"). The ICB, produced by FTSE, is a globally used classification index, which groups companies into ten macroscopic industries and further into increasingly granular supersectors, sectors, and subsectors. For this study, the macroscopic industry classification is used in conjunction with Nasdaq's respective indices, which uses the same classification method. Classification and index data has been retrieved from Nasdaq and Thomson Reuters.

Clustering of events and cross correlation

Since event windows overlap for some of the announcements in the data sample, an adjustment has to be made in order to make sure that there is no covariance between the abnormal returns. Campbell et. al. proposes two ways to solve this, one of which is to create a portfolio of abnormal returns for each event date, which is the method that has been chosen for this study. The variance for the aggregated sample cumulative abnormal returns has thus been calculated based on aggregate portfolios of events.

4.2 Variance ratio analysis

4.2.1 OMX Variance ratio results

NASDAQ OMX Stockholm: Daily returns						
Index	**n**	**q**				
		2	**4**	**8**	**16**	**Mean**
Stockholm All-Share	2481	1.002	0.933	0.827	0.773	0.88375
		0.0621	-1.1249	-1.7932*	-1.5804	
Stockholm Small Cap	2794	1.144	1.322	1.453	1.626	1.38625
		3.567**	4.3489**	4.074**	4.1015**	
Stockholm Mid Cap	2794	1.137	1.223	1.22	1.278	1.2145
		3.5992**	3.154**	2.021*	1.8049	
Stockholm Large Cap	2795	0.986	0.913	0.811	0.761	0.86775
		-0.4758	-1.5875	-2.1267*	-1.8056	

*"**" = Significant at 1% significance level, "*" at 5%*

Table 3 – Results from the variance ratio test on the NASDAQ OMX daily returns data points

Table 3 shows the results of the overlapping variance ratio test robust to heteroskedasticity applied to daily returns from four indices representing four segmentations of the main regulated Swedish stock market. Results significant at the 1% level can be found for three of the four indices, with only the Stockholm All-share index producing non-significant results at that level of confidence.

The Stockholm All-Share index lacks any significant values of the variance ratio at the 5% significance level, and thus no proof of inefficiency can realistically be claimed. The Q(8) observation number carry a weakly significant (10% significance level) result.

Serial correlation can be inferred from the results, and looking at the q(2) results, a weak serial correlation is seen in the All-Share (2%), and Large Cap index (-1.4%) returns, though none of these two results are significant. The strongly significant serial correlations seen in the Small and Mid cap indices are more substantial, with a similar positive serial correlation of 14.4% and 13.7%, which, in the absence of factors such as transaction costs, would imply that these indices are inefficient. If these serial correlations hold, a 1% increase for a certain day would imply a subsequent increase the day after of 0.144% in the case of e.g. the Small Cap index.

The Large Cap index yields mostly non-significant values, except for the Q(8) observation period, where a negative serial correlation of -18.9% is present, which infers mean reversion.

However, as previously noted, using daily returns is not ideal as there are potential micro market issues such non-trading and other idiosyncrasies, which is why weekly data is also studied and used as the main source of analysis.

NASDAQ OMX Stockholm: Weekly returns						
Index	**n**	**q**				
		2	**4**	**8**	**16**	**Mean**
Stockholm All-Share	491	0.899	0.884	0.942	1.029	0.9385
		-1.3202	-0.8674	-0.2799	0.0957	
Stockholm Small Cap	554	1.108	1.295	1.592	2.033	1.507
		1.5793	2.4121*	3.0415**	3.8183**	
Stockholm Mid Cap	554	1.003	1.099	1.204	1.381	1.17175
		0.0387	0.8147	1.0796	1.4244	
Stockholm Large Cap	554	0.898	0.872	0.91	1.015	0.92375
		-1.5069	-1.065	-0.4837	0.0569	

*"**" = Significant at 1% significance level, "*" at 5%*
Upper row is the VR, lower is the Z-score

Table 4 – Results from the variance ratio test on the NASDAQ OMX weekly returns data points

Table 4 shows the results of overlapping variance ratio tests robust to heteroskedasticity applied to weekly returns. Significant results can be found for only the Stockholm Small Cap index.

Once again, the All-Share index provides no significant values for any of the observation periods, which means that the null hypothesis cannot be rejected for this index. In contrast to the daily returns data, the Mid Cap index contains no significant values for the weekly data. The Large Cap index, with no significant values, provides no proof of a non-random walk either.

The Small Cap index provides several significant values, with significant values implying large serial correlation between Q(4) 29.5% and Q(16) 103.3%.

Summary of results

In summary, the results from studying the All-Share index implies that the overall market, taken in aggregate through the All-share index, provides no indication of the market not following a random walk with drift. However, certain segments of the market seem to deviate from this result, with noticeably the Small Cap index producing quite high serial correlation, both for daily and weekly data. The Mid Cap index provides significant numbers for daily returns, but lacks any significance when looking at weekly data. As the weekly returns are less prone to idiosyncrasies, this mixed result still provides moderate evidence for a weakly efficient mid-cap segment. In general, the significant numbers indicate a positive serial correlation across the board. The large cap, with no significant correlation for weekly return

The Large Cap index provides no significant results except for Q(8) daily returns which means that there is no major basis for rejecting a random walk with drift for the larger companies on the main market.

4.2.2 First North Variance ratio results

First North: Daily returns						
Index	**n**	**q**				
		2	**4**	**8**	**16**	**Mean**
FN All-share	1998	1.110	1.214	1.237	1.287	1.212
		3.0263**	3.1762**	2.3558*	2.0971*	
FN Oil & Gas	2981	1.083	1.129	1.133	1.173	1.1295
		2.8257**	2.3653*	1.5388	1.3889	
FN Basic Materials	2985	1.068	1.146	1.186	1.182	1.1455
		1.9432	1.93	1.61	1.188	
FN Industrials	2987	1.005	1.067	1.086	1.17	1.082
		0.1654	1.2129	1.0364	1.4098	
FN Consumer Goods	2987	0.94	0.892	0.831	0.812	0.86875
		-2.3923*	-2.248*	-2.2342*	-1.6854	
FN Healthcare	2987	0.908	0.898	0.908	0.979	0.92325
		-3.0974**	-1.9263	-1.1587	-0.192	
FN Consumer Services	2987	0.974	0.995	1.01	1.032	1.00275
		-0.8692	-0.089	0.1259	0.3001	
FN Utilities	2486	0.817	0.697	0.588	0.583	0.67125
		-2.7565**	-2.8581**	-2.9733**	-2.383*	
FN Financials	2986	1.006	1.000	0.984	1.058	1.012
		0.261	0.0096	-0.2079	0.5049	
FN Technology	2987	0.978	0.987	1.042	1.101	1.027
		-0.8515	-0.2772	0.5932	1.0146	

*"**" = Significant at 1% significance level, "*" at 5%*
Upper row is the VR, lower is the Z-score

Table 5 – Results from the variance ratio test on the First North daily returns data points

The First North All-Share index, which is calculated with a price return calculation method, gives a broad overview of the performance of the companies on First North. However, it's incomplete calculation method (no consideration of e.g. dividends), makes it worthwhile to also study the exchanges sector indices, where total return indices are available.

