Algorithmic trading and Benchmarks

-A Study of the Swedish market

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Abstract

Algorithmic trading has grown in popularity over the last few years. The large financial centres of the world are leading the development of this new kind of trading. We investigate the development of algorithmic trading in Stockholm by conducting interviews with major institutions on the financial market. The aim being to give a picture of what current practice is like in the Stockholm institutional equities market.

The trades done via algorithms are evaluated against benchmarks. Our perception is that VWAP is the most common benchmark in the Stockholm financial market place and therefore also in Sweden. To analyse the risks inherent in a guaranteed VWAP trade we investigate if there are factors that affect the relative spread between VWAP and TWAP, the proxy we use for the risk in a VWAP trade from the sell side trading desks perspective. We use common risk measures as well as micro factors in each constituent of the OMXS30 index together with the index itself to be able to identify both idiosyncratic and market risk. The initial economic reasoning is that over a longer period there should be no difference between the two benchmarks, VWAP and TWAP. This holds true for the majority of the dependent variables studied but in 11 out of 30 cases there seems to be a statistically significant difference. This is something we ascribe to our specific data sample. We find that for most constituents there are some significant variables that contribute to an idiosyncratic risk. However, on a portfolio or index level this risk might be different. This means that the pricing of a VWAP trade should be done individually with respect to the different levels of risk. A direct affect of this, for a sell side trading desk, would be to charge individual commissions for each stock dependant on its loadings of risk factors.

Keywords: Algorithmic trading, Benchmarks, VWAP

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1. Introduction

More and more of the activity on the stock markets is now attributed to the actions of computerized trading programs. Today 60 percent of all trades on the New York Stock Exchange (NYSE) are triggered by automatic trading programs or program trading[1] as they are also called (Automated trader (2007)). However only some of the orders included in program trading can be attributed to algorithmic trading. The difference between program trading and algorithmic trading is that program trading encompasses all trades that are put into a "program" while algorithmic trading only refers to a "non-human" trader.

These non human traders or algorithms are often programmed to take advantage of the small arbitrage opportunities that arise in the market, often because of human behaviour. There are also other purposes of trading algorithms. One is to provide cheaper execution to clients who want to trade. Studies have shown that trading via an automated algorithm is often cheaper than using a human trader for many orders (Næs and Ødegaard (2006)). Another reason is to make execution less risky and a third reason is to disguise the trades so as to be more anonymous.

To evaluate these trades to one another, traders and portfolio managers use benchmarks. Thus an algorithm is compared against a benchmark and is often designed to beat a benchmark (Kisell and Malamut (2005)).

In this thesis we use a series of interviews as the basis for our findings. These interviews were conducted in Stockholm during November and December 2007 and cover a broad spectrum of people involved in the institutional equities business. In total we made seven in depth interviews with portfolio mangers, sell side traders and sales people as well as buy side traders. This set of interviews was made to find answers for the questions posed by us and the Swedish bank S E B. The driving question was:

How widespread is the usage of algorithmic trading in Swedish institutions and what benchmarks do they use for equity orders?

A common benchmark on the Swedish market, according to the answers given in our interviews, is the volume weighted average price (VWAP). It is a widely used benchmark for larger orders worldwide and accounts for the liquidity factor (McCulloch Kazakov (2007)). This benchmark is also used to guarantee a price against the customers for the brokerage houses. One purpose of a benchmark is to give a fair picture of the performance of a trade irrespective of what type of stock that is traded. Thus a benchmark must be fair for all stocks. This raises a second question:

What risks are associated with guaranteeing VWAP and does it differ between stocks?

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[1] The NYSE defines program trading as an order including 15 or more individual equities with a total value of one million dollars or more (Stoll (2005)).

We find it interesting since in our interviews with players on the Swedish market we have found little indication of people thinking about the potential changes in risk profiles of using a common benchmark on different securities. However most of the people we talk to use the VWAP benchmark on a day to day basis. We further examine this question using regression analysis where we attempt to find risk factors that have bearing on the spread between the VWAP and the time weighted average price (TWAP). We argue that, with the assumption of liquid markets, it is always possible to trade on TWAP and therefore use it as a risk free price, or base risk indicator.

By answering this question together with the first question we aim to shed some light on the way Swedish institutions trade equities and more in detail, on how they use benchmarks to evaluate their orders. There seems to be no prior research on how equity trading actually is done and measured in the Swedish equity markets. Our results indicate firstly that there is a gap between the Swedish equity market and its counterparties in London and New York in algorithmic trading. Secondly there seems to be a large difference in level of sophistication and interest in the topic of benchmarking between individual institutions and people on the Swedish market. Our interviews support our initial expectations that players on the Swedish equity markets only consider the liquidity risks of a VWAP trade. They do not reflect over the suitability of the equity traded or the conditions under which the trade takes place. Our further research on the actual factors which could be influential on the risk of a VWAP trade provides some interesting findings. We view it as a first attempt and not as a final model or product. This thesis simply puts the spotlight on a new level of risk, previously overlooked by both the buy and sell side of the equity markets.

1.1 Purpose

Our goal with this paper is twofold. Firstly we want to establish a knowledge base of the attitude towards algorithmic trading among professionals in the institutional equities business in Sweden.

Secondly, since benchmarks and trade evaluation is an integer part of algorithmic trading we want to investigate the most used benchmark among the population sample interviewed and the risk factors associated with it.

There are three reasons why we want to investigate this area. The first reason is the lack of research done on the subject. The second reason is the fact that there is no truly dominant benchmark on the market (Kisell and Malamut (2005)). The third reason is the large economic impact of the subject on equity trading.

Today there is little research being done in this area because of the very limited development on the Swedish arena and the proprietary nature of the information. As the interest of algorithmic trading and the benchmarks used grows in Sweden this will be an area that should be better understood. Because of the limited knowledge we think there is money to be saved by better knowing how benchmarks work and when one should be more or less cautious about using them.

The more in depth statistical analysis is made with the intention of getting a better picture of the risks associated with the VWAP benchmark. VWAP is still the most used benchmark on the Swedish market while we do see other benchmarks taking some market share in the future, such as the implementation shortfall benchmark (Perold (1988)). VWAP today makes up about 50% of all institutional investor trading. (Domowitz and Yegerman (2005)).

Our measure of VWAP risk is the spread between VWAP and TWAP. If there is a discrepancy between these two benchmarks there could be market conditions where VWAP would give a skewed reflection of the market price level. There are several reasons why we have chosen the TWAP price as the reference point to VWAP. The reasons are given in a separate section below.

We have used interviews as well as statistical analysis since we believe that there are several factors at play, both behavioural factors such as tradition and common practice, but there could also be pure factual reasons for the differences. The latter ones will be discovered through our quantitative analysis.

We have also added some questions on MiFID since it could possibly change the picture fundamentally in the near future. Given that the MiFID rules do not come alone but are highly affiliated with for example UCITS III[2] they mean a large and definitive change to the regulatory landscape. This does not however, automatically mean that Swedish institutions will have to change the way they do business. There are several loopholes or ways of getting around the frameworks which might be exploited by less prominent player in the market (Interview wealth manager (2007)).

We have limited the research to contain only the companies included in the index OMXS30. These are the 30 largest companies on the Stockholm Stock Exchange. The main reason for this limit is that these are the companies traded most frequently which provides us with a greater possibility of using more reliable data. Also, these are the companies where brokers receive the largest orders, size wise, and where algorithmic trading would be most likely to occur. These large orders are usually traded against a benchmark while orders in smaller companies are more opportunistic or pegged to a certain price. There is not enough liquidity in the smaller markets for larger institutions to trade the size they need without moving the market price considerably against them selves.

[2] EU-wide legislation concerning open ended funds.

1.2 Contribution

Algorithmic trading is not very developed in the institutional equities business in Stockholm. The situation on the major stock exchanges in London or New York is different with a large relative share of the orders being generated by algorithms (Hendershott, Jones and Menkveld (2007)). The American markets have also been the subject of several studies while there are none on the Swedish market.

Our main contribution will therefore be to give a view of the Swedish market. Our results can then be seen in contrast with studies on the American market for a more international understanding of the area.

The data gathering on the consumer institutions prone to use algorithmic trading in Stockholm is difficult and time consuming. To conduct a survey using a professional survey manager would be hard since the people working in this business are very busy business and therefore generally reluctant to answer questions and spend time with questionnaires. Our interviews were made possible by the backing of the Stockholm School of Economics as well as S E B and alumni networks. We do not think other researchers would have been as successful in finding the same kind of people to interview. Also the time spent on each interview should not be underestimated.

Moreover the type of regression analysis performed in this thesis is not to be found among the literature written on the subject. To the best of our knowledge this is the first thesis of it kind investigating algorithmic trading and benchmarks in the Stockholm market.

1.3 Outline

We continue our thesis by defining the central elements associated with algorithmic trading. We then present previous research on the area, give a theoretical background to the treatment of risk in economic theory and thereafter present our data set. This is followed by the main results from our research. The thesis is finalised by the analysis of these results and the conclusions drawn. We also provide a section with a critical discussion of our findings as well as a causality check.

2. Definitions

2.1 Equity Trading

The type of traded securities we are interested in researching in this paper is strictly equities. Also we want to make it clear that the markets we have studied and the questions asked in the interviews are all concerning “cash equities”. This term stands for the simple stock market traded securities on the Stockholm Stock Exchange without concerning any other type of delta one product such as a Contracts For Difference (CFD).

2.2 Algorithmic trading

Defining algorithmic trading is best done by defining what it is not. The definition of algorithmic trading is not the same as the one for electronic trading or program trading. Electronic trading simply means that stocks are not traded in a physical market place but instead trades are made between interlinked computer terminals (Stoll (2005)). Program trading is a term that stands for computer programs that issue several orders at a time as part of a buy or sell “program”. It is usually a way for large buy side investors to decrease market risk when buying or selling an index or a sub index. This is done by the program trying to avoid beta-slippage (NYSE (2007)).

Algorithmic trading in the form we think of it in this paper is the pure form of a “smart” trading program that is set up to trade by itself in a way that is, only at the first point, instructed by a human. These algorithms are set up to scan the markets and at certain defined moments buy or sell the security in question. They can usually be instructed to follow a set of commandments but most often they are programmed to beat or follow a benchmark.

2.3 VWAP

VWAP is the abbreviation of Volume Weighted Average Price. It is calculated by multiplying the volume traded with the price it was traded at. If one wants the VWAP price for a certain day the calculation becomes the summation of all the individual trade prices multiplied by the volumes traded [the money value traded] divided by the total amount of stocks traded in that security over the day [total share volume traded] (Madhavan (2002)). There are several definitions of VWAP including or excluding certain trades. The one we have chosen to use is the Non-block VWAP. This VWAP measure excludes all trades over a certain size since these large “block trades” do not symbolize volume that can be accessed by anyone (Madhavan and Cheng (1997)).

$$VWAP = \frac{\sum_{t=1}^{T} P_i V_i}{\sum_{t=1}^{T} V_i}$$

2.4 TWAP

TWAP stands for Time Weighted Average Price. The definition is simpler than VWAP since TWAP does not encompass any volume weighting. Instead TWAP is just an average of all prices that have been traded on in the market. In effect, a TWAP over a day it is calculated as the sum of all prices [the price traded on the market] divided by the amount of observations.

$$TWAP = \frac{\sum_{t=1}^{T} P_i}{\sum_{t=1}^{T} T_i}$$

2.5 Implementation shortfall

The implementation shortfall benchmark was first defined in the eighties (Perold (1988)). It is a measure that tries to account for all possible costs that come with the trade. It comprises the commission costs as well as market impact and the cost of crossing the spread. By doing this the benchmark tries to account for all forms of risks and possible liquidity problems (Kritzman Myrgren and Page (2006)). As a definition one can say that Implementation Shortfall is equal to [total cost of execution including commission for the whole order] - [the cost of execution at time 0].

3. Previous research

Most articles written in this field have a clear technical and/or practical approach. They are dominantly occupied with the practical choices that buy side investors have to face when they execute an equity trade. However, this provides a minor problem since we are not primarily focused on the algorithms as such but want to provide a picture of the Swedish market of algorithmic trading. We have chosen to divide the previous research into two topics.

The first topic encompasses the research done on algorithms and the theories on how and why to use them. This section also touches upon the fields of pre trade and post trade analysis.

The second topic covers the benchmarks of focus in this thesis, VWAP, TWAP and Implementation Shortfall.

These two topics provide a view on the research done on the first of our two questions, the one concerning the situation in the Swedish market of algorithmic trading and benchmarks. The second question, about the risk factors associated with VWAP, is a field where there is little previous research. The basis for this, more theoretically orientated question, can be found under the section entitled Theoretical Framework.

3.1 Topic 1 – Algorithmic Trading

The main interest of research in this field is to answer the question "how do I choose an algorithm?". To answer this, theory says that you have to think about how and why certain types of algorithms perform. You also have to consider what you actually want to accomplish with your order. One main question is how price sensitive the investor is. Is it in your interest to perform the transaction regardless of price or is your main focus the price received from the algorithm? To concretize these decisions some authors have tried to develop a decision making framework. Among these authors are Robert Kissell and Roberto Malamut. They place much emphasis on the pre and post trade analysis and stress that before making a decision an investor has to be more proactive in aligning his needs with the chosen algorithm. The same authors do however see a problem incorporated in the selection process that stems from the opaque nature of the algorithms (Kisell and Malamut (2005)). They build their solutions on a framework based on the Efficient Trading Frontier (ETF) developed by other researchers.

The ETF is the curved face that is made up of all optimal trading strategies. To be considered optimal the trading strategy has to give the lowest timing risk for each cost and lowest cost for each timing risk. The figure becomes a concave line that in it self can be moved towards or away from the origin (Almgren and Chriss (1999)). Jian Yang and Brett Jiu are two authors that have tried to develop a decision making framework for choosing algorithms. They base their research on the notion that algorithmic trading will continue to grow as firms continuously seek to lower their trading costs. Investment managers will place more and more focus on getting so called "best execution" (Borkovec and Yang (2005)). They conclude that the positive aspects of using an algorithm is that the buy side trader gets a disciplined way of executing an order while maximizing his chances of achieving his trading objective. To achieve this and properly harness the power of the algorithms, traders have to keep some rules in mind. First of all they have to think about the *Suitability of algorithmic trading* for the specific order since more difficult orders might prove too hard for algorithms resulting in sub par execution. They also has to take the *Nature of the algorithm* chosen into mind as well as how well it fits with the order. Lastly he has to choose a certain benchmark that fits the order. The individual desks usually have a preferred benchmark or a benchmark policy but there is no use in deciding on a benchmark that will not fit the order (Jui and Yang (2006)).

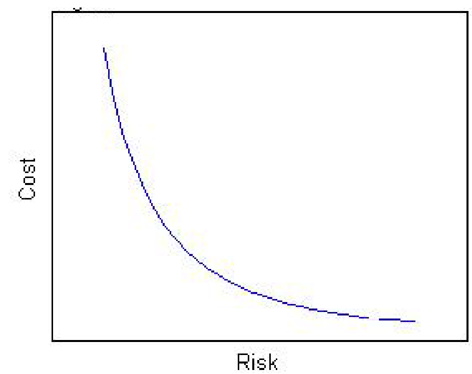

Fig 3.1 Efficient Trading Frontier (ETF). Curve pictures all efficient trading strategies. Higher risk gives lower transaction costs.

3.2 Topic 2 - Benchmarks

There are several types of benchmarks. Firstly there are those that are used when measuring performance of an investment. These are the ones that are most commonly known and usually consist of portfolios that measure the returns of a certain industry sector or country made up to simulate the risk characteristics of a portfolio. The benchmarks that are discussed in this paper measure performance over a much shorter time period. They are used to measure performance of a certain stock trade and as such they are usually used over the period of one day or less. A premier reason for using benchmarks is that the alternative, a limit order, involves more risk. The primary risks associated with a limit order are the news risks. Adversary news will move the price in a favourable way for the order but unfavourable for the investor. Positive news on the other hand will move the market away from the order which will not be positive for the owner if he has not managed to already fill the order. However, this is not to say that limit orders do not exist or can not be profitable. In an order driven market, where prices reflect imbalances between buy and sell pressure, a trading strategy of using limit orders will be more profitable than using benchmark orders. This is due to the mean reverting nature of the markets (Handa and Schwartz (1996)). The main benchmarks of interest to us are the ones most used in execution in the Swedish market. There is no data on this as all orders are proprietary in nature and work as a proxy for the investment decisions made by the individual portfolio manager. Therefore sharing this kind of information is sensitive.

