Improving Portfolio Performance

An investigation in how to construct and maintain a portfolio, tracking a multidimensional index, to obtain best performance in terms of transaction cost, active return and tracking error

Ebba Linde and Nina Rodling

Abstract

The objective of this thesis is to investigate performance for different investment alternatives for an investor wanting to track a multidimensional stock index. Performance is measured in terms of transaction cost, active return against the index and tracking error. The problem is approached by comparing performance for a full replication strategy against a strategy in which the traded portfolio is a dimension reduction of the index as well as against a strategy, trading the dimension reduced portfolio, aiming to predict and in turn minimize transaction costs. The full replication case and the dimension reduction case trade with a volume-weighted strategy, whilst the last strategy trades at times historically being least expensive to trade at. The dimension reduction is done based on results from a principal component analysis together with empiric results on transaction costs associated with trading a certain stock. The transaction cost prediction model implemented is the PAR-model, presented by Rashkovich and Verma (2012). The results show that when reducing the dimension of the index, meaning that stocks with undesired characteristics can be excluded, performance is improved. The transaction cost minimizing strategy show some improvement against the full replication strategy, but its performance is inferior to trading a dimension reduced portfolio with a volume-weighted strategy. This highlights the difficulties in predicting stock market behavior. Hence, the strategy recommended for an investor wanting to track a multidimensional index is to conduct a dimension reduction according to preferences and use a volume-weighted trading strategy.

Acknowledgments

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Ebba Linde and Nina Rodling

Contents

1 Introduction

The stock market contributes with two basic functions for the financial system; first by converting savings to financing; and second, by providing risk management. If an investor is willing to accept some risk, investing in stocks generally gives a higher return than traditional saving accounts. At the same time this provides companies with capital needed for their activities and enables them to reallocate their risk by transferring it to external investors.

This thesis has been written at Sales Trading at Handelsbanken Capital Markets. It will focus on the investor perspective. A part of the Sales Trading Group's function is to provide customers, i.e., potential investors, with investment proposals. If commissioned to create a portfolio tracking a certain performance benchmark, the sales trader is expected to deliver a portfolio meeting the constraints on return and risk determined by the customer.

1.1 Purpose

This thesis will investigate different investment alternatives for an imagined investor wanting to invest in a portfolio constructed out of Swedish stocks, with a restriction on its return being equal to, or better than that of a multidimensional index[1]. In order to draw conclusions about how to find an eligible investment strategy with good overall performance, three different investment strategies, referred to as test cases, will be analyzed. All test cases have the same restriction on its return, but will differ in their approach towards achieving best performance. The first test case will be a simple strategy, namely to fully replicate the index. The second test case will investigate if performance can be improved by conducting a dimension reduction of the index. The portfolio traded in this test case will be composed of a subset of the stocks included in the index. By doing a dimension reduction, stocks with undesirable characteristics, such as illiquidity, can be excluded from the portfolio. Illiquid stocks contribute to uncertainty which can imply that the cost of holding such a stock is high. The last case to be investigated is to, in addition to reducing the dimension of the index, also predict transaction costs[2] before deciding on execution strategy. This test case will explore the effect from optimizing trade times on performance.

Performance in this thesis is primarily evaluated in terms of resulting transaction costs, but also in terms of active return against the benchmark, i.e., the multidimensional index, and tracking error.

[1] I.e., the index is comprised of a large number of stocks

[2] Costs that arise when trading

1.2 Problem to be Solved

Assume that the Sales Trading Group is approached by a customer interested in investing in a portfolio tracking the multidimensional Stockholm Benchmark Index (OMXSB). This index is constructed of approximately 70 stocks listed on the Stockholm Stock Exchange. With this constraint on investment return, this thesis will investigate two questions:

- How does dimension reduction of a multidimensional index affect performance?
- Can optimizing trade time and order size based on predicted transaction costs improve performance?

The results from the questions posed above will serve as support for the problem to be solved in this thesis:

> *How to construct and maintain a portfolio, tracking a multidimensional index, to obtain best performance?*

In the scope of this project, Handelsbanken requested performance results on daily basis to be presented for a potential customer. These results are therefore attached in the Appendix section, where one can see how day to day results could be presented for a customer.