As seen in table 5, the All-Share index has highly significant variance ratio numbers, with all but the Q(16) variance ratio being significant at the 1% significance level. The variance ratios suggest positive serial correlations ranging between 11% and 28.7%, with Z-levels decreasing as the observation periods lengthen. However, since this index is not a total return index, some of this serial correlation might be explained by factors such as seasonal dividends, which weakens a rejection of the null hypothesis of a random walk from this result.

The sector indices, which are calculated as total returns, provides a mixed bag in terms of significance of results. Most indices provide a very low variance ratio, but five of nine sector indices provide no significant results at the 5% significance level.

The Oil & Gas index has significant results for the observation periods 2 and 4, where a positive serial correlation of 8.3% and 12.9% can be found. The Consumer Goods, Healthcare and Utilities indices also produces significant results, but in contrast to the All-Share and Oil & Gas index yields negative serial correlation, implying a mean reversion effect. This effect is especially noticeable in the Utilities sector, with serial correlations ranging between -18.7% and -41.7% depending on observation period.

The variance ratio mean for all the sector indices provide negative serial correlations of circa -2% for the 2, 4, and 8 observation periods, with the Q(16) observation period yielding a mean positive serial correlation of 1%. Note that these numbers include non-significant results.

In summary, the All-Share index and certain sector indices can be inferred to not follow a random walk from the daily returns, notably Utilities, Healthcare, Consumer Goods and Oil & Gas. Note that this does not necessarily imply a lack of market efficiency, as will be discussed further below.

First North: Weekly returns						
Index	**n**	**q**				
		2	**4**	**8**	**16**	**Mean**
FN All-share	391	1.065	1.087	1.111	1.294	1.13925
		0.8473	0.6705	0.6037	1.1641	
FN Oil & Gas	594	0.983	1.013	1.024	1.218	1.0595
		-0.2953	0.1092	0.1305	0.8306	
FN Basic Materials	595	1.027	0.979	1.108	1.145	1.06475
		0.3931	-0.1767	0.6381	0.6398	
FN Industrials	596	0.963	1.116	1.269	1.769	1.27925
		-0.6498	1.1088	1.6061	3.16**	
FN Consumer Goods	596	0.93	0.923	1.025	1.29	1.042
		-1.1028	-0.6837	0.1491	1.2445	
FN Healthcare	596	1.042	1.142	1.271	1.355	1.2025
		0.8749	1.6098	1.9403	1.7365	
FN Consumer Services	596	0.99	1.044	1.155	1.356	1.13625
		-0.1875	0.4632	1.0917	1.7293	
FN Utilities	494	0.895	0.936	0.971	1.305	1.02675
		-1.8551	-0.5218	-0.1368	0.9678	
FN Financials	596	0.985	1.089	1.302	1.64	1.254
		-0.214	0.7523	1.7854	2.7937**	
FN Technology	596	1.065	1.169	1.308	1.571	1.27825
		1.3754	1.9948*	2.3393*	2.9649**	

*"**" = Significant at 1% significance level, "*" at 5%*
Upper row is the VR, lower is the Z-score

Table 6 – Results from the variance ratio test on the NASDAQ OMX daily returns data points

In the weekly returns category, presented in table 6, far fewer significant results are found. The only indices with significant results above the 5% significance level are the Industrial, Financials and Technology indices.

The Industrial index shows a very high variance ratio value of 1.769 at Q(16), implying a positive serial correlation of 76.9% at a significance level of above 1%. However, none of the other observation periods yield a rejection of the null hypothesis. Likewise, the Financials index also yields a high variance ratio at Q(16), 1.64. The Technology index yields the most significant numbers, with significant variance ratios implying serial correlation between 16.9% and 57.1%.

With most of the indices showing results unable to reject the null hypothesis of a random walk with drift, it is difficult to reject the null hypothesis of a random walk in First North from these weekly results for all but a few sectors at lengthy observation periods.

Summary and comparison of results

Campbell et al (1997) found significant correlations in US total market indices, with variance ratios that generally exceeded 1 (implying positive correlation) and was statistically significant for all but the largest of the size-sorted indices. Frennberg and Hansson (1992), studying the Swedish stock market between 1919-1990, finds results broadly similar to but larger in magnitude compared with Campbell's US data, i.e. a weak-form inefficient Swedish market. Based on their results, and the fact that the market capitalizations of the firms in both the First North and the Main Market indices in general probably can be considered quite small in comparison to the US, one should expect significant correlation across the board for both the First North and the Main Market indices, with the possible exception of the main market large-cap index.

This is, however, not entirely the case. While the size-effect can be found, with significant correlation found in the small-cap segment of the main market but not clearly in the larger segments, the weekly returns data is generally found to be weak-form efficient for both the main market and First North, with some minor exceptions.

Thus, these results could be considered more in line with e.g. Worthington and Higgs (2004) study, in which the Swedish market was found to be weak-form efficient after an analysis with a multiple variance ratio test, as developed by Chow and Denning (1993). A major difference between the study by Worthington and Higgs and Frennberg and Hansson is the time period; while Frennberg and Hansson's study covers the lengthy period of 1919-1990, Higgs and Frennberg covers the more recent period of 1987-2003. A possible explanation can thus be that the markets has become more efficient as time has passed. The mixed results of the First North indices, with the more reliable weekly returns indicating significant correlation for only some of the indices are more surprising, as the assumption could be made that the young age of the market in concert with the low liquidity should produce weak inefficiency.