3.2.1 Theories on VWAP

VWAP is the most commonly investigated benchmark in the field (Konishi (2002)). One issue that is important when using VWAP is what percentage of total volume traded in the market that the order should execute. It is also a widely used benchmark, the primary reasons being its simplicity and limited market impact. The goal of any trader executing a VWAP strategy is to ex ante define a strategy that will achieve the VWAP price ex post. One main reason for this is the custom of evaluating the price of the executed trade against the VWAP price (Bialkowski, Darolles and Le Fol (2006)).

The VWAP benchmark can also be seen as a good proxy for the best possible price that can be achieved by a passive investor. It can therefore be called the optimal price or benchmark for a passive investor such as the average retail investor (Berkowitz, Logue and Noser (1988)). The VWAP benchmark can not be manipulated but follows the fluctuations of the volumes in the markets. The regular pattern for intraday volumes is a U-shaped curve with its highest values around the open and close of the market. It is possible to model the total volume in the market by using a CAPM approach. The total volume is then divided into regular volume and abnormal volume (Lo and Wang (2000)).

To achieve the VWAP price the trader only has to model, or have a view on, the volumes being transacted over the day. There is no reason for him to predict the price being transacted if his goal is to achieve a price as close to VWAP as possible (Bialkowski, Darolles and Le Fol (2006)).

3.2.2 Theories on TWAP

The time weighted average price is not a subject of great interest to many researchers. This is not due to its use since it is commonly used in the institutional equity markets. It is more due to the simple nature of the benchmark. The TWAP relies on the broker executing the same number of shares at every single time over the day, be it divided into seconds, minutes or hours. This benchmark is often used when there is ample liquidity in the market. This is an effect of the price driving quality a TWAP order in an illiquid instrument has due to its constant execution often with no regard to price (Interview with hedge fund trader (2007)).

3.2.3 Implementation shortfall

The implementation shortfall name came into use after a 1988 article by Perold. The term refers to the total cost of trading a stock or any other listed security. This total cost includes factual costs as the commission and crossing the bid ask spread as well as more vague costs like market impact. A study by Kritzman Page and Myrgren from 2006 gives a hint at the size of the market impact factor. Their data sample of 800 000 stock transactions shows that transacting the trades in the market is several times more costly than doing the same type of trade in house. Doing the trade in house excludes, to a large degree, the market impact cost. Thereby their research gives an indication of the size of the market impact cost component which in their study is around 80 percent of the cost of trade (Kritzman Myrgren and Page (2006)). Other studies have estimated the cost of an algorithm to be about 10 basis points extra cost above this benchmark (Domowitz and Yegerman (2005)). Implementation shortfall is theoretically hard to calculate in real life since the dominant market impact component is hard to determine due to other activity in the market. The benchmark is none the less increasingly used in the financial centres of London and New York. In Stockholm the use of Implementation shortfall is increasing and several of our interviews point to it as a benchmark of the future. However, today the benchmark is not widely used on the Swedish equity scene. Only one of our interviewees used the benchmark in a systematic fashion. A few players have started to devote more and more energy towards measuring components such as time to market which is a first step towards using implementation shortfall.

4. Hypotheses and Theoretical Framework

4.1 Hypotheses

To focus our research we have formed four hypotheses. These will be used to keep the regression analysis presented in the section Regressions: Results and analysis. When forming the individual hypotheses we took into account the previous research and framework on risk and portfolio theory. We also tested a number of variables that were not included in the final study to get a better view of the important variables and be able to present our findings in the clearest possible fashion.

Hypothesis one:

The dependant variable is positively affected by an increase in any of the risk factors in the Fama French three-factor model or the excess market return factors.

Hypothesis two:

The dependent variable is positively affected by an increase in the risk appetite in the market.

Hypothesis three:
The dependent variable is positively affected by an increase in liquidity as well as decreased risk of illiquidity in the market.

Hypothesis four:
Hypothesis one, two and three will hold on an index level. On a single stock level we do not expect to see the same consistency in the results.

4.2 Basic CAPM and early additions

A fundamental thought regarding risk is that investors are rational and will not take on risk without being paid for it. The amount he takes on differs due to his risk appetite. However the potential return should always increase with an increase in non diversifiable risk. This is called the risk-return trade off. The models we describe here are all based on the notion of efficient capital markets and rational human behaviour.

Asset pricing theory states that risk should be priced. There are numerous models that try to price an asset according to the risk attributed to certain factors in the model. The most well known model is the Capital Asset Pricing Model or CAPM (Fama and French (2004)).

The CAPM concludes that in equilibrium, investors will choose combinations of the portfolio and borrowing or lending. The proportion to which this is done is determined by the investors' willingness to bear risk to create higher possible returns. By carrying more of the market portfolio more risk is taken on. An investor that invests in the market portfolio carries only one risk, the market risk. If the portfolio does not replicate the market it will carry non-systematic risk, most commonly known as idiosyncratic risk (Fama and French (1996)).

There have been many attempts to develop new and better models. The three factor model developed by Fama and French is probably the most well known. There are however many more multifactor models that have been successful in competing with the CAPM due to the difficult nature of the problems associated with asset pricing. One of the main issues lies in the difficulty of determining the market portfolio (Roll (1977)). An incorrectly defined market portfolio will lead to a too low level of explanatory power and a significant intercept. This is usually referred to as alpha in economic literature. Other problems lie in the fact that most models are lacking in risk factors.

Another set of problems for these models lies in the assumption of frictionless markets which might not always be the case (MacKinlay (1995)).

What most researchers including Fama and French have done is to introduce additional variables to reduce the non-zero intercept from the CAPM regression (Fama and French (1993)). However their somewhat limited success can be interpreted as an indication that there might be other factors at work since the multifactor models can not explain the deviations from CAPM on their own. It is always possible to find risk factors that will be able to make the intercept equal to zero on an ex post basis. However it will be impossible to construct such a model on an ex ante basis without a theoretical framework that can identify the risk factors on an ex ante basis. (MacKinlay 1995).

4.3 Newer Models

Since the CAPM was first used to value assets there has been a lot of additional research on the area. Factors such as market capitalization, book to market ratios and previous returns have been used to complement the effect of the original market factor. There has been certain evidence that shows that a multi factor asset pricing model can better explain the effects on security prices then previous one factor models. An example is from the research done by Ball and Fama and French which try to take the level of valuation ratios determined in the market and make it a return specifying factor. (Amramov and Chordia (2006)). Other research focuses on the problems of justifying the equity risk premium and the relatively large volatility on the equity markets. One way of explaining the large volatility and large risk premium is the varying market outlook in the investor community. Economic data or political events can change the sentiment substantially resulting in a fluctuating economic uncertainty (Bensal and Yaron (2004)).

4.4 Risk theory applied to the subject

These frameworks of risk can be transferred to an institutional trading desk. Every guaranteed benchmark order the desk gets carries a certain risk. It can be a direct risk to the trading desk because it has to deliver the stocks at a certain pre agreed price such as VWAP. Therefore the desk will be short, or long, the order amount while it has to acquire, or sell, the shares in the market at a price as close to VWAP as possible. In this sense it has a price risk. It could also be an indirect risk in the sense that every below-standard execution represents a risk to the firm’s reputation. This is important since the reason that the desk gets its business is because of its reputation. Each order that represents a direct risk carries a lot of diversifiable risk. According to theory, each individual order carries idiosyncratic risk in the form of loadings on risk factors stemming from the volatility or volume traded in the specific stock. It might be possible to diversify away those risks according to the framework described above. However given the nature of trading, one could not simply assume that the desk will receive the same amount of orders in all stocks. This is due to both the cyclical nature of certain companies as well as the developments of certain sectors or companies being quicker then others in certain time spaces. This makes trading increase and decrease with the size and growth possibilities of the companies included in the index. Also one could argue that if some companies were more risky to trade then others, for the sell side trader, then the buy side traders might devise a strategy to profit from this situation, give that there were no differences in the cost to trade. All this makes it logical to assume that if there are differences between companies, in how the

VWAP-TWAP spread moves, then the sell side trading desk should charge a different number of points to facilitate a trade, depending on the company traded.

5. Methodology and Data description

We will here present and discuss our data set. We will also provide the reasoning for the alterations we have made and how and why we have included or excluded certain data point or variables. We will also explain the reasoning behind the choice of our dependant variable, the spread between VWAP and TWAP.

5.1 Data Description

The data sample we have used is comprised from two different sources. The main reason for this is that we were not able to obtain all the relevant data from one source. We have used data both from Bloomberg and Thomson Financial's DataStream. We have used data from a six and a half month period starting from April 30th and running to November the 19th. Since we have used hourly data and converted into daily data this ultimately makes for 142 observations comprising all trading days during the period. The days when one or more index was closed were not taken out of the sample since we believe this gives a better picture of reality. There were no days when more than one index was closed. An example of this is 4th July for the S&P500 Index which affects the HML and SMB factors.

We have used data for the 30 largest and most liquid stocks on the Stockholm Stock Exchange, the OMXS30. However we found one of the constituents, Nokia, to be too heavily traded on other Exchanges and not in significant volume on the Stockholm Stock Exchange to fit into the study. Therefore we excluded Nokia from our calculations and proceeded with the 29 remaining stocks. When we refer to the OMXS30 we mean the index of the 29 companies we have left after excluding Nokia. We calculated the performance of this index by adding the performances of all its constituents. These are ABB, Autoliv, Alfa Laval, Assa Abloy, Atlas Copco A, Atlas Copco B, Aztra Zeneca, Boliden, Electrolux, Ericsson B, Eniro, H&M, Investor B, Nordea, Sandvik, SCA A, Scania B, SEB A, Securitas B, Svenska Handelsbanken A, Skanska B, SKF B, SSAB A, Swedbank A, Swedish Match, Tele 2 B, Telia Sonera, Vostok GAS and Volvo B.

For all trading days in the sample we have computed the daily TWAP and VWAP benchmarks by using hourly average traded price figure and volumes. The spread between them is made by subtracting the TWAP from the VWAP. For all trading days we have calculated changes in percentage terms for the spread, instead of in absolute terms between VWAP and TWAP to better be able to compare the results. This is mainly due to the spread inherently being larger, in absolute terms, for companies with high stock prices. This is due to two effects. Firstly higher prices will by them selves make the spread bigger due to the calculations of the benchmarks. Secondly there will be a tick size effect that comes from the fact that when a stock reaches a certain price the tick size gets increased by the stock exchange.[3]

Table 5.1 Data Description Macro Variables. Descriptive statistics for the data concerning macro variables.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
SMB	108	-1,1700	1,6200	-,0435	,4336
HML	108	-,7100	1,1800	-,0789	,2631
RM-Rf MSCI WORLD	142	-,0247	,0190	-,0003	,0088
Rm-Rf OMXS30	144	-,0378	,0361	-,0012	,0137
USDJPY SPOT	144	-2,5758	1,1629	-,0545	,5683
Valid N (listwise)	106				

The table shows the statistics for the percentage change in the variables multiplied by 1000 to achieve numbers that are more convenient to handle. As seen above there are 144 observations of the index data while it is only 108 observations of Fama French factors. This is due to the lag in the updating of the homepage where the Fama French factors can be found.

The spread of VWAP and TWAP in all shares were also multiplied by 1000 to have numbers that are easier to grasp. The statistics for these variables can be seen on the next page.

[3] The definition of tick size is the minimum spread that is allowed in the market.

Table 5.2 Data Description for Dependent Variables. Descriptive statistics for the dependent variables.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
ABB	144	-4,6881	3,9449	,0588	1,1648
ALFA	144	-31,4040	5,1294	-,2006	3,1584
ALIV	144	-4,1994	5,0111	,0104	1,5004
ASSAB	144	-5,7090	4,5597	-,1548	1,4650
ATCOA	144	-10,1016	5,0532	-,4062	1,9119
ATCOB	144	-12,0522	3,8360	-,3108	2,0638
AZN	144	-14,8135	4,2418	,0363	1,6272
BOL	144	-6,5074	15,2798	,2476	2,1305
ELUXB	144	-10,1526	5,9562	-,1080	1,9508
ENRO	144	-5,8931	3,6363	-,2352	1,5497
ERICB	144	-3,9596	7,1812	,1481	1,4737
HMB	144	-7,6220	4,0308	-,2838	1,4033
INVEB	144	-7,5414	3,4125	-,1507	1,5538
NDA	144	-11,1314	9,7946	-,2832	2,3243
SAND	144	-8,3552	3,2919	-,1800	1,7668
SCAB	144	-4,4309	3,8134	,0152	1,3474
SCVB	144	-14,6490	12,4201	,1370	2,8328
SEBA	144	-6,4483	4,4954	-,2139	1,6399
SECUB	144	-6,0731	6,1722	-,0136	1,6609
SHBA	144	-4,1084	5,1101	,0887	1,1957
SKAB	144	-7,5217	8,6198	-,1850	1,9973
SKFB	144	-6,8670	5,3794	-,1681	1,6776
SSABA	144	-8,9408	9,8167	,1513	3,1267
SWEDA	144	-9,4876	6,2596	-,2528	1,6017
SWMA	144	-9,0434	6,8053	,1338	1,8930
TEL2B	144	-5,6466	6,4713	,0250	1,6552
TLSN	144	-5,1792	3,2003	-,0247	1,2686
VGAS	144	-7,3210	5,4115	,1814	1,6601
VOLVB	144	-9,7565	7,3835	-,0080	1,9847
OMXS30DIFF	144	-3,5955	2,5393	-,0740	,8226
Valid N (listwise)	144				

Here we can see that there are 144 observations in the panel data. Some stocks show more radical spreads than others at some point. The highest value in absolute numbers is Alfa Laval that has a 0,03 percent negative spread at the minimum point. The highest value is Boliden that has the highest positive spread at 15,27 which corresponds to 0,015 percent spread. The means seem equally distributed around zero. 17 of the variables have means below zero while the other 12 have means above zero. The standard deviation varies in size between the variables. The lowest standard deviation for a constituent company is represented by ABB at 1,16 and the highest by Alfa Laval at 3,16. The index has the least volatile with a standard deviation of 0,8226 units.

5.2 Testing the spread

As explained before the assumption that the TWAP is something that can be traded at all times without taking risk implies that the difference between VWAP and TWAP should be zero over time. This was tested for all spreads in both stocks and the index. The outcome is that we can reject that the spread is equal to zero in 11 of the 29 cases on a ten percent confidence level. The values of the test are found in table 1 in Appendix.

$$H_0: (VWAP - TWAP) = 0$$
$$H_1: (VWAP - TWAP) \neq 0$$

The stocks were we could reject that the difference is equal to zero are: Assa Abloy, Atlas Copco A, Atlas Copco B, Boliden, Eniro, HM, Nordea, SEB A, SKF B, Swedbank and Vostok Gas. For these cases there is proof of the difference being other than zero which is not suitable if the assumption about a zero spread is made. By comparing the results to each other there is no obvious pattern that could explain why the stocks above have a non-zero difference. By comparing size one could conclude that among the five largest companies in the OMXS30 index there are two, HM and Nordea, with non-zero difference. Also among the five smallest companies there are three with the same trait, Vostok Gas, Boliden and Eniro. This random pattern is further enhanced when looking at the variable betas to find any other patterns, there are no characteristics that seems typical for the group of non-zero stocks. A pattern that could be observed is that three out of the four banks in the OMXS30 index are represented among the stocks with non-zero difference. If this is a coincidence is hard to elaborate over but nevertheless worth mentioning. However, we strongly believe that a larger sample would correct these results. The sample of the Stockholm Stock Exchange in recent times is not representative for a longer period. Therefore we will still use all variables in our regressions, even though we are aware of that our results will not be as reliable for those stocks. For a normal period we would expect the standard deviation to be lower and the sample to have less drift. This might have caused many of the non-zero differences in our sample. Thus it would be comforting to extend the data period.

The spreads are expected to follow a random path and thus show no drift. To show this we have plotted the spread variables in a graph shown below.

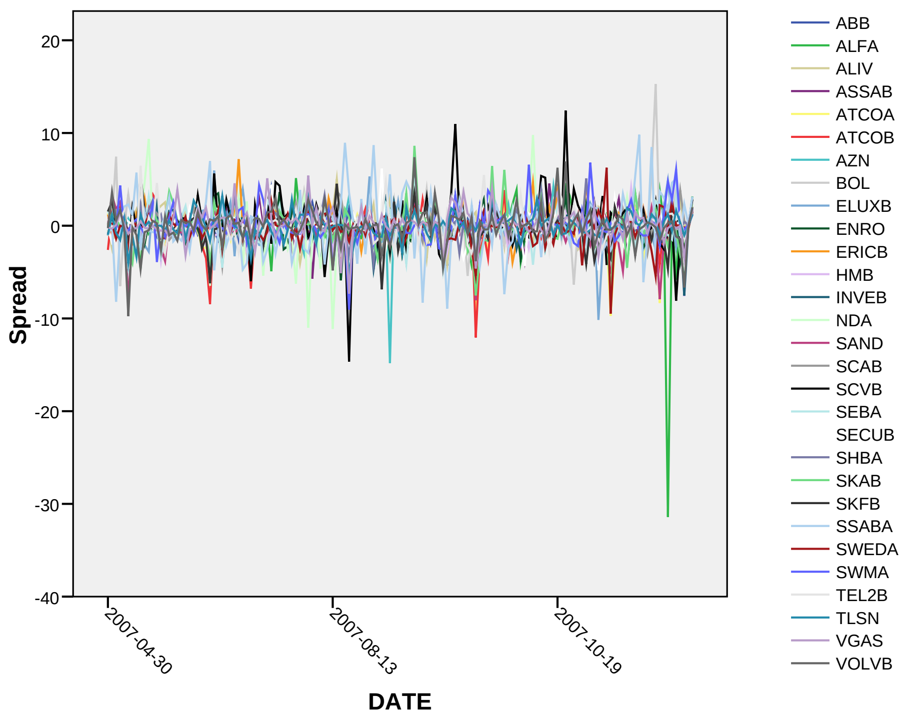

Fig. 5.1 Figure picturing the spread variable (VWAP – TWAP) for each share against time.

Putting all individual stocks together in the same graph gives no information about the trends in the single stock. However, we can see that there is no obvious drift in the data sample. Some values do come out as extraordinary as explained before.

We repeated the procedure for the index spread variable to find any significant distortions, which there are not.

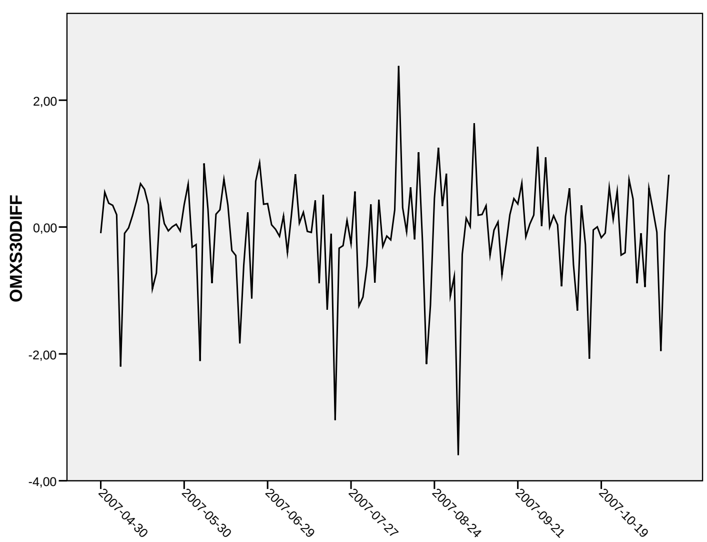

Fig. 5.2 Figure showing the spread variable (VWAP – TWAP) for the OMXS30 Index plotted against time.

As with the stock variables there are some dates that come out with larger changes. However, on a aggregated level the changes are more smoothed than for the stocks which is natural because we are plotting the change in difference in the index. For the rationale behind the lower volatility in the index, see the theoretical framework section above.

5.3 Autocorrelation

We tested for autocorrelation in our variables to find if any of the observations in the variables were dependent on each other. If we would have found autocorrelation the estimates would still be unbiased and consistent but not efficient. Also we would have too high R^2 and too low standard errors. There were no strong indications of autocorrelation in our sample. However, we find two variables worth mentioning. These are Atlas Copco A and Nordea where we could se traces of autocorrelation as can be seen below.

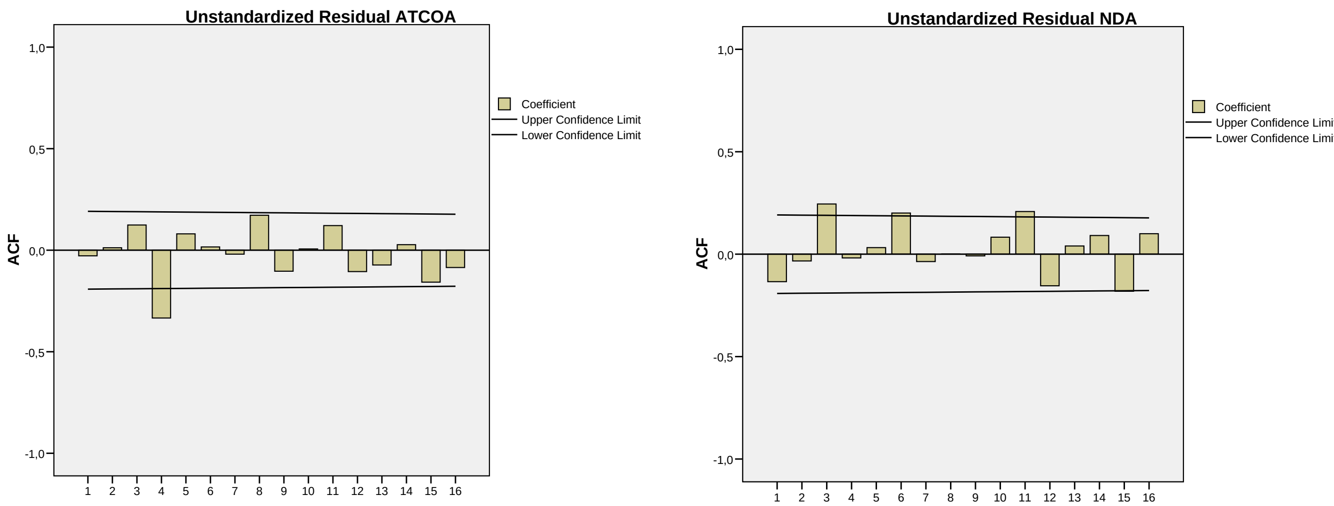

Fig. 5.3 and 5.4 Figures showing the lags of the unstandardised residuals of Atlas Copco A and Nordea respectively. The horizontal lines represent a 95% confidence interval.

In the plots of the correlation in the unstandardized residuals we see that for Atlas Copco A the autocorrelation is significantly different from zero in the fourth lag. This is very likely a coincidence since the stock price and thus the spread should have no economical reason to be correlated with such a lag. The same applies for Nordea where the autocorrelation appears in the third lag. It is unlikely that the first observation should have a strong correlation with the third throughout a large sample. We are confident that these effects would be diminished if the sample was extended.

5.4. Multicollinearity

Multicollinearity arises when two or more explanatory variables show linear correlation with each other in the sample. If the correlation is too strong it will be difficult to find the effect of each variable, the effect will instead be nested. Multicollinearity could result in distorted beta coefficients as well as opposing signs. Due to multicollinearity we excluded all explanatory variables based upon volume traded and the stock price. Instead we used a variable based on value traded since value is a function of both volume traded and the price in the market.

$$Value_x = Volume_x \times Price_x$$

We tested for multicollinearity in our sample and found little evidence of such bias. Of all the constituent companies we tested there were only one where there was substantial multicollinearity. This company was the telecommunication equipment company Ericsson. In this regression there were several variable pairs where the correlations were above 0,5 and two variable pairs that came out above 0,8 in correlation. The first pair are the standard deviation in the traded volume in Ericsson, *stdERICB*, and the same variable for OMX index, *stdOMXS30.* The second pair are the *pvalueERICB* and *ERIC VAL- MEAN.*

The correlation matrix is displayed below where we can see that the correlation for the first pair is 0,975 and for the second pair the correlation between the two variables is 0,901. The first pairs correlation is more of a problem then the second pairs. This is because the second pair are two ways of finding the same effect and therefore are likely to be highly correlated. The correlation with the index can be explained by that a large part of the index is driven by Ericsson. A large drop in the Ericsson share price will thus drag the index with it which creates a high correlation both in absolute terms and in terms of standard deviation in the volume. During our time period Ericsson has experienced a large drop in its stock price which resulted in a high turnover and record volumes traded in the stock. The intraday drop was over 20 percent on the worst day.

Table 5.3 Table shows the correlations between the macro variables. Ericsson is also included since it has a significant correlation with some of the macro variables. Other shares (micro variables) did not show the same correlation when tested.

Correlations

		SMB	HML	RM-Rf MSCI WORLD	Rm-Rf OMXS30	USDJPY SPOT	stdOMXS30	pvalue OMXS30	stdERICB	pvalueERICB	ERIC VAL-MEAN	ERIC VALBIG D	ERIC VAL D
SMB	Pearson Correlation	1	-,108	-,003	-,015	-,031	,049	,207*	,064	,256**	,052	-,028	,081
	Sig. (2-tailed)		,268	,977	,878	,752	,615	,032	,510	,008	,597	,777	,408
	N	108	108	106	108	108	108	108	108	108	106	106	106
HML	Pearson Correlation	-,108	1	,001	-,010	-,103	,091	-,028	,113	-,039	-,002	-,036	,046
	Sig. (2-tailed)	,268		,993	,919	,290	,348	,777	,245	,691	,986	,715	,643
	N	108	108	106	108	108	108	108	108	108	106	106	106
RM-Rf MSCI WORLD	Pearson Correlation	-,003	,001	1	,769**	,578**	-,033	-,150	-,028	-,121	-,115	-,055	-,140
	Sig. (2-tailed)	,977	,993		,000	,000	,701	,075	,744	,150	,171	,518	,098
	N	106	106	142	142	142	142	142	142	142	142	142	142
Rm-Rf OMXS30	Pearson Correlation	-,015	-,010	,769**	1	,616**	-,147	-,298**	-,120	-,217**	-,229**	-,141	-,118
	Sig. (2-tailed)	,878	,919	,000		,000	,078	,000	,152	,009	,006	,095	,160
	N	108	108	142	144	144	144	144	144	144	142	142	142
USDJPY SPOT	Pearson Correlation	-,031	-,103	,578**	,616**	1	-,052	-,137	-,050	-,129	-,166*	-,119	-,167*
	Sig. (2-tailed)	,752	,290	,000	,000		,534	,102	,548	,124	,048	,157	,047
	N	108	108	142	144	144	144	144	144	144	142	142	142
stdOMXS30	Pearson Correlation	,049	,091	-,033	-,147	-,052	1	,394**	,975**	,607**	,693**	,599**	,155
	Sig. (2-tailed)	,615	,348	,701	,078	,534		,000	,000	,000	,000	,000	,065
	N	108	108	142	144	144	144	144	144	144	142	142	142
pvalueOMXS30	Pearson Correlation	,207*	-,028	-,150	-,298**	-,137	,394**	1	,316**	,691**	,483**	,165*	,100
	Sig. (2-tailed)	,032	,777	,075	,000	,102	,000		,000	,000	,000	,049	,238
	N	108	108	142	144	144	144	144	144	144	142	142	142
stdERICB	Pearson Correlation	,064	,113	-,028	-,120	-,050	,975**	,316**	1	,624**	,731**	,626**	,176*
	Sig. (2-tailed)	,510	,245	,744	,152	,548	,000	,000		,000	,000	,000	,036
	N	108	108	142	144	144	144	144	144	144	142	142	142
pvalueERICB	Pearson Correlation	,256**	-,039	-,121	-,217**	-,129	,607**	,691**	,624**	1	,901**	,447**	,230**
	Sig. (2-tailed)	,008	,691	,150	,009	,124	,000	,000	,000		,000	,000	,006
	N	108	108	142	144	144	144	144	144	144	142	142	142
ERIC VAL-MEAN	Pearson Correlation	,052	-,002	-,115	-,229**	-,166*	,693**	,483**	,731**	,901**	1	,659**	,418**
	Sig. (2-tailed)	,597	,986	,171	,006	,048	,000	,000	,000	,000		,000	,000
	N	106	106	142	142	142	142	142	142	142	142	142	142
ERIC VALBIG D	Pearson Correlation	-,028	-,036	-,055	-,141	-,119	,599**	,165*	,626**	,447**	,659**	1	,259**
	Sig. (2-tailed)	,777	,715	,518	,095	,157	,000	,049	,000	,000	,000		,002
	N	106	106	142	142	142	142	142	142	142	142	142	142
ERIC VAL D	Pearson Correlation	,081	,046	-,140	-,118	-,167*	,155	,100	,176*	,230**	,418**	,259**	1
	Sig. (2-tailed)	,408	,643	,098	,160	,047	,065	,238	,036	,006	,000	,002	
	N	106	106	142	142	142	142	142	142	142	142	142	142

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

5.5 Dependant variable: VWAP – TWAP

The main variable of interest in this thesis is the VWAP benchmark. To measure the risks associated with the VWAP benchmark one can not simply look at it by itself. It has to be compared to the prices in the market. The VWAP is closely linked to the price in the market which any one can trade on at any time given the main assumptions of liquid and continuous markets. Theoretically an active person, such as a sell side trader, can continuously trade at the price in the market. This is due to the fact that he can continuously buy the same amount of stocks which results in him getting a time weighted average price also called the TWAP. There are several reasons we have chosen the TWAP as the benchmark to compare to VWAP. Firstly the sell side firm has accepted to deliver a certain amount of stocks at the VWAP price. To hedge themselves they need to buy these stocks in the market. This can be done at any time during the day but acquiring a large portion of the stocks at a single time and price increases the price risk. The more the trades are spread out the lower will the risk be.

There are two main assumptions that have to be made to make the TWAP benchmark viable for trading. Firstly the market has to be liquid. This means that there has to be a certain amount of stocks available on both the bid and the offer price at all times. If there are not enough stocks available to buy or sell then it will not be possible to execute the TWAP price in respect to the VWAP. The second assumption is that markets have to be continuous. There can not exist times when there is no liquidity.

The reason we have chosen the TWAP benchmark to compare to the VWAP is the assumption that the trader could trade the same amount of stocks at any time during the day thereby having no view on the market. If he is guaranteeing an order to a customer at VWAP he will usually take a view on this meaning that he will try to trade at a more favourable price than VWAP. He could however always trade at TWAP. Over the long run there should be no clear bias towards higher or lower prices than the TWAP. The trader should trade as much over the TWAP as below resulting in him, over time, trading on the TWAP as well as the VWAP. This also means that VWAP and TWAP should be the same over time and that the spread between them should be equal to zero.

The factor making VWAP different from TWAP is volume. If a great part of the volume is traded at high prices then VWAP will be larger than TWAP and the spread between them positive. If more volume is traded at prices low prices then VWAP will be smaller than TWAP and the spread negative for that time period.

5.6 Explanatory Variables

Below we give a brief descriptions of the explanatory variables used in this thesis and the names we have given them in the regressions we have performed.