No general trend of mean reversion or positive serial correlation can be found, with daily data returning significant variance ratios indicating both negative and positive serial correlation. In the weekly data, the sparse significant results indicate an exclusive positive serial correlation.

4.3 Event analysis

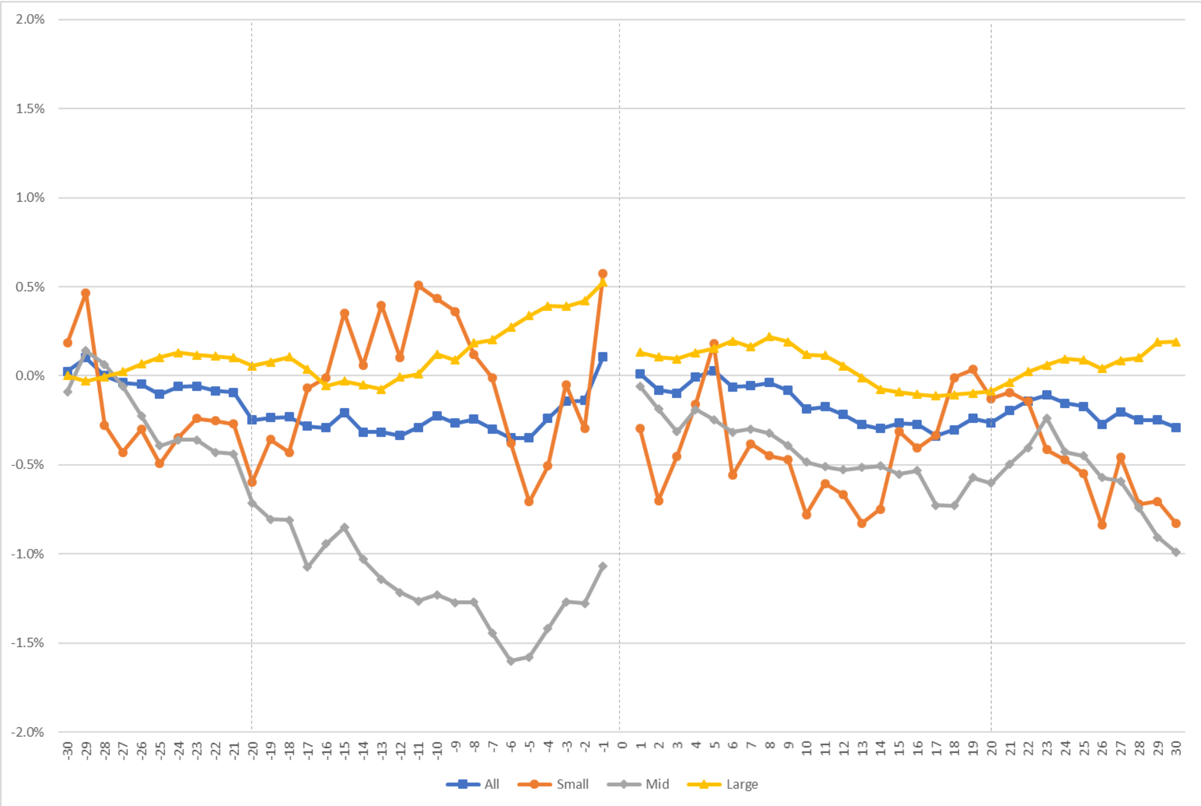
Provided on the next few pages are the results, in terms of mean abnormal returns, from the study of the gathered equity event data.

4.3.1 OMX Event results

Abnormal return OMX (%)								
Days	All		Small (206)		Mid (513)		Large (939)	
	AR	CAR	AR	CAR	AR	CAR	AR	CAR
-30	0.025	0.025	0.184	0.184	-0.088	-0.088	0.001	0.001
-29	0.076	0.101	0.283	0.467	0.228	0.14	-0.031	-0.03
-28	-0.101	0	-0.744	-0.277	-0.076	0.064	0.025	-0.005
-27	-0.039	-0.039	-0.152	-0.429	-0.123	-0.059	0.027	0.022
-26	-0.009	-0.048	0.129	-0.3	-0.166	-0.225	0.044	0.066
-25	-0.056	-0.104	-0.192	-0.492	-0.167	-0.392	0.038	0.104
-24	0.043	-0.061	0.146	-0.346	0.032	-0.36	0.026	0.13
-23	0.003	-0.058	0.107	-0.239	0.001	-0.359	-0.013	0.117
-22	-0.027	-0.085	-0.014	-0.253	-0.071	-0.43	-0.007	0.11
-21	-0.009	-0.094	-0.018	-0.271	-0.009	-0.439	-0.008	0.102
-20	-0.155	-0.249	-0.324	-0.595	-0.275	-0.714	-0.047	0.055
-19	0.013	-0.236	0.238	-0.357	-0.092	-0.806	0.023	0.078
-18	0.006	-0.23	-0.073	-0.43	-0.003	-0.809	0.028	0.106
-17	-0.053	-0.283	0.361	-0.069	-0.266	-1.075	-0.069	0.037
-16	-0.008	-0.291	0.059	-0.01	0.133	-0.942	-0.092	-0.055
-15	0.084	-0.207	0.362	0.352	0.090	-0.852	0.026	-0.029
-14	-0.109	-0.316	-0.294	0.058	-0.179	-1.031	-0.023	-0.052
-13	0.000	-0.316	0.339	0.397	-0.111	-1.142	-0.024	-0.076
-12	-0.020	-0.336	-0.295	0.102	-0.074	-1.216	0.069	-0.007
-11	0.046	-0.29	0.405	0.507	-0.049	-1.265	0.016	0.009
-10	0.065	-0.225	-0.074	0.433	0.035	-1.23	0.113	0.122
-9	-0.041	-0.266	-0.072	0.361	-0.042	-1.272	-0.033	0.089
-8	0.023	-0.243	-0.242	0.119	0.001	-1.271	0.096	0.185
-7	-0.056	-0.299	-0.128	-0.009	-0.173	-1.444	0.018	0.203
-6	-0.050	-0.349	-0.368	-0.377	-0.157	-1.601	0.068	0.271
-5	0.001	-0.348	-0.329	-0.706	0.022	-1.579	0.066	0.337
-4	0.108	-0.24	0.200	-0.506	0.159	-1.42	0.056	0.393
-3	0.096	-0.144	0.456	-0.05	0.152	-1.268	-0.003	0.39
-2	0.005	-0.139	-0.246	-0.296	-0.010	-1.278	0.031	0.421
-1	0.246	0.107	0.870	0.574	0.210	-1.068	0.104	0.525
0	0.026		-0.821		0.221		0.130	
1	0.012	0.012	-0.295	-0.295	-0.058	-0.058	0.131	0.131
2	-0.091	-0.079	-0.405	-0.7	-0.128	-0.186	-0.026	0.105
3	-0.018	-0.097	0.249	-0.451	-0.127	-0.313	-0.010	0.095
4	0.089	-0.008	0.292	-0.159	0.123	-0.19	0.035	0.13
5	0.037	0.029	0.340	0.181	-0.056	-0.246	0.025	0.155
6	-0.091	-0.062	-0.739	-0.558	-0.069	-0.315	0.040	0.195
7	0.007	-0.055	0.177	-0.381	0.017	-0.298	-0.033	0.162
8	0.017	-0.038	-0.069	-0.45	-0.024	-0.322	0.057	0.219
9	-0.044	-0.082	-0.020	-0.47	-0.070	-0.392	-0.028	0.191
10	-0.104	-0.186	-0.310	-0.78	-0.093	-0.485	-0.073	0.118
11	0.013	-0.173	0.176	-0.604	-0.026	-0.511	-0.004	0.114
12	-0.045	-0.218	-0.064	-0.668	-0.016	-0.527	-0.059	0.055
13	-0.057	-0.275	-0.159	-0.827	0.012	-0.515	-0.065	-0.01
14	-0.021	-0.296	0.079	-0.748	0.009	-0.506	-0.065	-0.075
15	0.031	-0.265	0.436	-0.312	-0.046	-0.552	-0.015	-0.09
16	-0.008	-0.273	-0.093	-0.405	0.019	-0.533	-0.013	-0.103
17	-0.064	-0.337	0.071	-0.334	-0.194	-0.727	-0.009	-0.112
18	0.034	-0.303	0.325	-0.009	-0.002	-0.729	0.006	-0.106
19	0.063	-0.24	0.044	0.035	0.157	-0.572	0.009	-0.097
20	-0.024	-0.264	-0.164	-0.129	-0.029	-0.601	0.010	-0.087
21	0.068	-0.196	0.036	-0.093	0.107	-0.494	0.051	-0.036
22	0.055	-0.141	-0.051	-0.144	0.091	-0.403	0.058	0.022
23	0.033	-0.108	-0.270	-0.414	0.166	-0.237	0.038	0.06
24	-0.047	-0.155	-0.057	-0.471	-0.191	-0.428	0.034	0.094