Table 5.4 Descriptions of the independent variables

Macro variables	Description
Rm-Rf MSCI World	Excess return of the MSCI World Index above the US 90 day T-bill rate.
Rm-Rf OMXS30	Excess return of the OMXS30 Index above the Swedish 90 day T-bill rate.
SMB	Small Minus Big, Fama French three factor model
HML	High Minus Low, Fama French three factor model
USD/JPY Spot	Change, in percent of the Japanese Yen for one US Dollar exchange rate
Micro variables	Description
stdOMXS30	Change, in percent, for the value traded on the Stockholm Stock Exchange for the OMXS30 index
pvalueOMXS30	Change, in percent, for the value traded on the Stockholm Stock Exchange for the OMXS30 index
stdX	Standard Deviation of the change between day (t) and day (t -1) in the volume of security X
pvalueX	Change, in percent, for the value traded on the Stockholm Stock Exchange for security X
X Val-Mean	Difference of value traded from the mean value of the period
X ValBig D	Dummy variable: value = 1 if value traded is higher then one standard deviation above mean
X Val D	Dummy variable: value = 1 if value traded is above the mean of the period

5.6.1 Macro-variables
The following variables are all designed to measure exogenous effects on the spread. By this we mean that the macro variables are not influenced by the spread or the movements of the stock for which we have measured the spread. The obvious exception is the excess return of the OMXS30 index since it is made up by the respective constituents. We have however included it in the macro variables due to its nature as a large and popular equity index.

5.6.1.1 Excess return on Morgan Stanley World index (Rm-Rf MSCI World):
The Morgan Stanley Capital International World index comprises stocks from 22 developed countries of which 14 are European markets. We have included it as the general market index used to measure market exposure of the dependant variable, the VWAP –TWAP spread. The index has existed since December 31 1969.The index is market capitalisation weighted and denominated in USD.

5.6.1.2 Excess return on Stockholm large-cap index (Rm-Rf OMXS30):
The index of the 30 largest stocks on the Stockholm Stock Exchange is used to measure if there is a general effect on the spread between VWAP and TWAP that is more related to the movement of the Stockholm Stock Exchange. It could be that higher index levels trigger events that increase the spread. Since we are looking at the companies included in the S30 index it is logic to use this index as an explanatory variable. The index is market capitalisation weighted and denominated in SEK.

5.6.1.3 Small Minus Big (SMB):
At the end of June each year NYSE, AMEX and NASDAQ stocks are allocated to two groups, small and big, based on whether their June market equity value is above or below the median market equity value

for NYSE stocks. This variable is one of the factors in the Fama French three factor model. This variable was included since the three factor model is acknowledged as suitable to measure risk, which is one of our goals.

5.6.1.4 High Minus Low (HML):

The same stocks as mentioned above, the ones listed on NYSE, AMEX and NASDAQ, are also allocated in three groups depending on their market to book ratio. The groups are low, medium and high and divided so that the companies with the 30 percent lowest ratios are put in group ow, the 40 percent middle ratios in medium and the 30 percent highest in group high. Values are just as above based on NYSE stocks.

5.6.1.5 USD/JPY Exchange rate (USDJPY Spot):

The exchange rate between the US Dollar and Japanese Yen is often used as a measurement of risk appetite in the financial markets. Investors take loans in yen to invest in Dollars. This drives the price of the Yen up. This trading which aims at capturing the positive carry is called carry trading. When there is a chock to this equilibrium and the US economy is not performing as expected many investors close their short positions in Yen to decrease the risk and the exchange rate falls. We included this exchange rate as a proxy for risk appetite to see if that has an impact on our sample from a macro perspective.

5.6.2 Micro-variables

Not all micro factors are used in regressions on both the index level and single stock level. The effect of this is that in the regressions we will include both a variable called *pvalueOMXS30* as well as *pvalueX* variable for the stock. This applies for the *stdX* variable, described below, as well. For the three other variables there are no index level counterparties included.

5.6.2.1 Standard Deviation in value difference (stdX) :

The standard deviation in the changes of value traded is used to capture periods where there is more uncertainty in the market. Here we try to capture the effect of periods when the value traded was hard to predict. This could very well affect the difference between VWAP and TWAP since traders are risk averse and will decrease their exposure to the VWAP/TWAP spread as the risk in trading the underlying stock increase. By this we want to say that when the standard deviation in the change of value increases the risk of having insufficient liquidity also increases. We assume that insufficient liquidity will make traders, on average, be more cautions in their trading. This should decrease the spread between VWAP and TWAP.

5.6.2.2 Value traded 1 (pValue):

Value traded is the combined effect of volume traded and average traded price. To minimize multicollinearity we only included the value traded variables and excluded the volume traded variables.

The two variables that make up volume traded are also explanatory factor when it comes to deriving the benchmarks. This variable is expressed as a percentage change in value traded. The rational behind choosing this variable is that large price variations could increase the spread between the benchmarks. These variables are named *pvalue* followed by the name of the index or stock that is measured. The expectations are that high differences in value will have a significant effect on the spread.

5.6.2.3 Value traded 2 (Val - Mean):

This variable measures the difference between the value traded at day t and the mean value traded during our data sample. Our expectations are that high value traded will have a significant effect on the spread. However it is hard to make a prediction on the sign of the regression beta.

5.6.2.4 Value traded Dummy 1 (ValBig D):

We included two dummy variables in the regression to capture the effect of days with more of an outlier effect on the sample. This first variable is designed to find and measure the effect of some of the larger, positive or negative, events for any specific stock. Our expectations are that large effects, which we characterise as days when the value traded is larger then one standard deviation above the mean of the period, can have substantial positive or negative effect on the spread. On these days the dummy value is equal to one.

5.6.2.5 Value traded Dummy 2 (Val D):

This dummy is used to find normal high value traded days and measures their effect on the spread. It fills a void left by the above variable since that dummy only measures a small amount of days while this dummy takes many more days into consideration. We expect this variable to have the same type of characteristics as the one above but possibly with a less clear effect due to its lower demands for a positive dummy value. The dummy value will be equal to one for days where the traded value is above the mean of the period.

5.7 Methodology

Obtaining a better knowledge about the factors that might have an impact on a VWAP price for a certain individual security should be of interest to institutions that either provide or buy the algorithmic services. Since, if systematic differences are found these should be prised as they would represent hidden risk factors in today's VWAP price. However sell side firms guarantee VWAP in all liquid securities. What we will focus on is the portfolio of stocks where the securities house does the absolute highest amount of their business. In the Swedish market this would be the OMX S30.

As was stated before, this paper is made up of two interlocking sections. One is based on an interview study while the other one is based on a more in depth statistical study. These two different market studies complement each other since the market for institutional equities is to an equally large degree a relationship market as it is a market based on hard numbers (Interview wealth manager (2007)).

We have looked at micro factors as well as macro factors possibly affecting the benchmark. The micro factors could be volume, price and volatility. We have decided also to look at macro factors such as the index movements, currency rates and interest rates movements to get a measurement if there are macro factors driving the benchmarks for all stocks in the sample. As a measure of the stability of VWAP we have used the difference between it and the time weighted average price, TWAP. This gives a good reference point to the VWAP price since it is made up of the same prices but without the volume weighting. Therefore TWAP can be seen as the un-weighted market price.

Our analysis of the data is made up of the main OLS Regressions of the constituents of the OMXS30 index as well as the index itself. The dependant variable is the relative spread between the VWAP and TWAP, expressed as a percentage of share price, for each constituent or the index. The model used for the OLS regression of the OMX index is the following:

$$Y = \alpha + \beta_1 Rm - Rf\ OMXS30index + \beta_2 Rm - Rf\ MSCI\ World + \beta_3 SMB + \beta_4 HML \\ + \beta_5 USDJPY\ SPOT + \ \beta_6 \mathrm{std} OMXS30 + \ \beta_7 \mathrm{pvalue} OMXS30$$

The model includes the variables of the Fama French three factor model. They were included done since the Fama French three factor model is perceived as a good measurement of risk, which is what we want to measure in our dependent variable. The Japanese Yen to US Dollar exchange rate is a well known globally used proxy for risk appetite since investors will seek to be invested in relatively high yielding currencies such as the US dollar when risk appetite is high while they will buy low yielding, safe, currencies when risk aversion is lower. The rationale behind this is the fact that carry trades make the low yielding currencies undervalued when risk appetite is high. Thereby they will increase in value, back to a more fundamentally correct level, when risk aversion increases. In the time period for our sample we have seen a clear hiking of risk aversion due to the subprime crisis in the US which has led to a decline in equity price, widening credit spreads and higher asset volatilities (BNZ Strategist (2007)). However, it should be pointed out that using this exchange rate as a proxy for risk appetite as we have done in this thesis has little or no backing in financial research. Our reasons for including it as a factor is its well known characteristics as the major carry trading vehicle. It is also used in the same way we have used it on many FX-trading desks around the world. However if there would be large changes to the rates, or economies, of either Japan or the US, it could severely decrease the exchange rate’s suitability as a proxy. However, at this point in time we feel comfortable in using it in our regressions.

The difference in the model used for the single stocks is that the *pvalue*, *std Val-Mean*, *ValBig dummy* and *Val dummy* variables for the single stock is added. The formula looks as follows:

$$Y = \alpha + \beta_1 Rm - Rf\ OMXS30index + \beta_2 Rm - Rf\ MSCI\ World + \beta_3 SMB + \beta_4 HML + \beta_5 USDJPY\ SPOT + \beta_6 \mathrm{std} OMXS30 + \beta_7 \mathrm{pvalue} OMXS30 + \beta_8 \mathrm{std} X + \beta_9 \mathrm{pvalue} X + \beta_{10} X\ Val - Mean + \beta_{11} X\ ValBig\ D + \beta_{12} X\ Val\ D$$

The last five variables are the stock specific variables. These are added to be able to observe if there are significant characteristics that distinguish the different stocks from each other.

6. Interview survey: Results and Analysis

6.1 Interview results

We present the main results from the interview in a table format. This is to make it easier to compare the results from the different interviews. On some questions we see more conforming results then on other questions. Overall we see one outlier in interview seven which seems to be more advanced in the approach taken to the topics discussed. We have divided the questions into three sections after the three main topics discussed in the interviews.

Table 6.1 Table showing the data collected from the interviews

		Algorithmic trading and MiFID		
Respondent	Algorithmic trades	Proprietary algorithms	MiFID effect	Future of algorithms
1	30%	No	None	somewhat increasing importance
2	2-4%	Yes	None	somewhat increasing importance
3	-	No	None	Increasing importance
4	-	No	None	somewhat increasing importance
5	3-5%	No	Already implemented	Increasing importance
6	5%	No	Minor	somewhat increasing importance
7	10%	Yes	Major (dependent on FI)	Increasing importance

		Orders; benchmarks and specifics		
Respondent	Investment Horizon	Time horizon for orders	When is VWAP/TWAP used	Nature of orders
1	1 day - several years	1 day	No clear view of market or industry/exchange	Aggressive/urgent
2	1 Month - years	1-2 days	Dependent on fund	long term/no footprint
3	-	1 day	Investing in foreign countries	short term/market timing
4	-	1 day	Foreign investors investing in SWE	over the day/ VWAP
5	1 Month - years	1- several days	Used for most orders	-
6	Very long (> 1 year)	1- several days	Beta orders	-
7	1 Month - years	1-2 days	Very seldom	-

		Pre and post -trade analysis		
Respondent	Systematically evaluation	Dominant factor pre trade analysis	Dominant factor post trade analysis	Interest of trade analysis systems
1	No	Volume, trend, dominant players	Feeling	No
2	No	volume, dominant players	Feeling	Yes, but not from counterparty
3	No	volume, trend	Time to market, feeling	Yes
4	No	volume	Feeling	Yes
5	No	volume	Feeling	Yes, if simple
6	Yes	volume	sysem evalutaion and feeling	Yes
7	Yes	Proprietary pre-trade analysis	Implementation shortfall	Yes

6.2 Interview Analysis

The interviews made for our study were conducted during November and December 2007 with seven different people working in the Stockholm equity markets. They all have positions where they encounter algorithms and benchmarked orders on a day to day basis.

Institutional trading is a business that often generates large returns in absolute amounts and every competitive advantage that can be seized is important we expected a high awareness towards the area. We also expected to find several different examples of pre and post trade analysis represented. A good pre and post trade analysis system is something that we expect creates a competitive advantage.

When we finalised the results of the interviews made we had consensus on some issues as well as disagreement on others. One of the issues where we saw near unanimous results were the questions around the VWAP benchmark. All interviewees, except one, felt that the benchmark was an important part of their day to day trading life.

Our main results of the interview study points towards a diverse market that in median is lagging its equivalent in London. However we see a strong will to evolve and a collective mindset with a common goal to increase the sophistication in equity trading.

6.2.1 Algorithmic trading and MiFID

Assumptions: *We anticipated the Swedish equity market to be quite evolved and in some ways on par with London. The area where we expected Stockholm to be most advanced was the beta trading aspect; there are many large sophisticated funds in Sweden including the state owned AP funds. On the alpha trading scene we expected them to use algorithms but not on the same scale as the London based buy side due to the lagging development by Swedish algorithm providers.*

Results: From the interviews we conclude that Sweden is still getting used to automated trading via algorithms. Algorithmic trading is neither uncommon nor especially common and the players have, on average, but with one exception, a somewhat limited interest in the field. Most people know that the option exists but are not sure about what it could do for them. They use it when they give an order to a sell side trader who then puts it in to an algorithm but few use proprietary algorithms.

One way of interpreting the situation is that there seems to be a prevailing practice that is hard to change. The limited number of professionals in Sweden is given as a reason for slower change in more than one of our interviews. As one of the interviewees says "Sweden is a small market and there are only a handful of larger institutions. This makes our trading comparable to an "elephant in a porcelain store". He and others go on to discuss the large importance of liquidity. The primary concern for larger Swedish institutions, probably to a larger degree than for institutions in bigger markets, is finding volume while staying under the radar. As we interpret it, this means that commission is a relatively lower priority for a Swedish portfolio manager or buy side trader compared to the equivalent professional in London.

However, since this technology is better established in the bigger financial centres of the world there seems to be no doubt among our interviewees that it will be introduced to Sweden to a larger extent than today.

It could be that because of Sweden's limited market size it takes more time for new technologies to be introduced. This is according to our analysis both because of the above reason but also because of the stronger relationships that have been formed due to the relatively lower turnover of people. This is indicated in some of our interviews: several of the interviewees talk about the close nature of the business and the feeling that “everybody knows one another, at least by name”.

From the interviews with the large financial institutions in Stockholm it is obvious that there is work being done to get algorithmic trading started. The question is how long time it will take to get it up and running. It is clear that the volumes traded on the Stockholm Stock Exchange do not drive this development as fast as it has been driven in for example London. Two institutions are said to have come a long way. On the sell side the firm that is mentioned the most is NeoNet which provides its own algorithmic trading systems. These systems are also being sold by other sell side firms. On the buy side the Norwegian investment management firm DnB NOR is named as a leader in the Nordic Area. The main reason for this is the modern order management system that they have implemented making time to market a much more important measure than before.

Moreover it is evident from our interview analysis that the customers are not driving this development in the way they have in other places. They often know that the service exist but are reluctant to try it. A main reason for this seems to be the limits in order management systems. Some firms do not see the importance in measuring time to market and other more quantitative evaluation measures. The main argument for this is that market impact is such a large part of the cost of equity trading that focusing on it is most important. This is in full accordance with theory. A remark might be that the whole focus on single basis points won by using an algorithm could very well be of lower importance in such a fragmented market as Sweden, compared to larger European markets. Today however there is no evidence that using more algorithmic trading would make it less likely to stay “under the radar”. Even though, as is pointed out by one of our interviewees, there are algorithms that are designed to sniff out other algorithms and even some that are designed as countermeasures against these sniffers.

Another reason for the perceived reluctance is that there might be difficulties in evaluating whether or not the trading done by the algo is better than their normal trading or not. This is most likely an effect of that the service is not fully developed yet and that the brokers do not push this service towards their customers. Many of the respondents are convinced that this is the area where we will se most development in the years to come. It is also evident that the institutions will be most engaged in algorithmic trading in stocks that are very liquid. This is where there is most room for error and where it is easiest to construct an algorithm.

The thoughts on MiFID differ a lot between the respondents. There is no clear view of what MiFID will mean to them. One main interest from the interviewees is about what will happen to the liquidity of the Stockholm Stock Exchange after the implementation of MiFID. One person says that he expects the block trading world to become more opaque when fewer and fewer people will post their block trades on the Stockholm Stock exchange. He predicts that the new interbank exchanges such as Turquise and Boat[4] will take a large piece of the block trades. In one interview these new interbank liquidity pools are seen with scepticisms and just another way of the banks profiting, this time on the expense of the stock exchanges. Another interviewee seems positive about the change even though the effects are not known. One respondent feels that it is good to have common legislation in the EU and welcomes MiFID, with new regulations which he says are already implemented in his organization. He points out that there are many loop holes, especially in the adjacent UCITS III legislation. Overall there seems to be a larger awareness of MiFID in the organisations that have non-professional, or smaller, investors. This is in line with our expectations since MiFID has much larger effects when it comes to supporting less knowledgably inventors. Here it could be interesting to conduct further interviews on this subject to get a clearer picture of the knowledge about these new standards.

6.2 .2 Orders; benchmarks and specifics

Assumptions: We had no strong anticipation when it came to what benchmarks that were being used the most on the Swedish market. We knew that VWAP and TWAP were regularly used but our original thought was that implementation shortfall-like benchmarks were the most abundant. We did find that this type of benchmark was used by many traders. However only one referred to it in a systematic way. Most people instead referred to it in a more implicit way, citing market impact and liquidity as important aspects of a trade. However their approach to dealing with the problems were not based on numbers or systematic reviews

The people we have interviewed work in different roles in the equity markets. They all have a relationship to trading but the number of orders they handle on a day to day basis varies highly from person to person. The characteristics of the orders they handle are also very different among the respondents. On one end of the scale lies the hedge fund that has almost only orders over the day while the private wealth managers or more long term asset managers often see orders that last for several days or even more.

One respondent says that he sometimes has worked larger or more complicated orders over several months. A very distinct pattern is that the hedge fund is a more frequent user of the VWAP

[4] Turquise and Boat are two cooperative projects between multi-national investment banks. The purpose is to create an alternative to the national stock excahgnes.

benchmark than the other firms. They use VWAP to buy stocks that they have no clear view of and with a longer investment perspective. They also were more inclined to use VWAP when trading stocks further away from themselves on exchanges in Europe. This goes well with what several other respondents answers; as one states “the further away the portfolio manager is from the order, country wise, the more likely he is to use VWAP”.

According to the answers given in the interviews much of the trading business in Stockholm is built around personal contact. There are few people on every type of position and the ones that are there all know each other. One difference with using London based brokers is that people feel they know one another on a more personal level in Stockholm. The majority of people we talked to who issue orders and execute them feel a comfort in having someone on the other side of the line to talk to in case something happens. This comfort is something all respondents value, while they on the same time welcome further development of algorithmic trading. This system is largely built around trust and long relationships which give the sell side trader and sales-traders a lot of space for own judgment and expertise. Portfolio managers also seem to evaluate sell side traders on a very proprietary basis which we will discuss in the next section.

Benchmarks are most commonly used where there is not much trust or where the buy-side has no particular view of how the stock will develop over the execution period. The interviews confirm the initial thought that VWAP is the prevailing benchmark used. Some institutions try to use implementation shortfall-like benchmarks but develop a good estimation of the cost rather than a scientific way to calculate it which lowers the reliability of the benchmark. One of the respondents says that most people claim to use implementation shortfall but questions whether or not they really do so. The systems that are used are either too positive or too advanced or affected by factors that are not connected with the actual order. Therefore the buy side traders we talked to were suspicious of using them.

6.2.3 Pre and post -trade analysis

Assumptions: Our thoughts going in to the interview process were that every asset manager and buy side trader that we interviewed would have a pre and post trade evaluation program. Weather or not he would base his decisions solely on it was unclear to us but we at least expected it to be used as a guiding tool. What we found was that it was only in a few cases where the trades were evaluated by quantitative goals and even then these measures were subordinate to more qualitative measures. Only one respondent had a well developed pre/post trade system for all trades.

The overshadowing result in this category was that most pre and post trade analysis in the Swedish market is based on personal estimations, experience and knowledge. Few of the respondents use a computerized system to perform the analysis on a regular basis.

For our respondents the first variable to examine when doing the pre trade analysis is volume. It is important to all respondents that the volume to be executed is a reasonable, not too large, proportion of the total volume traded. If, according to historical volumes or the present situation, it will be hard to execute the order amount, the funds with the largest orders try to get a hold of liquidity through more discrete sources and only trade as little as possible in the open market. The hedge fund on the other hand uses more aggressive tactics such as placing VWAP or TWAP orders. The post trade analysis of these two ways is very different. The VWAP order being equally easy to evaluate as the discrete order is hard to evaluate.

Another important factor for the interviewees is if there are any trends in the individual stock, or the market as a whole, and which brokers show high activity in trading. This activity check is twofold. Firstly the buy side trader or portfolio manager checks what kind of orders that are being done today and by which broker. Secondly this is matched with the experience of the person in charge of the order. Normally, in the Swedish market, one broker is big in a certain type of stocks or one particular large stock.

One respondent tells about a system they have access to but which is too complicated to use or does not give enough value adding to be worth the effort when there are only a few orders to keep track of. Many respondents also say that the pre trade analysis could include many soft variables that are hard to measure. As stated previously the trading business has an abundance of personal contact which makes the buy side think about what sell side traders are good at regarding certain orders. Some respondents give the picture that they have such an extensive knowledge of the sell side that they know which person is good at which type of order and under what market conditions. This could not be explained by economic rationale at all times but rather with behavioural theory. Only one respondent has invested in a proprietary pre and post trade evaluation system. The primary reasons being the full access to the data used as well as the reliability and flexibility guaranteed.

In the post trade analysis there is much the same tendency as with pre trade analysis. It is unusual that the trades are thoroughly evaluated. The large degree of reliance on the feeling for what is good and bad still prevails. One respondent mentions SimCorp as the company that has the most well developed program for order management systems (OMS). All respondents agree on that if more orders were done via algorithms the need for an evaluation system would increase. As it is today nearly all respondents feel that they can manage to evaluate the orders without a computerized system. One of the respondents point out that simplicity is important if the system should work and tells about bad experiences with a previous system of this kind. He states that reliability is also an important factor when choosing system. The previous system that they have tried was always making the trades look good no matter what they did. This undermines the reliability and is fatal for the use of the system.

One of the respondents say that DnB NOR is in the forefront with the use of OMS which they use for all orders. He also states that this is a question of education from the suppliers. If they do not provide the customers with the service and educate them in how to use it, they will not request it. The level of education about these systems is apparently very low in Sweden. This is confirmed by another respondent who says that if he was provided with the service there is a high likeliness that they would demand more. The conclusion would be that with increasing technical level of the trading, and as algorithmic trading grows, the need for good systems to evaluate the orders will also grow. Not a very surprising result maybe but on the other hand an important sign to what needs to be done.

7. Regressions: Results and Analysis

7.1 Regression results

The results are divided into three different sections; micro factors, macro factors and the index regression. The factors called micro factors are endogenous to the movements of the stock or the index. The macro factors are mostly exogenous to the stocks or the index. The possible exception to this rule is the excess market return of the Swedish index as one half of that variable is made up of the OMXS30 index return. Both types of regression factors were used to explain the spread between the VWAP and TWAP benchmarks as a percentage of the respective stock or index price.

The results in this section are all from ordinary least squares regressions. We have performed the regressions for all 29 constituents and the index.

7.1.1 Micro factors

The significant results of the micro level regression factors are evenly spread out between the seven different factors with the exception of *X Val dummy*. Of the seven factors used two (*pvalueOMXS30* and *X Val –Mean)* are significant in six cases, another three (*stdOMXS30*, *stdX* and *X ValBig dummy*) are significant in five regressions and a third (*pvalueX*) in three regressions. The *X Val dummy* is significant only in two cases.

The seven micro factors can either be grouped by sort (value versus standard deviation), index versus single stock or dummy versus other variables. Of the three choices no grouping seems more natural to us.

Value versus standard deviation: Of the three value variables one is consistent in sign while the other two show mixed results. On the other hand two of the three variables are significant in six regressions which makes them the most significant variables. The standard deviation variables are both significant in five regressions but like the previous group show mixed results sign wise.

Index versus single stock: When comparing index versus single stock variables there are no obvious advantages or disadvantages. The *pvalueOMXS30* variable is the most significant along with the single stock *Val-Mean* variable. However the index variable has a better sign consistency. The same goes for the other variables, the index variables are more consistent sign wise.

Dummy versus other variables: The dummy variables are somewhat worse then the other variables both when it comes to significance and sign stability. On the other hand we have only tested two dummies which could mean that if we included other dummies we could get better results for that type of variable.

It should be noted that, as is presented in the section on multicollinearity, the standard deviation and percentage change in volume for the constituent Ericsson is highly correlated with the same variables of the index. This makes the regression results for Ericsson susceptible to errors making the R^2 value too high and with no, or few, significant variables. This is obvious in the table below where Ericsson only has two statistically significant variables but the highest R^2 value of all constituents.

The table below shows the results from the regressions. It gives the R^2 value in the top row. The values in the variable rows are the betas given by the OLS regressions for the respective dependent variable. Only variables that are significant at the ten percent level are included. Beneath each beta we have included the standard deviation for that variable in parentheses.

Table 7.1 Regression results for each variable. Number in parenthesis shows standard deviation.

Significance	ABB	ALFA	ALIV	ASSA	ATCO A	ATCO B	AZN	BOL	ELUX	ENRO	ERIC B	HM	INVE B	NDA	SAND
R^2	0,076	0,199	0,096	0,244	0,294	0,256	0,316	0,327	0,218	0,286	0,414	0,271	0,377	0,374	0,165
Macro variables															
Intercept					-0,673 (0,387)	-1,180 (0,538)									
Rm-Rf MSCI World								64,303 (28,086)				49,141 (23,783)	61,143 (25,711)		
Rm-Rf OMXS30					36,288 (20,763)						51,158 (16,847)			58,277 (29,678)	
SMB							-0,760 (0,392)					-0,478 (0,286)			
HML		1,461 (0,587)		0,965 (0,518)	1,334 (0,626)		1,043 (0,616)			1,148 (0,553)			1,134 (0,514)		
USD/JPY Spot				0,569 (0,302)											
Micro variables															
stdOMXS30						0,016 (0,009)									
pvalueOMXS30			-0,090 (0,005)					-0,008 (0,005)					-0,100 (0,005)		
stdX								-0,961 (0,276)		0,470 (0,273)			0,608 (0,351)		
pvalueX				-0,589 (0,356)				0,729 (0,303)							
X Val-Mean							-1,669 (0,586)							2,569 (0,826)	
X ValBig D					1,437 (0,748)		1,365 (0,763)				6,089 (1,366)	-1,416 (0,510)			
X Val D							0,786 (0,442)								

Significance	SCA	SCV B	SEB A	SECU B	SHB A	SKA B	SKF B	SSAB A	SWED	SWMA	TEL2 B	TLSN	VGAS	VOLV B	OMXS30
R^2	0,325	0,367	0,289	0,266	0,309	0,236	0,282	0,318	0,175	0,183	0,311	0,235	0,264	0,189	0,457
Macro variables															
Intercept		-1,421											0,607		
		(0,561)											(0,363)		
Rm-Rf MSCI World			77,657		59,886			-200,514					67,984	84,667	30,391
			(30,473)		(20,560)			(53,771)					(31,946)	(35,906)	(13,089)
Rm-Rf OMXS30	25,877	56,573									58,035	40,611			19,748
	(15,702)	(30,150)									(21,052)	(17,385)			(8,680)
SMB				0,677											
				(0,371)											
HML			1,191		1,380										0,638
			(0,611)		(0,422)										(0,275)
USD/JPY Spot				0,586							-0,748	-0,543	0,613		
				(0,344)							(0,368)	(0,297)	(0,365)		
Micro variables															
stdOMXS30	0,009	0,015					0,016	-0,018							
	(0,005)	(0,009)					(0,006)	(0,010)							
pvalueOMXS30	-0,015	-0,130					-0,013								
	(0,004)	(0,002)					(0,070)								
stdX				-0,509					-0,695						
				(0,244)					(0,336)						
pvalueX	0,500														
	(0,227)														
X Val-Mean	1,047	-4,018			-0,802		1,713								
	(0,535)	(1,382)			(0,466)		(0,905)								
X ValBig D							-2,425								
							(0,805)								
X Val D		2,022													
		(0,796)													

7.1.2 Macro factors

The picture becomes much clearer when looking at the macro factors. The variables that are significant in most regressions are the excess market return for the MSCI World index and the HML factor. This goes well with our first hypothesis that a positive market sentiment in the index behaviour will lead to larger spreads. The MSCI excess market return variable has a positive beta in all regressions except one while the HML factor is positive in all nine regressions where it is significant. This is the same for the third most significant variable, the excess return for the OMXS30 index. It also has a positive beta in all eight regressions where it is significant.

The other Fama Frech factor does not perform on the same level. The SMB factor is only significant in three regressions of which it has a positive beta in two cases and a negative beta in one case. This is in line with the findings by previous researchers that have shown that both the SMB and HML have a positive risk return relationship. Meaning that when one increases the loadings on the HML factor the expected spread between VWAP and TWAP will increase.

The forth most significant factor in our regressions is the exchange rate between US Dollar and Japanese Yen. It is significant in five of the 30 regressions. However sign wise it is not consistent, having a positive beta in three cases and a negative beta in two cases. This can not be interpreted as strong evidence supporting our thought that when the USDJPY cross increases (USD increasing in value against the JPY) the spread between the VWAP and TWAP benchmarks will increase, on average. Therefore this result is not in line with our second hypothesis that when investors risk appetite increases so will the spread between VWAP and TWAP.

7.1.3 Index regression

The regression of the spread on an index level is of extra importance given that our assumption is that it is the best proxy for the risk of the whole equity trading desk.

In the index regression there are three significant variables including both the excess market return of the MSCI world and the OMZS30 as well as the HML factor. In short the factors that are significant in most single stock regressions are also significant in the index regression. The assumptions about positive market sentiment of the investor base being important for the spread between the VWAP and TWAP seem to hold also for the index. There are, as we expected, no micro variables that are significant in the index regression.

7.2 Regression analysis

The results from the interviews give an indication that the most well used benchmark, when it comes to orders put into an algorithm, is VWAP. We decide to investigate the implications of this benchmark as it is used today. We look at the risks that a sell side trading desk take on when guaranteeing an order at VWAP. This is especially interesting since with the increase of algorithmic trading we see coming, from analysing the interview results, the VWAP measure will probably be continued to be heavily used, at least in the early phases of the build out of algorithmic trading.

7.2.1 Overview

The first conclusion that we can make from the regression results are that the constituent regressions differs substantially from each other and most differ from the index regression due to their large dependence on micro factors.

Our fourth and final hypothesis was that on an index level the factors determining the spread were going to be different from the ones that were to determine the spread on a single stock level. The reasons being that there might be different factors affecting each constituent making each single stock regression hard to predict. As we see in the table in the above section the micro factors are irrelevant in the index regression. Of the micro variables the changes in value traded on the OMXS30 and the value traded measured against the mean of the period were significant in six out of 30 and 29 regressions respectively making them the most universally significant variable of the micro factors. They are obviously important for certain stocks but not for the entire index which is in line with our fourth hypothesis.