25	-0.016	-0.171	-0.078	-0.549	-0.021	-0.449	-0.005	0.089
26	-0.101	-0.272	-0.288	-0.837	-0.123	-0.572	-0.049	0.04
27	0.069	-0.203	0.382	-0.455	-0.019	-0.591	0.046	0.086
28	-0.046	-0.249	-0.266	-0.721	-0.152	-0.743	0.016	0.102
29	0.000	-0.249	0.017	-0.704	-0.162	-0.905	0.086	0.188
30	-0.040	-0.289	-0.124	-0.828	-0.083	-0.988	0.002	0.19

Table 7 – Results from the event study on the NASDAQ OMX equity data set



Graph 1 – CAR of NASDAQ OMX equities in the event study

Table 7 presents the results of the event study on the NASDAQ OMX equities, while graph 1 depicts the development of the cumulative abnormal return, based on the mean abnormal return for each segmentation category. In the non-segmented category, there is a minor positive pre-announcement drift, with a 20-day CAR of 0.36% and a 30-day CAR of 0.11%. With a positive jump of 0.24%, in mean abnormal return prior to the announcement, it is possible that there is either a pervasive leaking of information or a psychological effect, with the latter not compatible with market efficiency.

The segmented results show more drift, both prior and post announcement, except for the Large Cap companies, which exhibits lower degrees of drift than all the other segments as well as the aggregate in the post-announcement period.

The Small Cap events exhibit a pre-announcement positive drift of 1.16% (20 days) and 0.56% (30 days) CAR on average, as well as a negative post-event CAR of -0.16% (20 days) and -0.83% (30 days).

The Mid Cap events exhibits negative pre-event drifts of -0.35% (20 days) and -1.1% (30 days) CAR, with the post-event window yielding comparable negative CAR values of -0.60% (20 days) and -0.98% (30 days).

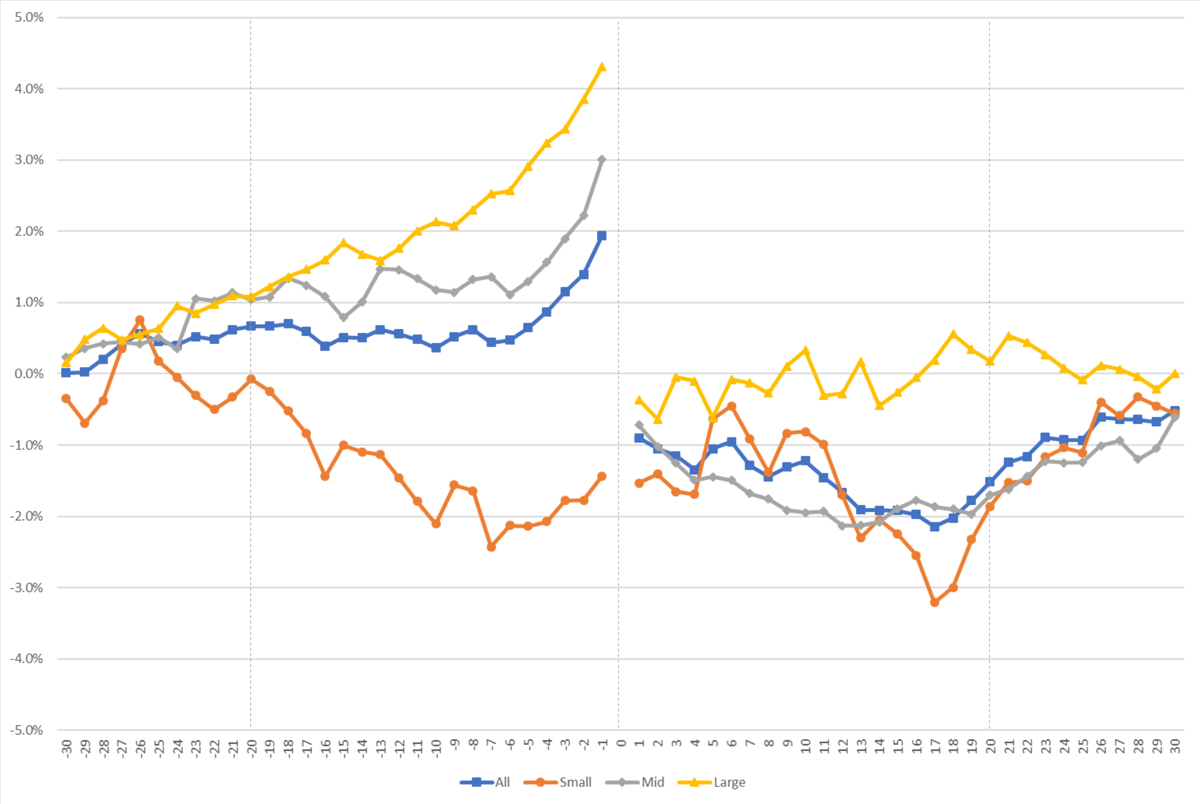
The Large Cap events yields positive CAR values of 0.47% (20 days) and 0.53% (30 days) on average for the pre-event period. The post-event period yields only a small amount of drift, with CAR values of -0.09% (20 days) and 0.19% (30 days).