Several of the liquidity variables are significant in single stock regressions. This is in line with *our third hypothesis* that states that liquidity risks will impact the spread. The factors seem to be important for some constituents. One conclusion from this result could be that these stocks are more affected by liquidity problems, something that is reinforced by the fact that most of the companies where these factors are most important (large betas and or many significant regressors) are not among the largest of the index constituents. However these results are not clear and need to be investigated further to provide any practically useful results. There are several reasons for this. Firstly, when looking at the different constituents we feel that it might be hard to find factors that work for all companies given their varied business areas. Another reason for the micro variables not being able to explain the spread on an index level might be that the whole market seldom shows a lack of liquidity while single stock might very well be affected by such phenomena. Therefore it seems natural that these variables are only significant on a single stock level. We can, however, not explain the differences between individual companies.

The second hypothesis, that market risk appetite, constructed with US dollar / Japanese Yen Spot exchange rate as a proxy, would affect the spread does not seem to hold. This is a clear negative result since we expected it to be significant in the index regression as well as many of the constituent regressions. We also expected it to carry a positive sign given that when the exchange rate move upward risk appetite is high and the VWAP-TWAP spread should increase. However this is not the case since the signs for the exchange rate are mixed with three positive and two negative.

Our first hypothesis deals with the two factors included from the three factor model developed by Fama and French, SMB and HML. These factors prove to be significant in several regressions. The SMB factor is however only significant in three out of 30 regressions and might therefore be considered uninteresting for further study. This goes, in a way, against our first hypothesis of the two Fama French factors, SMB and HML, both being important for the spread due to their high explanatory power on equity indices in previous research.

On the other side the HML factor is highly significant in nine of the 30 regressions where it is included. This goes well with the thought we had about these factors. It also carries a positive sign in all regressions which is in line with our first hypothesis.

The first hypothesis also deals with the two excess market returns included in the regression. These two variables are among the most significant in all regressions. This is a clear supportive result for our thought that links the market movements with the spread. A positive market sentiment will be highly correlated to larger spreads.

From a birds view perspective the results from the regressions can be interpreted as, in most areas, being in line with our expectations. The most flagrant difference from what we expected was the lack of explanatory variable of the US Dollar/ Japanese Yen exchange rate and the low number of regressions where the SMB factor was significant.

7.2.2 Constituent Regression Analysis

The 29 regressions made for the constituents give some of the results expected from our assumptions. The first assumption being that the stock specific factors have a large effect on the spread for the individual stock. This can be interpreted from the regression results seen in the Main Results section. The change in the value traded in the OMXS30 index is the micro level variable that is significant in most regressions. However it is only significant in six regressions which is less then we expected. Surprising is the fact that the same variable for the single stock is not at all as significant. It is significant in only three regressions with a non consistent beta sign, in contrast to its index stock equivalent.

In five of the 29 regressions we find the currency cross to be a significant variable. This is not in line with our hypothesis of the risk appetite being an explanatory variable for the spread. Not all betas are positive which we had assumed in accordance with our hypothesis. This means another failure for the variable.

On the negative side there are several regressions where there are no, or very few, significant explanatory variables. There are also some where the R^2 is low meaning that the regression model does not explain enough of the variations in the spread to be meaningful. A second problem lies in the large variations between the single stock regressions. There are a multitude of different combinations of variables that are significant in the individual cases but not in same combinations. This makes it very hard to say that we have identified the right variables for explaining the movements in the VWAP-TWAP spread on a single stock index. This is something that we expected due to the large difference in nature between the stocks making up the OMXS30 index. The different constituents are affected by a diverse set of underlying factors given their wide range of business areas.

7.2.3 Index Regression Analysis

The regression of the index is the final phase of the analysis. The risk of the trading desk from guaranteeing the VWAP price will be more adequately modelled by a regression of the index than of the specific constituents. This does not mean that the index is the most suitable measure due to the idiosyncratic risks being diversified away. The reason why we treat it as the most important variable is that this thesis aims at putting the spotlight on this specific kind of risk, not finding the best possible model for every single stock. Our aim is to test the effects of the better known risk factors in financial economics, as well as some of the factors we believe could be important, for the VWAP-TWAP spread. Therefore it is the index regression that is most important. We leave it open to find the most important risk factors for each individual stock. Not meaning, however, that any stock is less important to the risk of a trading desk. The deciding factor for that is the amount of orders and stocks traded in the respective stock.

All three of the factors that are significant in the index regression are macro factors. This is very much in line with our fourth hypothesis.

The three macro factors have positive betas meaning that when they increase the spread will also increase. The two excess return variables have much higher betas then the HML factor but they are all significant at the same level.

The regression results can be considered an indication of the first and the fourth hypotheses being correct. The results support our hypotheses since the variables are significant and have the right sign beta. The third and second hypothesis can not be considered supported.

8. Causality Check

The different variables we have tested might have more, or different, effects on the dependant variable then first realised when looking at the results. This can be determined from more research on the specific factors preferably by using data samples from other time spaces or countries. The variables might also be affected by the dependant variable itself. This would result in a correlation that is not desired since it would mean that the dependant variable is not affected by the movements in the explanatory variables as we presume. A simple test of this is to perform a causality check of which might be the cause and which is the effect.

Our variables can be divided into three different categories according to origin, the indices, the Fama French risk factors, and the value variables. The foreign exchange rate falls into neither category.

The first category does not seem to be affected by the dependant variable simply because an investor puts on a stock trade for other reasons then the VWAP-TWAP spread. There is no reason to suspect any investor buying or selling an index due to the value of our spread.

The same line of reasoning goes for the second category. There is no clear reason why any investor should try to buy or sell the different Fama French portfolios and thereby change the corresponding risk factors because of the spread we have analysed. The same goes for the foreign exchange rate.

The third group has a more close relationship to the dependant variable. The value traded in the OMXS30 index or the specific share is clearly dependant on how many, and how large, orders are given to the trading desks covering the index. Therefore there might be an unclear bias in the results simply because some of our explanatory variables could, in themselves, be dependant on the value of the dependant variable.

9. Conclusion and Discussion

This thesis had a twofold purpose. Firstly we wanted it to shed some light on the situation in the Swedish equity markets. More specifically we wanted to know three things, how people involved in the business think about equity trading, how they use benchmarks (and what considerations they have when choosing these) and thirdly we wanted to find out how developed algorithmic trading was in Sweden.

From this there evolved a second objective. The results we got from our interviews pointed in the direction of VWAP as an important benchmark. However most interview subjects were concerned only with the risks of liquidity and not with what could affect the trading benchmarks when there is ample liquidity. This is the situation in the absolute majority of cases for the largest stocks, which are the ones we study and which are the most traded by our interview subjects. Therefore we chose to investigate if there are risks associated with the VWAP benchmark.

The first purpose, although important in itself, thereby came to be only the beginning of the thesis even though it could satisfy an end in itself.

The interview subjects give the picture of a Swedish equity market that is lagging its larger peers in London and New York. Algorithmic trading, in Stockholm, is quite undeveloped as is the science of benchmarking. This does not mean that money managers and traders do not benchmark their equity orders. Rather, it means that this is done in an unscientific way with many personal variables such as knowledge of skill level of different counterparties. What is most effective is hard to determine but a clear difference is that the scene in Stockholm is less scientific then its larger counterparties, for good or for bad. We do not pass any judgement in this question. However we agree with most of our interview subjects that a large factor for Stockholm being this way is its smaller size and familiar atmosphere. There also seems to be a consensus that what happens in London and New York sooner or later comes to Stockholm. Some see it taking a long time while others are surprised that it has not gone quicker.

The regression results are less clear. What we first expected were to find little or no significant variables among the main risk factors known and used today. Our results were somewhat surprising since they indicate that there are several factors that affect the risk of a VWAP trade.

They indicate that on a single equity level the micro level factors such as volatility of the value traded as well as total value traded is important for the risk of a VWAP trade which we proxy by the spread between VWAP and TWAP. On an index level there are less clear effects from the micro level factors and none of these are statistically significant at the 10 percent level.

On an index level there are three factors that seem to matter. These are the two equity indices as well as the Fama French HML variable. All these are established risk factors in their own right. However it is not evident through economic theory why and how they should affect the risk of a VWAP trade. Our research does however indicate this. All together our results bring the message that sell side brokerage firms such as S E B should think about how they price a VWAP order for a particular security. By facilitating every order at the same price the firm takes on different amount of risk but gets paid the same. It received different loadings of underlying risk factors while it does not charge for it.

Regarding the time period it is clear that there would have been benefits to have more data over a longer period of time. When measuring excess returns it is always good to measure over a whole cycle, which could not be done with the limited access to data that we had. However, it is also clear that it is troublesome to get these amounts of data for at longer period of time. There are no commonly used systems that could provide this. Among the most common systems, Bloomberg, Thomson Financial and Datastream there were not more than 128 days of data available. Even after trying to find more data via SEB we concluded that 128 days were the maximum amount of data we could get.
The period chosen is also characterized by high volatility and drift which makes it not very similar to a normal period during a cycle on the stock exchange. It is certain that this has in some way affected our results. However it is impossible to know to what extent they have been affected.

For further research we would suggest that a longer period is chosen if there is a possibility to save data over a longer period of time. This would make the results more reliable and thus the outcome of the regressions more statistically significant.

10. Appendix

10.1 T-tests

Table 1.
Table shows the t-test performed to test where the spread was different from zero. Variables marked * are outside the 10 percent interval where the hypothesis that the difference is zero is rejected.

Significance	ABB*	ALFA*	ALIV	ASSA	ATCO A	ATCO B	AZN*	BOL	ELUX*	ENRO
T	0,51975	0,84299	0,00043	1,34769	2,62835	1,88596	0,18365	1,30526	0,74580	1,90035
Sigma	0,00117	0,00317	0,00151	0,00147	0,00192	0,00207	0,00163	0,00214	0,00196	0,00155
μ	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000
n	142	142	142	142	142	142	142	142	142	142
X	0,00005	-0,00022	0,00000	-0,00017	-0,00042	-0,00033	0,00003	0,00023	-0,00012	-0,00025

Significance	ERIC B*	HM	INVE B*	NDA	SAND	SCA*	SCV B*	SEB A	SECU B*	SHB A*
T	1,11750	2,50549	1,24377	1,54153	1,30253	0,05177	0,49480	1,64484	0,18125	0,80340
Sigma	0,00148	0,00141	0,00156	0,00233	0,00177	0,00135	0,00284	0,00164	0,00167	0,00120
μ	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000
n	142	142	142	142	142	142	142	142	142	142
X	0,00014	-0,00030	-0,00016	-0,00030	-0,00019	0,00001	0,00012	-0,00023	-0,00003	0,00008

Significance	SKA B*	SKF B	SSAB A*	SWED	SWMA*	TEL2 B*	TLSN*	VGAS*	VOLV B*	OMXS30*
T	1,19146	1,28245	0,49504	1,97322	0,76125	0,09699	0,31617	1,22217	0,13147	1,15985
Sigma	0,00200	0,00168	0,00314	0,00161	0,00190	0,00166	0,00127	0,00167	0,00199	0,00082
μ	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000	0,00000
n	142	142	142	142	142	142	142	142	142	142
X	-0,00020	-0,00018	0,00013	-0,00027	0,00012	0,00001	-0,00003	0,00017	-0,00002	-0,00008

10.2 Model summaries

Tables below show model summary for dependent variables

ABB & ALFA LAVAL

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,275[a]	,076	-,044	1,2492

a. Predictors: (Constant), ABB VAL D, SMB, stdOMXS30, RM-Rf MSCI WORLD, HML, ABB VALBIG D, stdABB, pvalueABB, USDJPY SPOT, pvalueOMXS30, Rm-Rf OMXS30, ABB VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,446[a]	,199	,105	1,5187

a. Predictors: (Constant), ALFA VAL D, stdOMXS30, USDJPY SPOT, SMB, HML, pvalueALFA, RM-Rf MSCI WORLD, stdALFA, ALFA VAL-MEAN, pvalueOMXS30, Rm-Rf OMXS30

ALIV & ASSA ABLOY

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,310[a]	,096	-,009	1,5229

a. Predictors: (Constant), ALIV VAL D, stdALIV, HML, Rm-Rf OMXS30, SMB, ALIV VALBIG D, pvalueOMXS30, USDJPY SPOT, stdOMXS30, RM-Rf MSCI WORLD, ALIV VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,494[a]	,244	,147	1,2868

a. Predictors: (Constant), ASSA VAL D, stdOMXS30, USDJPY SPOT, HML, SMB, ASSA VALBIG D, stdASSAB, RM-Rf MSCI WORLD, pvalueOMXS30, pvalueASSAB, Rm-Rf OMXS30, ASSA VAL-MEAN

ATLAS COPCO A & B

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,542[a]	,294	,203	1,5706

a. Predictors: (Constant), ATCOA VAL D, stdOMXS30, HML, USDJPY SPOT, SMB, ATCOA VALBIG D, pvalueATCOA, RM-Rf MSCI WORLD, stdATCOA, pvalueOMXS30, Rm-Rf OMXS30, ATCOA VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,506[a]	,256	,159	2,0768

a. Predictors: (Constant), ATCOB VAL D, SMB, RM-Rf MSCI WORLD, stdOMXS30, HML, ATCOB VALBIG D, pvalueATCOB, USDJPY SPOT, stdATCOB, pvalueOMXS30, Rm-Rf OMXS30, ATCOB VAL-MEAN

AZTRA ZENECA & BOLIDEN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,563[a]	,316	,228	1,5333

a. Predictors: (Constant), AZN VAL D, RM-Rf MSCI WORLD, HML, stdOMXS30, SMB, AZN VALBIG D, USDJPY SPOT, stdAZN, pvalueOMXS30, pvalueAZN, Rm-Rf OMXS30, AZN VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,572[a]	,327	,240	1,4109

a. Predictors: (Constant), BOL VAL D, HML, pvalueOMXS30, USDJPY SPOT, BOL VALBIG D, SMB, RM-Rf MSCI WORLD, stdOMXS30, stdBOL, pvalueBOL, Rm-Rf OMXS30, BOL VAL-MEAN

ELECTROLUX & ENIRO

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,467[a]	,218	,117	1,6739

a. Predictors: (Constant), ELUX VAL D, RM-Rf MSCI WORLD, stdOMXS30, SMB, HML, stdELUXB, ELUX VALBIG D, USDJPY SPOT, pvalueOMXS30, pvalueELUXB, Rm-Rf OMXS30, ELUX VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,535[a]	,286	,194	1,4340

a. Predictors: (Constant), ENRO VAL D, HML, USDJPY SPOT, stdENRO, SMB, ENRO VALBIG D, pvalueOMXS30, RM-Rf MSCI WORLD, stdOMXS30, pvalueENRO, Rm-Rf OMXS30, ENRO VAL-MEAN

ERICSSON B & HENNES&MAURITZ B

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,643[a]	,414	,338	1,2299

a. Predictors: (Constant), ERIC VAL D, stdOMXS30, SMB, Rm-Rf OMXS30, HML, ERIC VALBIG D, pvalueOMXS30, USDJPY SPOT, stdERICB, RM-Rf MSCI WORLD, pvalueERICB, ERIC VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,521[a]	,271	,177	1,1966

a. Predictors: (Constant), HM VAL D, stdOMXS30, SMB, USDJPY SPOT, HML, stdHMB, HM VALBIG D, RM-Rf MSCI WORLD, pvalueHMB, pvalueOMXS30, Rm-Rf OMXS30, HM VAL-MEAN

INVESTOR B & NORDEA

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,614[a]	,377	,297	**********

a. Predictors: (Constant), INVEB VAL D, stdINVEB, HML, Rm-Rf OMXS30, SMB, stdOMXS30, INVEB VALBIG D, pvalueINVEB, USDJPY SPOT, RM-Rf MSCI WORLD, pvalueOMXS30, INVEB VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,611[a]	,374	,293	**********

a. Predictors: (Constant), NDA VAL D, stdOMXS30, SMB, USDJPY SPOT, HML, NDA VALBIG D, stdNDA, RM-Rf MSCI WORLD, pvalueOMXS30, pvalueNDA, Rm-Rf OMXS30, NDA VAL-MEAN