Using Campbell et. al.'s (1997) test statistic, with adjustments made for cross-correlation, the mean CAR of all the events is tested with a null hypothesis of a zero mean, for both a 20- and 30-day overall, pre- and post-event window. The null hypothesis of a zero mean cannot be rejected for the overall event window and post-event window but is rejected for the pre-event window at the 1% significance level. This is applicable for both lengths of observation. The small and mid-capitalization companies both have cumulative abnormal returns post-event that are significant and non-zero at the 1% significance level.

4.3.2 First North event results

Abnormal return First North								
Days	All		Small		Mid		Large	
	AR	CAR	AR	CAR	AR	CAR	AR	CAR
-30	0.014	0.014	-0.349	-0.349	0.230	0.230	0.154	0.154
-29	0.007	0.022	-0.344	-0.692	0.126	0.356	0.327	0.481
-28	0.184	0.206	0.315	-0.377	0.065	0.421	0.158	0.639
-27	0.212	0.418	0.737	0.359	0.026	0.446	-0.161	0.478
-26	0.146	0.564	0.394	0.754	-0.028	0.418	0.074	0.552
-25	-0.113	0.451	-0.576	0.178	0.094	0.513	0.085	0.637
-24	-0.047	0.404	-0.225	-0.047	-0.161	0.352	0.318	0.955
-23	0.116	0.520	-0.256	-0.303	0.704	1.056	-0.109	0.846
-22	-0.034	0.485	-0.198	-0.500	-0.034	1.022	0.126	0.972
-21	0.136	0.621	0.175	-0.325	0.118	1.141	0.124	1.097
-20	0.050	0.671	0.254	-0.071	-0.100	1.041	-0.015	1.082
-19	-0.001	0.670	-0.171	-0.243	0.038	1.079	0.139	1.221
-18	0.033	0.703	-0.281	-0.524	0.261	1.340	0.143	1.364
-17	-0.111	0.592	-0.317	-0.840	-0.098	1.243	0.104	1.468
-16	-0.208	0.384	-0.601	-1.442	-0.158	1.085	0.132	1.600
-15	0.129	0.513	0.439	-1.002	-0.294	0.791	0.240	1.840
-14	-0.008	0.505	-0.094	-1.096	0.218	1.010	-0.159	1.681
-13	0.115	0.620	-0.035	-1.131	0.461	1.471	-0.089	1.593
-12	-0.062	0.558	-0.328	-1.459	-0.008	1.463	0.170	1.763
-11	-0.075	0.483	-0.330	-1.789	-0.130	1.333	0.242	2.005
-10	-0.120	0.363	-0.319	-2.108	-0.157	1.176	0.125	2.130
-9	0.157	0.520	0.550	-1.558	-0.033	1.142	-0.051	2.079
-8	0.102	0.622	-0.082	-1.639	0.184	1.326	0.223	2.303
-7	-0.185	0.437	-0.791	-2.431	0.037	1.363	0.223	2.525
-6	0.033	0.470	0.304	-2.127	-0.252	1.111	0.042	2.567
-5	0.175	0.645	-0.014	-2.141	0.185	1.297	0.346	2.913
-4	0.228	0.873	0.067	-2.074	0.271	1.567	0.329	3.243
-3	0.275	1.148	0.296	-1.778	0.328	1.895	0.193	3.436
-2	0.247	1.396	0.003	-1.774	0.326	2.222	0.421	3.856
-1	0.544	1.940	0.338	-1.436	0.785	3.007	0.459	4.315
0	-0.608		-0.796		-0.548		-0.363	
1	-0.897	-0.897	-1.532	-1.532	-0.717	-0.717	-0.364	-0.364
2	-0.153	-1.049	0.122	-1.410	-0.303	-1.021	-0.274	-0.639
3	-0.102	-1.152	-0.243	-1.653	-0.231	-1.251	0.228	-0.410
4	-0.195	-1.346	-0.040	-1.693	-0.241	-1.492	-0.328	-0.738
5	0.293	-1.053	1.060	-0.633	0.046	-1.446	-0.284	-1.023
6	0.100	-0.953	0.181	-0.452	-0.047	-1.493	0.203	-0.819
7	-0.332	-1.285	-0.462	-0.914	-0.188	-1.681	-0.330	-1.149
8	-0.161	-1.446	-0.469	-1.383	-0.073	-1.754	0.059	-1.090
9	0.137	-1.309	0.548	-0.835	-0.161	-1.915	0.045	-1.045
10	0.089	-1.220	0.025	-0.810	-0.033	-1.948	0.287	-0.757
11	-0.234	-1.454	-0.182	-0.992	0.015	-1.933	-0.590	-1.347
12	-0.211	-1.665	-0.711	-1.703	-0.200	-2.133	0.316	-1.031
13	-0.247	-1.912	-0.601	-2.304	0.002	-2.131	-0.144	-1.176
14	-0.001	-1.913	0.257	-2.047	0.054	-2.077	-0.299	-1.475
15	-0.010	-1.923	-0.200	-2.246	0.186	-1.890	0.040	-1.435
16	-0.051	-1.974	-0.302	-2.548	0.116	-1.774	-0.092	-1.527
17	-0.172	-2.145	-0.659	-3.208	-0.094	-1.868	0.284	-1.242
18	0.121	-2.024	0.212	-2.995	-0.029	-1.897	0.277	-0.965
19	0.248	-1.776	0.673	-2.322	-0.072	-1.969	0.065	-0.900
20	0.263	-1.514	0.460	-1.862	0.269	-1.700	0.112	-0.789
21	0.273	-1.241	0.336	-1.526	0.080	-1.620	0.423	-0.366
22	0.081	-1.160	0.026	-1.500	0.183	-1.437	0.016	-0.350
23	0.264	-0.896	0.333	-1.167	0.211	-1.227	0.252	-0.097
24	-0.028	-0.924	0.129	-1.038	-0.022	-1.249	-0.174	-0.272
25	-0.006	-0.930	-0.067	-1.105	0.003	-1.246	0.088	-0.184
26	0.321	-0.609	0.711	-0.394	0.238	-1.007	0.030	-0.154
27	-0.030	-0.639	-0.191	-0.585	0.072	-0.936	0.035	-0.120
28	-0.005	-0.644	0.259	-0.326	-0.265	-1.201	-0.073	-0.193
29	-0.032	-0.676	-0.125	-0.451	0.157	-1.044	-0.142	-0.335
30	0.158	-0.518	-0.105	-0.555	0.433	-0.611	0.146	-0.189