SANDVIK & SCA

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,406[a]	,165	,057	**********

a. Predictors: (Constant), SAND VAL D, stdSAND, HML, Rm-Rf OMXS30, SMB, stdOMXS30, pvalueSAND, SAND VALBIG D, USDJPY SPOT, RM-Rf MSCI WORLD, pvalueOMXS30, SAND VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,570[a]	,325	,238	1,1721

a. Predictors: (Constant), SCA VAL D, stdSCAB, USDJPY SPOT, SMB, HML, SCA VALBIG D, RM-Rf MSCI WORLD, pvalueOMXS30, stdOMXS30, pvalueSCAB, Rm-Rf OMXS30, SCA VAL-MEAN

SCANIA B & SEB A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,606[a]	,367	,285	2,2779

a. Predictors: (Constant), SCVB VAL D, Rm-Rf OMXS30, stdOMXS30, HML, SMB, stdSCVB, pvalueSCVB, SCVB VALBIG D, USDJPY SPOT, pvalueOMXS30, RM-Rf MSCI WORLD, SCV VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,538[a]	,289	,197	1,5139

a. Predictors: (Constant), SEBA VAL D, HML, pvalueOMXS30, RM-Rf MSCI WORLD, SMB, USDJPY SPOT, stdSEBA, SEBA VALBIG D, stdOMXS30, Rm-Rf OMXS30, pvalueSEBA, SEB VAL-MEAN

SECURITAS & HANDELSBANKEN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,516[a]	,266	,171	1,4907

a. Predictors: (Constant), SECU VAL D, USDJPY SPOT, SMB, stdOMXS30, HML, pvalueSECUB, SECU VALBIG D, RM-Rf MSCI WORLD, stdSECUB, pvalueOMXS30, Rm-Rf OMXS30, SECU VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,556[a]	,309	,220	1,0478

a. Predictors: (Constant), SHBA VAL D, stdOMXS30, RM-Rf MSCI WORLD, HML, SMB, stdSHBA, SHBA VALBIG D, USDJPY SPOT, pvalueOMXS30, pvalueSHBA, Rm-Rf OMXS30, SHB VAL-MEAN

SKANSKA & SKF

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,486[a]	,236	,137	1,8698

a. Predictors: (Constant), SKA VAL D, Rm-Rf OMXS30, stdOMXS30, SMB, HML, stdSKAB, SKA VALBIG D, pvalueSKAB, USDJPY SPOT, pvalueOMXS30, RM-Rf MSCI WORLD, SKA VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,531[a]	,282	,189	1,5076

a. Predictors: (Constant), SKF VAL D, stdSKFB, SMB, HML, RM-Rf MSCI WORLD, SKF VALBIG D, USDJPY SPOT, pvalueSKFB, stdOMXS30, Rm-Rf OMXS30, pvalueOMXS30, SKF VAL-MEAN

SSAB & SWEDBANK

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,564[a]	,318	,230	2,6959

a. Predictors: (Constant), SSAB VAL D, SMB, stdOMXS30, RM-Rf MSCI WORLD, stdSSABA, HML, USDJPY SPOT, SSAB VALBIG D, pvalueSSABA, pvalueOMXS30, Rm-Rf OMXS30, SSAB VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,418[a]	,175	,068	1,1306

a. Predictors: (Constant), SWED VAL D, USDJPY SPOT, stdOMXS30, SMB, HML, stdSWEDA, SWED VALBIG D, pvalueSWEDA, RM-Rf MSCI WORLD, pvalueOMXS30, Rm-Rf OMXS30, SWED VAL-MEAN

SWEDISH MATCH & TELE2

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,428[a]	,183	,078	1,7604

a. Predictors: (Constant), SWMA VAL D, stdSWMA, SMB, USDJPY SPOT, HML, stdOMXS30, pvalueSWMA, RM-Rf MSCI WORLD, SWMA VALBIG D, pvalueOMXS30, Rm-Rf OMXS30, SWMA VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,558[a]	,311	,223	1,5848

a. Predictors: (Constant), TEL2 VAL D, stdOMXS30, RM-Rf MSCI WORLD, SMB, HML, TEL2 VALBIG D, USDJPY SPOT, stdTEL2B, pvalueTEL2B, pvalueOMXS30, Rm-Rf OMXS30, TEL2 VAL-MEAN

TELIA SONERA & VOSTOK GAS

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,485[a]	,235	,137	1,2925

a. Predictors: (Constant), TLSN VAL D, SMB, USDJPY SPOT, stdOMXS30, HML, TLSN VALBIG D, RM-Rf MSCI WORLD, pvalueTLSN, stdTLSN, pvalueOMXS30, Rm-Rf OMXS30, TLSN VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,514[a]	,264	,169	1,5856

a. Predictors: (Constant), VGAS VAL D, RM-Rf MSCI WORLD, stdOMXS30, HML, SMB, pvalueVGAS, VGAS VALBIG D, USDJPY SPOT, stdVGAS, pvalueOMXS30, VGAS VAL-MEAN, Rm-Rf OMXS30

VOLVO B & OMXS30 INDEX

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,435[a]	,189	,085	1,8265

a. Predictors: (Constant), VOLV VAL D, SMB, stdOMXS30, USDJPY SPOT, HML, VOLV VALBIG D, pvalueVOLVB, RM-Rf MSCI WORLD, stdVOLVB, pvalueOMXS30, Rm-Rf OMXS30, VOLV VAL-MEAN

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,676[a]	,457	,400	,6636

a. Predictors: (Constant), INDEX VAL D, stdOMXS30, SMB, RM-Rf MSCI WORLD, HML, USDJPY SPOT, INDEX VALBIG D, pvalueOMXS30, Rm-Rf OMXS30, INDEX VAL-MEAN

10.3 Regression results

Tables below show regression results for dependent variables.
ABB

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,386	,307		1,258	,212
	SMB	-,019	,295	-,007	-,064	,949
	HML	,107	,504	,023	,212	,833
	RM-Rf MSCI WORLD	34,538	24,478	,243	1,411	,162
	Rm-Rf OMXS30	-11,980	16,659	-,138	-,719	,474
	USDJPY SPOT	,122	,299	,056	,409	,683
	stdOMXS30	,005	,005	,122	,869	,387
	pvalueOMXS30	-,002	,005	-,064	-,380	,705
	stdABB	-,460	,394	-,150	-1,169	,246
	pvalueABB	,312	,351	,144	,888	,377
	ABB VAL-MEAN	,615	,592	,242	1,039	,301
	ABB VALBIG D	-,360	,759	-,078	-,475	,636
	ABB VAL D	-,587	,478	-,210	-1,228	,222

a. Dependent Variable: ABB

ALFA LAVAL

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,283	,368		-,770	,443
	SMB	-,331	,357	-,090	-,927	,356
	HML	1,461	,587	,240	2,491	,015
	RM-Rf MSCI WORLD	47,257	30,271	,253	1,561	,122
	Rm-Rf OMXS30	17,350	20,013	,152	,867	,388
	USDJPY SPOT	-,057	,356	-,020	-,160	,874
	stdOMXS30	-,004	,006	-,081	-,626	,533
	pvalueOMXS30	,007	,006	,192	1,219	,226
	stdALFA	,221	,269	,114	,819	,415
	pvalueALFA	-,307	,274	-,185	-1,120	,265
	ALFA VAL-MEAN	-,574	,714	-,118	-,803	,424
	ALFA VAL D	,553	,624	,127	,887	,377

a. Dependent Variable: ALFA

AUTOLIV

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,527	,385		-1,368	,175
	SMB	,251	,356	,072	,706	,482
	HML	,280	,597	,049	,468	,641
	RM-Rf MSCI WORLD	-43,495	30,679	-,247	-1,418	,160
	Rm-Rf OMXS30	19,620	20,598	,182	,953	,343
	USDJPY SPOT	,047	,358	,017	,132	,895
	stdOMXS30	,008	,006	,172	1,284	,202
	pvalueOMXS30	-,009	,005	-,241	-1,726	,088
	stdALIV	,265	,284	,117	,933	,353
	ALIV VAL-MEAN	,126	,744	,038	,169	,866
	ALIV VALBIG D	-,593	,805	-,115	-,736	,464
	ALIV VAL D	,572	,517	,182	1,106	,271

a. Dependent Variable: ALIV

ASSA ABLOY

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,251	,324		-,774	,441
	SMB	,285	,324	,089	,879	,382
	HML	,965	,518	,182	1,862	,066
	RM-Rf MSCI WORLD	12,889	25,102	,080	,513	,609
	Rm-Rf OMXS30	2,449	17,268	,025	,142	,888
	USDJPY SPOT	,569	,302	,229	1,886	,062
	stdOMXS30	,003	,005	,065	,558	,578
	pvalueOMXS30	,006	,005	,184	1,326	,188
	stdASSAB	-,116	,316	-,038	-,368	,714
	pvalueASSAB	-,859	,356	-,365	-2,412	,018
	ASSA VAL-MEAN	-,297	,541	-,109	-,549	,585
	ASSA VALBIG D	-,140	,689	-,027	-,203	,840
	ASSA VAL D	,347	,354	,125	,983	,328

a. Dependent Variable: ASSAB

ATLAS COPCO A

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,671	,387		-1,736	,086
	SMB	,331	,378	,082	,877	,383
	HML	1,334	,626	,200	2,130	,036
	RM-Rf MSCI WORLD	19,752	30,934	,097	,639	,525
	Rm-Rf OMXS30	36,288	20,763	,290	1,748	,084
	USDJPY SPOT	,217	,363	,069	,599	,551
	stdOMXS30	,005	,007	,088	,701	,485
	pvalueOMXS30	-,007	,007	-,163	-1,022	,309
	stdATCOA	,312	,368	,107	,847	,399
	pvalueATCOA	,130	,398	,051	,328	,744
	ATCOA VAL-MEAN	-,895	,945	-,187	-,947	,346
	ATCOA VALBIG D	1,437	,748	,240	1,921	,058
	ATCOA VAL D	,044	,545	,012	,080	,936

a. Dependent Variable: ATCOA

ATLAS COPCO B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-1,180	,538		-2,194	,031
	SMB	,738	,486	,142	1,520	,132
	HML	1,217	,825	,142	1,475	,144
	RM-Rf MSCI WORLD	60,803	40,586	,231	1,498	,137
	Rm-Rf OMXS30	32,506	27,531	,201	1,181	,241
	USDJPY SPOT	-,040	,481	-,010	-,083	,934
	stdOMXS30	,016	,009	,228	1,774	,079
	pvalueOMXS30	-,003	,008	-,059	-,402	,689
	stdATCOB	,022	,527	,006	,041	,967
	pvalueATCOB	-,362	,462	-,115	-,785	,434
	ATCOB VAL-MEAN	-1,267	1,190	-,219	-1,064	,290
	ATCOB VALBIG D	,376	,890	,057	,423	,673
	ATCOB VAL D	,922	,722	,205	1,277	,205

a. Dependent Variable: ATCOB

ASTRA ZENECA

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,392	,310		-1,266	,209
	SMB	-,760	,392	-,189	-1,936	,056
	HML	1,043	,616	,157	1,691	,094
	RM-Rf MSCI WORLD	48,132	30,865	,237	1,559	,122
	Rm-Rf OMXS30	-8,098	20,603	-,065	-,393	,695
	USDJPY SPOT	,330	,362	,106	,911	,365
	stdOMXS30	-,001	,006	-,011	-,089	,930
	pvalueOMXS30	,008	,007	,198	1,232	,221
	stdAZN	-,012	,229	-,006	-,054	,957
	pvalueAZN	-,290	,308	-,163	-,943	,348
	AZN VAL-MEAN	-1,669	,586	-,532	-2,851	,005
	AZN VALBIG D	1,365	,763	,240	1,789	,077
	AZN VAL D	,786	,442	,218	1,778	,079

a. Dependent Variable: AZN

BOLIDEN

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,370	,290		1,278	,204
	SMB	,220	,336	,059	,655	,514
	HML	,593	,558	,097	1,062	,291
	RM-Rf MSCI WORLD	64,303	28,086	,342	2,290	,024
	Rm-Rf OMXS30	-28,107	18,787	-,244	-1,496	,138
	USDJPY SPOT	,228	,328	,079	,694	,489
	stdOMXS30	,009	,006	,175	1,540	,127
	pvalueOMXS30	-,008	,005	-,205	-1,645	,103
	stdBOL	-,961	,276	-,410	-3,486	,001
	pvalueBOL	,729	,303	,346	2,406	,018
	BOL VAL-MEAN	,562	,393	,254	1,430	,156
	BOL VALBIG D	,273	1,198	,032	,228	,820
	BOL VAL D	-,250	,354	-,076	-,706	,482

a. Dependent Variable: BOL

ELECTROLUX B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,232	,413		-,562	,575
	SMB	,314	,398	,077	,788	,433
	HML	,752	,695	,111	1,082	,282
	RM-Rf MSCI WORLD	31,159	34,536	,151	,902	,369
	Rm-Rf OMXS30	20,020	22,796	,158	,878	,382
	USDJPY SPOT	,448	,396	,141	1,132	,261
	stdOMXS30	,010	,007	,192	1,563	,121
	pvalueOMXS30	-,001	,006	-,021	-,138	,891
	stdELUXB	-,067	,327	-,023	-,204	,839
	pvalueELUXB	-,518	,379	-,231	-1,366	,175
	ELUX VAL-MEAN	,092	,764	,026	,120	,905
	ELUX VALBIG D	,189	1,019	,030	,186	,853
	ELUX VAL D	,095	,504	,026	,188	,851

a. Dependent Variable: ELUXB

ENIRO

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,207	,327		-,633	,528
	SMB	,328	,350	,089	,937	,351
	HML	1,148	,553	,189	2,075	,041
	RM-Rf MSCI WORLD	16,057	28,487	,087	,564	,574
	Rm-Rf OMXS30	29,219	19,266	,257	1,517	,133
	USDJPY SPOT	,469	,350	,164	1,340	,183
	stdOMXS30	-,004	,006	-,072	-,582	,562
	pvalueOMXS30	-,003	,006	-,089	-,592	,555
	stdENRO	,470	,273	,209	1,721	,089
	pvalueENRO	-,411	,284	-,205	-1,449	,151
	ENRO VAL-MEAN	,510	,719	,147	,709	,480
	ENRO VALBIG D	-,340	,721	-,070	-,472	,638
	ENRO VAL D	,347	,510	,105	,680	,498

a. Dependent Variable: ENRO

ERICSSON B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,099	,291		-,342	,733
	SMB	-,277	,290	-,080	-,956	,342
	HML	,585	,472	,102	1,239	,219
	RM-Rf MSCI WORLD	6,948	24,928	,040	,279	,781
	Rm-Rf OMXS30	51,158	16,847	,475	3,037	,003
	USDJPY SPOT	-,162	,295	-,060	-,548	,585
	stdOMXS30	-,008	,008	-,176	-1,080	,283
	pvalueOMXS30	,005	,005	,144	,977	,331
	stdERICB	,489	,532	,131	,918	,361
	pvalueERICB	-,053	,416	-,020	-,127	,899
	ERIC VAL-MEAN	-1,012	,658	-,292	-1,539	,127
	ERIC VALBIG D	6,089	1,366	,551	4,458	,000
	ERIC VAL D	,255	,437	,082	,584	,561

a. Dependent Variable: ERICB

HENNNES&MAURITZ B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,093	,281		,331	,742
	SMB	-,478	,286	-,158	-1,668	,099
	HML	,515	,472	,103	1,091	,278
	RM-Rf MSCI WORLD	49,141	23,783	,321	2,066	,042
	Rm-Rf OMXS30	6,841	15,714	,073	,435	,664
	USDJPY SPOT	-,346	,279	-,147	-1,239	,218
	stdOMXS30	,002	,005	,044	,379	,706
	pvalueOMXS30	,000	,005	,005	,035	,972
	stdHMB	-,458	,353	-,150	-1,298	,198
	pvalueHMB	-,101	,370	-,041	-,274	,784
	HM VAL-MEAN	,325	,570	,109	,570	,570
	HM VALBIG D	-1,416	,510	-,405	-2,776	,007
	HM VAL D	-,128	,373	-,049	-,344	,731