Table 8 – Results from the event study on the First North equity data set



Graph 2 – CAR of First North equities in the event study

In comparison with the main market, the events of First North show a considerably higher amount of drift, as presented in table 8 and depicted in graph 2. Except for the smallest tercile of companies, all events have a positive pre-event CAR of approximately 1-3% (20 days) and 2-4% (30 days). This trend is broken following the event, with all abnormal returns showing a downward trend until approximately the 15th day following the event, after which they reverse most of their abnormal return. Generally, only small amounts of differentiation can be seen in the post-event window in terms of drift between the different terciles of the event companies, apart from the smallest tercile, which reaches a full percentage point lower than the rest at the 17th day, but subsequently regains most of this abnormal loss.

In the non-segmented category, a positive pre-event drift of 1.28% (20 days) and 1.96% (30 days) is seen. Following the event, a downward trend can be identified, reaching a maximum of -2.13% at the 17th day. Following that, the abnormal return trends positive, reaching -1.51% at the 20-day mark and -0.53% after 30 days.

The largest tercile exhibits the lowest degrees of abnormal returns in the post-event period, but the highest in the pre-event period. The smallest tercile, contrary to assumptions that lower liquidity leads to higher degrees of inefficiency, shows the lowest degree of drift among the terciles in the pre-event window. The pre-event window shows at most approximately a -2% drift for both the 20-day and 30-day period. In the post-event period the drift reaches a maximum level of -3.19% at the 17th day, and then from there quickly recovering to a 20-day CAR of -1.88% and a 30-day CAR of -0.59%.

The mean CAR of the First North events, as with the main market events, are tested with adjustments made for cross-correlation. The mean CAR of all the events is tested with the null hypothesis of a zero mean, for both a 30-day pre- and post-event period, and a 20-day. The null hypothesis of a zero mean can be rejected for the pre-, post- and overall event period at the 1% significance level. This is applicable for both lengths of observation. This indicates, in the absence of other factors, such as transaction costs, that the First North market is not semi strong-form efficient.

4.4 Comparative test of results

Cross-testing the results allows for conclusions regarding the comparative levels of cumulative abnormal returns. Using the estimators for variance as before, the pre- and post-levels of observed CAR between the exchanges are tested against each other, with the null hypothesis of no difference, i.e. that there is no difference in the levels of cumulative abnormal returns between the exchanges. The results are strongly indicative of the two exchanges not having the same or similar levels of CAR, as the null hypothesis of no difference in mean is rejected at the 99% confidence level for both the pre and post period.

The same results hold true whether the entire sample of each exchange is considered or if different size categories is used, e.g. the large category of First North is matched against the small category of the Main Market. Not using Campbell et. al's (1997) estimators and instead relying on a paired t-test yields the same results. For z- and t-test scores of the relevant segments, see the appendix.

4.5 Transaction costs

While the tests provide a limited rejection of a mathematical random walk with drift for certain indices and mostly rejects a zero-mean abnormal return in the event study, a rejection or confirmation of market efficiency would be incomplete without setting the results in comparison with the transaction costs. As discussed in the theoretical section, if an anomaly cannot be exploited, due to e.g. the presence of transaction costs, it is hard to argue that there is an inefficiency.

First North		
Small	Mid	Large
3,20%	1,91%	1,37%

NASDAQ OMX		
Small	Mid	Large
1,06%	0,55%	0,16%

Table 9 – Bid-ask spread comparison, late 2016 – 2017

In order to highlight the relative transaction costs, table 9 lists the ask-bid spreads present on the studied exchanges. The data is based on averages for the last year, with the First North classification of Small-Mid-Large being made based on what tercile the listed company belongs to in terms of market capitalization.

As can be expected, First North companies has a significantly larger bid-ask spread, between three to four times as high as the comparable segment on the main market. While the bid-ask spread cannot be stated to be an exhaustive representation of transaction costs for all investors, with Malkiel (2005) also noting e.g. brokerage costs and market impact as costs to the investor, it likely represents the largest single transaction cost for many investors.

In relation to the event study results, this counterintuitively makes the smallest tercile of stocks in the First North study the most efficient, as the abnormal returns seen are all within the plus or minus two percent range. Trying to exploit the statistical arbitrage would be more difficult than for the other segments, where larger abnormal returns can be found concurrently with lower transaction costs.

4.6 Validity and reliability

The scope of this study is limited to Nordic data and the nature of self-regulated exchanges makes generalizability of the results unfeasible beyond the Nordics and the studied exchanges. Studies where the sample is constituted of firms belonging to different exchanges or domicile could reach different results. The measurement and definition of market efficiency lacks consensus in academia and our findings are dependent on our choice of measurement and definition of market efficiency.