a. Dependent Variable: HMB

INVESTOR B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,077	,317		-,244	,808
	SMB	-,028	,311	-,008	-,090	,928
	HML	1,134	,514	,194	2,208	,030
	RM-Rf MSCI WORLD	61,143	25,711	,342	2,378	,019
	Rm-Rf OMXS30	19,560	17,102	,178	1,144	,256
	USDJPY SPOT	-,065	,307	-,024	-,213	,832
	stdOMXS30	,003	,005	,070	,619	,537
	pvalueOMXS30	-,010	,005	-,267	-1,800	,075
	stdINVEB	,608	,351	,180	1,730	,087
	pvalueINVEB	,042	,373	,016	,112	,911
	INVEB VAL-MEAN	1,159	,819	,273	1,415	,160
	INVEB VALBIG D	-,565	,700	-,108	-,807	,422
	INVEB VAL D	-,350	,456	-,107	-,767	,445

a. Dependent Variable: INVEB

NORDEA

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,097	,505		-,192	,848
	SMB	,088	,529	,014	,165	,869
	HML	,997	,953	,099	1,047	,298
	RM-Rf MSCI WORLD	-12,119	43,856	-,039	-,276	,783
	Rm-Rf OMXS30	58,277	29,678	,309	1,964	,053
	USDJPY SPOT	-,223	,523	-,047	-,426	,671
	stdOMXS30	,001	,009	,018	,153	,879
	pvalueOMXS30	-,009	,009	-,140	-,995	,322
	stdNDA	,144	,311	,055	,464	,644
	pvalueNDA	,131	,397	,056	,329	,743
	NDA VAL-MEAN	2,569	,826	,631	3,110	,002
	NDA VALBIG D	-1,051	1,243	-,116	-,846	,400
	NDA VAL D	-,878	,638	-,166	-1,376	,172

a. Dependent Variable: NDA

SANDVIK

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,212	,391		-,542	,589
	SMB	,255	,383	,068	,667	,507
	HML	,441	,629	,071	,701	,485
	RM-Rf MSCI WORLD	44,117	31,641	,232	1,394	,167
	Rm-Rf OMXS30	14,221	21,492	,122	,662	,510
	USDJPY SPOT	,040	,374	,014	,108	,914
	stdOMXS30	,002	,007	,046	,347	,730
	pvalueOMXS30	-,008	,007	-,209	-1,215	,228
	stdSAND	,317	,510	,072	,622	,535
	pvalueSAND	,590	,546	,181	1,080	,283
	SAND VAL-MEAN	-,527	1,070	-,122	-,493	,623
	SAND VALBIG D	,701	,938	,126	,747	,457
	SAND VAL D	-,189	,563	-,055	-,336	,738

a. Dependent Variable: SAND

SCA B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,001	,267		,003	,998
	SMB	,088	,282	,028	,311	,756
	HML	,389	,454	,076	,855	,395
	RM-Rf MSCI WORLD	17,906	23,489	,115	,762	,448
	Rm-Rf OMXS30	25,877	15,702	,271	1,648	,103
	USDJPY SPOT	-,101	,270	-,042	-,373	,710
	stdOMXS30	,009	,005	,229	1,877	,064
	pvalueOMXS30	-,015	,004	-,476	-3,565	,001
	stdSCAB	-,136	,235	-,077	-,576	,566
	pvalueSCAB	,500	,227	,327	2,208	,030
	SCA VAL-MEAN	1,047	,535	,385	1,957	,053
	SCA VALBIG D	-,300	,593	-,078	-,507	,614
	SCA VAL D	-,460	,370	-,168	-1,241	,218

a. Dependent Variable: SCAB

SCANIA B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-1,421	,561		-2,535	,013
	SMB	-,005	,555	-,001	-,009	,993
	HML	,893	,917	,087	,973	,333
	RM-Rf MSCI WORLD	56,907	45,903	,182	1,240	,218
	Rm-Rf OMXS30	56,573	30,150	,295	1,876	,064
	USDJPY SPOT	-,399	,522	-,083	-,764	,447
	stdOMXS30	,015	,009	,186	1,682	,096
	pvalueOMXS30	-,013	,008	-,207	-1,690	,094
	stdSCVB	-,103	,442	-,022	-,234	,816
	pvalueSCVB	,610	,615	,144	,992	,324
	SCV VAL-MEAN	-4,018	1,382	-,684	-2,908	,005
	SCVB VALBIG D	1,894	1,164	,239	1,627	,107
	SCVB VAL D	2,022	,796	,359	2,539	,013

a. Dependent Variable: SCVB

SEB A

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,039	,336		-,117	,907
	SMB	,331	,372	,085	,890	,376
	HML	1,191	,611	,186	1,947	,055
	RM-Rf MSCI WORLD	77,657	30,473	,396	2,548	,012
	Rm-Rf OMXS30	21,764	19,988	,181	1,089	,279
	USDJPY SPOT	-,284	,360	-,094	-,790	,432
	stdOMXS30	,000	,007	-,009	-,074	,941
	pvalueOMXS30	-,005	,007	-,113	-,616	,539
	stdSEBA	-,340	,336	-,135	-1,013	,314
	pvalueSEBA	,386	,366	,189	1,053	,295
	SEB VAL-MEAN	-,770	,687	-,238	-1,121	,265
	SEBA VALBIG D	,285	,807	,059	,353	,725
	SEBA VAL D	,102	,497	,029	,206	,837

a. Dependent Variable: SEBA

SECURITAS B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,470	,298		1,580	,117
	SMB	,677	,371	,180	1,828	,071
	HML	,850	,604	,137	1,407	,163
	RM-Rf MSCI WORLD	10,125	30,788	,053	,329	,743
	Rm-Rf OMXS30	18,686	20,203	,160	,925	,357
	USDJPY SPOT	,586	,344	,200	1,700	,092
	stdOMXS30	,00009	,006	,002	,015	,988
	pvalueOMXS30	-,007	,005	-,168	-1,253	,213
	stdSECUB	-,509	,244	-,246	-2,084	,040
	pvalueSECUB	,329	,266	,177	1,238	,219
	SECU VAL-MEAN	,260	,467	,111	,557	,579
	SECU VALBIG D	,632	,946	,108	,668	,506
	SECU VAL D	-,121	,419	-,035	-,289	,773

a. Dependent Variable: SECUB

HANDELSBANKEN A

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,047	,265		-,178	,859
	SMB	,091	,249	,033	,364	,717
	HML	1,380	,422	,306	3,272	,002
	RM-Rf MSCI WORLD	59,886	20,560	,434	2,913	,004
	Rm-Rf OMXS30	-2,515	14,036	-,030	-,179	,858
	USDJPY SPOT	-,008	,244	-,004	-,032	,975
	stdOMXS30	,002	,004	,063	,557	,579
	pvalueOMXS30	-,002	,004	-,055	-,396	,693
	stdSHBA	-,224	,234	-,106	-,956	,341
	pvalueSHBA	,015	,248	,009	,061	,952
	SHB VAL-MEAN	-,802	,466	-,312	-1,720	,089
	SHBA VALBIG D	,555	,513	,154	1,083	,282
	SHBA VAL D	,295	,331	,123	,891	,375

a. Dependent Variable: SHBA

SKANSKA B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,422	,491		-,861	,392
	SMB	,057	,449	,012	,126	,900
	HML	,486	,774	,064	,627	,532
	RM-Rf MSCI WORLD	33,077	37,995	,141	,871	,386
	Rm-Rf OMXS30	32,469	25,208	,226	1,288	,201
	USDJPY SPOT	,443	,435	,123	1,016	,312
	stdOMXS30	,000	,008	-,003	-,028	,978
	pvalueOMXS30	,009	,007	,182	1,243	,217
	stdSKAB	-,245	,486	-,059	-,504	,615
	pvalueSKAB	-,613	,494	-,179	-1,241	,218
	SKA VAL-MEAN	-,944	1,068	-,196	-,884	,379
	SKA VALBIG D	1,005	,854	,184	1,177	,242
	SKA VAL D	,787	,654	,195	1,204	,232

a. Dependent Variable: SKAB

SKF B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,149	,321		,465	,643
	SMB	-,068	,363	-,018	-,187	,852
	HML	,852	,612	,134	1,392	,167
	RM-Rf MSCI WORLD	25,900	31,190	,133	,830	,408
	Rm-Rf OMXS30	26,341	20,249	,221	1,301	,197
	USDJPY SPOT	-,333	,347	-,111	-,957	,341
	stdOMXS30	,016	,006	,305	2,460	,016
	pvalueOMXS30	-,013	,007	-,323	-1,849	,068
	stdSKFB	-,290	,475	-,071	-,611	,543
	pvalueSKFB	,449	,521	,141	,862	,391
	SKF VAL-MEAN	1,713	,905	,365	1,894	,061
	SKF VALBIG D	-2,425	,805	-,444	-3,011	,003
	SKF VAL D	-,590	,529	-,161	-1,114	,268

a. Dependent Variable: SKFB

SSAB A

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,565	,718		,787	,433
	SMB	,055	,666	,008	,083	,934
	HML	-1,343	1,061	-,115	-1,266	,209
	RM-Rf MSCI WORLD	-200,514	53,771	-,562	-3,729	,000
	Rm-Rf OMXS30	7,808	35,961	,036	,217	,829
	USDJPY SPOT	,833	,646	,152	1,289	,201
	stdOMXS30	-,018	,010	-,190	-1,754	,083
	pvalueOMXS30	,012	,009	,165	1,390	,168
	stdSSABA	-,512	,340	-,181	-1,505	,136
	pvalueSSABA	,108	,464	,038	,233	,817
	SSAB VAL-MEAN	,460	1,335	,095	,344	,731
	SSAB VALBIG D	-1,522	1,488	-,158	-1,023	,309
	SSAB VAL D	,844	,901	,130	,937	,351

a. Dependent Variable: SSABA

SWEDBANK A

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,063	,307		-,204	,839
	SMB	,234	,273	,087	,858	,393
	HML	,463	,448	,104	1,033	,304
	RM-Rf MSCI WORLD	27,527	23,521	,202	1,170	,245
	Rm-Rf OMXS30	6,801	15,001	,082	,453	,651
	USDJPY SPOT	,317	,293	,152	1,084	,281
	stdOMXS30	,002	,005	,046	,359	,720
	pvalueOMXS30	,000	,005	,017	,094	,925
	stdSWEDA	-,695	,336	-,243	-2,067	,042
	pvalueSWEDA	,110	,359	,051	,307	,759
	SWED VAL-MEAN	-,367	,742	-,121	-,494	,623
	SWED VALBIG D	-,105	,734	-,025	-,143	,886
	SWED VAL D	,315	,438	,123	,720	,474

a. Dependent Variable: SWEDA

SWEDISH MATCH A

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,020	,435		,046	,963
	SMB	,020	,410	,005	,048	,962
	HML	1,098	,673	,158	1,631	,106
	RM-Rf MSCI WORLD	44,026	34,568	,207	1,274	,206
	Rm-Rf OMXS30	1,603	23,565	,012	,068	,946
	USDJPY SPOT	,307	,415	,094	,741	,461
	stdOMXS30	-,007	,007	-,131	-1,059	,292
	pvalueOMXS30	-,006	,006	-,132	-,994	,323
	stdSWMA	,272	,318	,105	,854	,395
	pvalueSWMA	,263	,288	,123	,913	,364
	SWMA VAL-MEAN	-,661	,754	-,212	-,877	,383
	SWMA VALBIG D	-,312	,796	-,066	-,391	,696
	SWMA VAL D	,610	,578	,165	1,055	,294

a. Dependent Variable: SWMA

TELE2 B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,085	,394		,216	,830
	SMB	,301	,381	,073	,790	,432
	HML	-,346	,637	-,051	-,544	,588
	RM-Rf MSCI WORLD	48,502	31,501	,232	1,540	,127
	Rm-Rf OMXS30	58,035	21,052	,453	2,757	,007
	USDJPY SPOT	-,748	,368	-,233	-2,034	,045
	stdOMXS30	,004	,006	,082	,694	,490
	pvalueOMXS30	-,001	,006	-,029	-,194	,847
	stdTEL2B	-,355	,286	-,141	-1,240	,218
	pvalueTEL2B	,282	,312	,133	,904	,369
	TEL2 VAL-MEAN	,003	,818	,001	,004	,997
	TEL2 VALBIG D	,063	,683	,012	,092	,927
	TEL2 VAL D	-,227	,584	-,060	-,388	,699

a. Dependent Variable: TEL2B

TELIA SONERA

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,081	,297		,274	,785
	SMB	,211	,302	,066	,698	,487
	HML	-,171	,516	-,032	-,332	,741
	RM-Rf MSCI WORLD	24,693	25,741	,153	,959	,340
	Rm-Rf OMXS30	40,611	17,385	,410	2,336	,022
	USDJPY SPOT	-,543	,297	-,219	-1,831	,070
	stdOMXS30	,005	,005	,122	,958	,341
	pvalueOMXS30	-,004	,005	-,130	-,875	,384
	stdTLSN	-,399	,303	-,214	-1,318	,191
	pvalueTLSN	,234	,255	,144	,917	,361
	TLSN VAL-MEAN	,575	,453	,246	1,272	,207
	TLSN VALBIG D	,051	,638	,011	,079	,937
	TLSN VAL D	-,320	,349	-,114	-,916	,362

a. Dependent Variable: TLSN

VOSTOK GAS

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,607	,363		1,672	,098
	SMB	,336	,374	,084	,898	,371
	HML	,055	,619	,008	,089	,930
	RM-Rf MSCI WORLD	67,984	31,496	,336	2,158	,033
	Rm-Rf OMXS30	-17,143	21,464	-,138	-,799	,426
	USDJPY SPOT	,613	,365	,197	1,679	,097
	stdOMXS30	-,008	,006	-,141	-1,159	,249
	pvalueOMXS30	-,008	,006	-,189	-1,331	,187
	stdVGAS	-,006	,325	-,002	-,018	,986
	pvalueVGAS	,019	,288	,009	,066	,948
	VGAS VAL-MEAN	,566	,397	,237	1,425	,157
	VGAS VALBIG D	-,138	,750	-,026	-,184	,855
	VGAS VAL D	-,090	,430	-,026	-,209	,835

a. Dependent Variable: VGAS

VOLVO B

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	,106	,436		,243	,809
	SMB	-,229	,429	-,052	-,534	,595
	HML	,844	,732	,116	1,154	,252
	RM-Rf MSCI WORLD	84,667	35,906	,382	2,358	,020
	Rm-Rf OMXS30	-1,461	25,090	-,011	-,058	,954
	USDJPY SPOT	-,203	,432	-,060	-,471	,639
	stdOMXS30	-,007	,007	-,112	-,913	,363
	pvalueOMXS30	,003	,007	,063	,438	,662
	stdVOLVB	,341	,484	,087	,703	,484
	pvalueVOLVB	-,581	,443	-,185	-1,312	,193
	VOLV VAL-MEAN	-,212	1,019	-,047	-,208	,836
	VOLV VALBIG D	-,887	,983	-,142	-,902	,369
	VOLV VAL D	,289	,614	,073	,472	,638

a. Dependent Variable: VOLVB

OMXS30 INDEX

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-,091	,156		-,585	,560
	SMB	,040	,162	,020	,246	,806
	HML	,638	,275	,196	2,319	,023
	RM-Rf MSCI WORLD	30,391	13,089	,305	2,322	,022
	Rm-Rf OMXS30	19,748	8,680	,324	2,275	,025
	USDJPY SPOT	,042	,153	,027	,274	,785
	stdOMXS30	,002	,003	,066	,670	,504
	pvalueOMXS30	-,003	,002	-,128	-1,189	,237
	INDEX VAL-MEAN	-,156	,517	-,048	-,302	,763
	INDEX VALBIG D	,421	,349	,151	1,206	,231
	INDEX VAL D	-,062	,196	-,036	-,316	,753

a. Dependent Variable: OMXS30DIFF