While no direct uncertainty exists surrounding the date of the event, it is possible that some of the earnings announcements are made during the evening, after the close of trading, which could impact the analysed cumulative abnormal return if, on average, the news during the last eleven years has skewed consistently negative/positive in terms of surprise earnings announcements. This seems unlikely but remains a possibility.

It should also be noted that a few of the largest companies on the First North marketplace belongs to the First North Premier category, which have regulations more akin to the main market, which possibly might explain some of the observed similarities.

Infrequent trading is a possible explanation for some of the results in the variance ratio analysis, especially considering that the multilateral trading facility that is included in the study tends to cater to smaller firms with lower market capitalizations and thus often lower liquidity. As pointed out in the methodological section, such effects are however expected to impact the results by at most a few percentage points unless there are widespread and systemic non-trading of shares on the market, which does not seem to be the case, even for the smaller firms that are listed on the MTF.

The use of index observations for First North that stretch the full length of the indices life span might carry some issues, in that it is possible that at initiation of the marketplace liquidity was extraordinarily low and infrequent trading was significantly more common. In this case our use of an extended timeline was motivated by the need to acquire as many observations as possible, as the current timeline already trends towards the short side.

The model of normal returns for the event study is a possible and probable source of error. As Fama repeatedly has stated, no perfect model for normal returns exist.

5. Conclusion

The exploratory study of market efficiency between the two exchanges at a glance largely confirms the standard assumption of higher degrees of inefficiency in lower liquidity markets such as First North, at least in terms of its semi-strong form efficiency. The variance ratio provides little rejection at the weekly level, beyond certain sub-indices, of the null hypothesis of a random walk with drift for First North, while the event study provides some evidence of abnormal returns in the post-event period, despite the non-rejection of a random walk of the variance ratio analysis. Our findings are in line with some earlier research, such as Worthington and Higgs (2004), which finds the Swedish stock market to be weak-form efficient in general, while somewhat contradicting earlier studies such as Frennberg and Hansson (1992), which found significant amounts of correlation in the main market. This difference can be explained by the market becoming more efficient as time has passed. Unfortunately, there is lack of earlier research to compare the results from the First North empirical data to.

While the difference between the exchanges in mean cumulative abnormal returns are confirmed by comparative tests and some of these abnormal post-event returns are rather large, around 3% in the case of the smallest tercile, considering the relatively high transaction costs compared to the main market (again, in the case of the smallest tercile of companies on First North, roughly 3%) it might not be enough to conclusively state that the market is inefficient according to the modified efficient market definition proposed by Malkiel (2005) or Jensen (1978).

A significant amount of abnormal return prior to the earnings announcement was detected, especially for the First North exchange. This could be explained by either early and partial dissemination of information about the contents of earnings announcement, or by the investors becoming increasingly more certain about the contents as the event date approaches. This would need to be coupled with a general skew towards positive or negative earnings announcement for each of the segments during the time period studied, as both negative and positive earnings announcements are included in the mean. None of these two explanations are necessarily contrary to the efficient market hypothesis, at least not in its semi-strong form.

The most interesting comparison is between the somewhat similar in size small capitalization segment of the main market and the largest tercile (consisting of companies in excess of 200 MSEK in market capitalization at the time of the event) of the First North companies. Notwithstanding the pre-announcement abnormal returns, the small capitalization companies on the main market compares on par in terms of post-announcement abnormal return compared to the largest tercile of companies on First North, especially when considering the difference in transaction costs. The size of post-event abnormal return, which for both segments were significantly separated from a zero mean, coupled with differences in the bid-ask spread to explain some of the additional abnormal return seen in the First North large segment, provides limited evidence of the non-impact of the differences between the exchanges in the terms of the earlier described dissimilarities such as e.g. the disclosure rules, board composition rules and access to certain investors.

5.1 Contribution and further research

As there was a lack of research on the market efficiency of the generally smaller multilateral trading facilities that exists in Europe, this paper contributes empirical research on the subject matter.

While the Small Cap index was deemed to not follow a random walk according to daily data and the weekly data, a similar size segmentation was not available for direct comparison on the First North marketplace, where only certain sub-indices were deemed not to follow a random walk. The weekly returns variance ratio study could potentially be improved with access to size-segmented total return indices with longer timeframes for the First North marketplace.

Other than better size-adjusted random walk tests, the possibility of an event study on the effects of the new MiFID regulations entering into force early 2018 on market efficiency, once enough time has passed, might provide further clarity on the relationship between regulations and market efficiency.

6. Appendix

6.1 References

- Bachelier, L; *Théorie de la speculation;* University of Paris; 1900
- Campbell, John Y., Lo, Andrew, MacKinlay, A. Craig; *The Econometrics of Financial Markets*; Princeton; 1997
- Chow. K.V., & Denning, K.; *A simple multiple variance ratio test*; Journal of Econometrics 58(3), 385-401, 1993
- Constantinides G., Harris M., Stulz R.M.; *Handbook of the Economics of Finance Volume 1B: Asset Pricing*; 2013
- De Bondt, W., Thaler, R.; *Does the stock market overreact?*; Journal of Finance 40: 793-805; 1985
- Fama, Eugene F.; *Efficient Capital Markets: A Review of Theory and Empirical Work*; Journal of Finance, Vol. 25, Issue 2; 1970
- Fama, Eugene F.; *The Behavior of Stock-Market Prices*; The Journal of Business, Vol. 38, No. 1, pp. 34-105; January 1965
- Fama, Eugene F.; *Two Pillars of Asset Pricing*; American Economic Review, 104(6): 1467–1485; 2014
- Fama, Eugene. F.; *Efficient capital markets II*, Journal of Finance 46:1575-1617; 1991
- Frennberg, P., Hansson, B.; *Testing the random walk hypothesis on Swedish stock prices: 1919-1990*; Journal of Banking and Finance 17 175-191; 1992
- Jegadeesh, N., Titman S.; *Returns to buying winners and selling losers: Implications for stock market efficiency*; Journal of Finance 48:65-91; 1993
- Jensen, M.C.; *Some anomalous evidence regarding market efficiency*, Journal of Financial Economics 6:95-102; 1978

- Keim, D.B., W.T. Ziemba; *Security Market Imperfections in Worldwide Equity Markets*; Cambridge University Press, Cambridge, pp 169-178; 2000
- Keim, D.B.; *Size-related anomalies and stock return seasonality: further empirical evidence*, Journal of Financial Economics 12:13-32; 1983
- Kothari, S.P. and Warner, Jerold B.; *The Econometrics of Event Studies*; October 20, 2004
- Lo and MacKinlay, *Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test*; The Review of Financial Studies, Volume 1, Issue 1, Pages 41–66; 1 January 1988
- Lo, Andrew, *The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective*, 2004
- Malkiel, B.; *Reflections on the Efficient Market Hypothesis: 30 Years Later*; The Financial Review 40 1—9; 2005
- Malkiel, Burton G.; *The Efficient Market Hypothesis and Its Critics*; Journal of Economic Perspectives Vol. 17, Nr. 1, pp. 59-82; 2003
- Reinganum, M.R.; *The anomalous stock market behavior of small firms in january: empirical tests for tax-loss selling effects*, Journal of Financial Economics 12:89-104; 1983
- Riordan, R, Storkenmeier, A, Wagener, M.; *Do Multilateral Trading Facilities Contribute to Market Quality?*; 25 May, 2011
- Samuelson, Paul A.; *Proof That Properly Anticipated Prices Fluctuate Randomly*; Industrial Management Review, Vol. 6, Issue 2, Spring 1965
- White, H., Domowitz I.; *Nonlinear Regression with Dependent Observations*; Econometrica 52, 143-162; 1984
- White, Halbert; *A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity*, Econometrica 48, 817-38; 1980

❖ Worthington, Andrew and Higgs, Helen; *Random walks and market efficiency in European equity markets*; Global Journal of Finance and Economics 1(1):pp. 59-78, 2004

6.2 Test data

6.2.1 Using variance estimator

30-day Pre-event period, FN Allcap == MM Allcap				
Variable	**Obs.**	**Mean**	**Std. Error**	**Std. Dev.**
(a) Main Market All cap	30	-1.5785	0.182574	1
(b) First North All cap	30	-0.09698	0.182574	1
H0: mean(a - b) = 0	z = -5.7379			
Ha: mean(a - b) < 0	Ha: mean(a - b) != 0		Ha: mean(a - b) > 0	
Pr(Z < z) = 0.0000	Pr(|Z| > |z|) = 0.0000		Pr(Z > z) = 1.0000	

30-day Post-event period, FN Allcap == MM Allcap				
Variable	**Obs.**	**Mean**	**Std. Error**	**Std. Dev.**
(a) Main Market All cap	30	-1.13852	0.182574	1
(b) First North All cap	30	-4.28025	0.182574	1
H0: mean(a - b) = 0	z = 12.1679			
Ha: mean(a - b) < 0	Ha: mean(a - b) != 0		Ha: mean(a - b) > 0	
Pr(Z < z) = 1.0000	Pr(|Z| > |z|) = 0.0000		Pr(Z > z) = 0.0000	

30-day Pre-event period, FN Large == MM Small				
Variable	**Obs.**	**Mean**	**Std. Error**	**Std. Dev.**
(a) Main Market Small cap	30	-0.4974	0.182574	1
(b) First North Large cap	30	2.104741	0.182574	1
H0: mean(a - b) = 0	z = -10.0780			
Ha: mean(a - b) < 0	Ha: mean(a - b) != 0		Ha: mean(a - b) > 0	
Pr(Z < z) = 0.0000	Pr(|Z| > |z|) = 0.0000		Pr(Z > z) = 1.0000	

30-day Post-event period, FN Large == MM Small				
Variable	**Obs.**	**Mean**	**Std. Error**	**Std. Dev.**
(a) Main Market Small cap	30	-0.86695	0.182574	1
(b) First North Large cap	30	-1.47874	0.182574	1
H0: mean(a-b) = 0	z = 2.3694			
Ha: mean(a-b) < 0	Ha: mean(a-b) != 0		Ha: mean(a-b) > 0	
Pr(Z < z) = 0.9911	Pr(|Z| > |z|) = 0.0178		Pr(Z > z) = 0.0089	

6.2.2 Using paired t-test

30-day Pre-event period, FN Allcap == MM Allcap				
Variable	**Obs.**	**Mean**	**Std. Error**	**Std. Dev.**
(a) Main Market All cap	30	-0.00214	0.000277	0.001519
(b) First North All cap	30	-0.00047	0.000629	0.003447
H0: mean(a-b) = 0	t = -3.6267	degrees of freedom =	29	
Ha: mean(a-b) < 0	Ha: mean(a-b) != 0		Ha: mean(a-b) > 0	
Pr(T < t) = 0.0005	Pr(|T| > |t|) = 0.0011		Pr(T > t) = 0.9995	

30-day Post-event period, FN Allcap == MM Allcap				
Variable	**Obs.**	**Mean**	**Std. Error**	**Std. Dev.**
(a) Main Market All cap	30	-0.00178	0.000193	0.001058
(b) First North All cap	30	-0.01944	0.000975	0.005338
H0: mean(a-b) = 0	t = 21.2538	degrees of freedom =	29	
Ha: mean(a-b) < 0	Ha: mean(a-b) != 0		Ha: mean(a-b) > 0	
Pr(T < t) = 1.0000	Pr(|T| > |t|) = 0.0000		Pr(T > t) = 0.0000	

30-day Pre-event period, FN Large == MM Small				
Variable	**Obs.**	**Mean**	**Std. Error**	**Std. Dev.**
(a) Main Market Small cap	30	-0.00202	0.000627	0.003432
(b) First North Large cap	30	0.018488	0.002292	0.0138
H0: mean(a-b) = 0	t = -8.3864	degrees of freedom =	29	
Ha: mean(a-b) < 0	Ha: mean(a-b) != 0		Ha: mean(a-b) > 0	
Pr(T < t) = 0.0000	Pr(|T| > |t|) = 0.0000		Pr(T > t) = 1.0000	

30-day Post-event period, FN Large == MM Small				
Variable	**Obs.**	**Mean**	**Std. Error**	**Std. Dev.**
(a) Main Market Small cap	30	-0.00396	0.000507	0.002778
(b) First North Large cap	30	-0.00804	0.00079	0.004325
H0: mean(a-b) = 0	t = 4.0556	degrees of freedom =	29	
Ha: mean(a-b) < 0	Ha: mean(a-b) != 0		Ha: mean(a-b) > 0	
Pr(T < t) = 0.9998	Pr(|T| > |t|) = 0.0003		Pr(T > t) = 0.0002	