1.3 Disposition

The remainder of this thesis is disposed as follows: Chapter 2 provides a brief background to exchange trading and explains some important concepts, such as transactions costs and stock indexes. In the subsequent chapter the theoretical concepts and models used in this thesis are introduced, such as models for transaction cost analysis and dimension reduction. The implementation of these models are described in Chapter 4. Furthermore, the results are presented in Chapter 5, followed by discussion and conclusion in Chapters 6 and 7 respectively.

2 Background

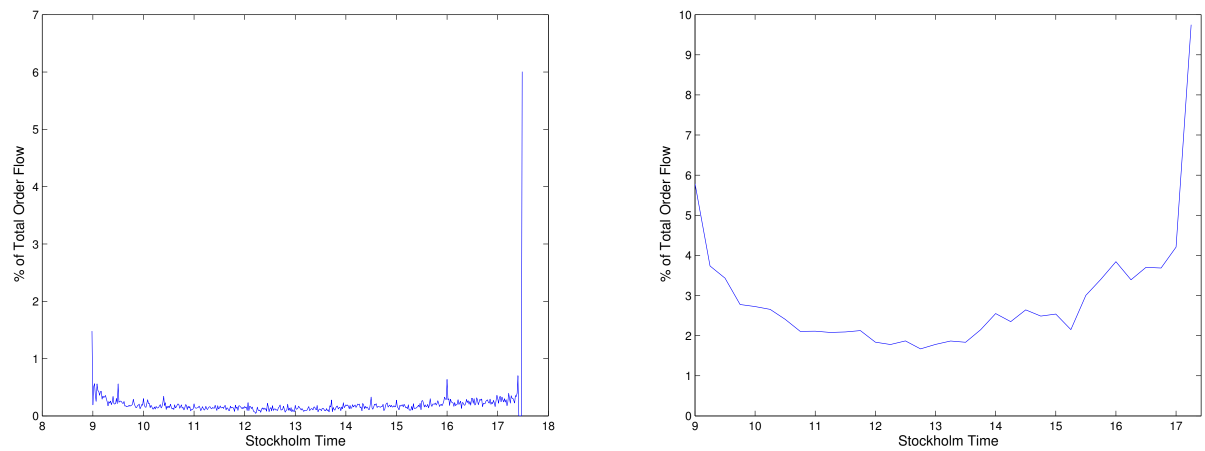
In this chapter, background explaining the trading environment is presented. For the reader to get an idea of how trade is conducted, the first section explains exchange trading in general followed by a more specific description on how trade is conducted on the Stockholm Stock exchange. Furthermore, this chapter defines and explains transaction costs and their characteristics and relevance for a trader. Lastly, the reader is introduced to stock indexes and certain investment strategies which have the objective to perform according to a specified index.

2.1 Exchange Trading

Stock trading on exchanges is of great importance for the modern financial system. Exchange trading dates back to the late 18th century and during its lifetime it has faced many developments. Still, however, the exchanges' main objective remains the same: to act as a market place where sellers and buyers meet and trade. Today these market places are often electronic platforms where submission and matching of orders are done automatically. A term often heard in the context of trading is *algorithmic trading*. This is basically a term describing that trade is conducted by automated processes following a set of rules. Among others, Kolm & Maclin (2010) state that the use of algorithmic trading has evolved and increased in importance over the past years.

The largest exchange in Sweden is the Stockholm Stock Exchange, owned by Nasdaq OMX Group (hereinafter referred to as OMX Stockholm). Data from stocks traded on this exchange will serve as basis for this thesis. The exchanges accept numerous types of orders, one being *limit orders* where buyers (sellers) submit a specified price and trade is executed if there is a counterpart willing to sell (buy) at that specified price or lower (higher). If not, the order is stored in a limit order book for stand-by. Another order type is *market orders* where buyers (sellers) submit an order to buy (sell) a certain quantity of a stock to the best available price. Thus, the trader submitting a market order is more concerned with having an immediate execution than getting the best price. The resting limit orders assure that there is liquidity meeting this immediate liquidity demand (Kolm & Maclin 2010). The highest buy order price is called the bid price and the lowest sell order price defines the ask price. The difference between the two is called the *bid-ask spread*. The largest bid-ask spread is often found in the beginning of the trading day which Groß-Klußmann et al. (2011) explains by a higher adverse selection component in spreads due to the processing of overnight information.

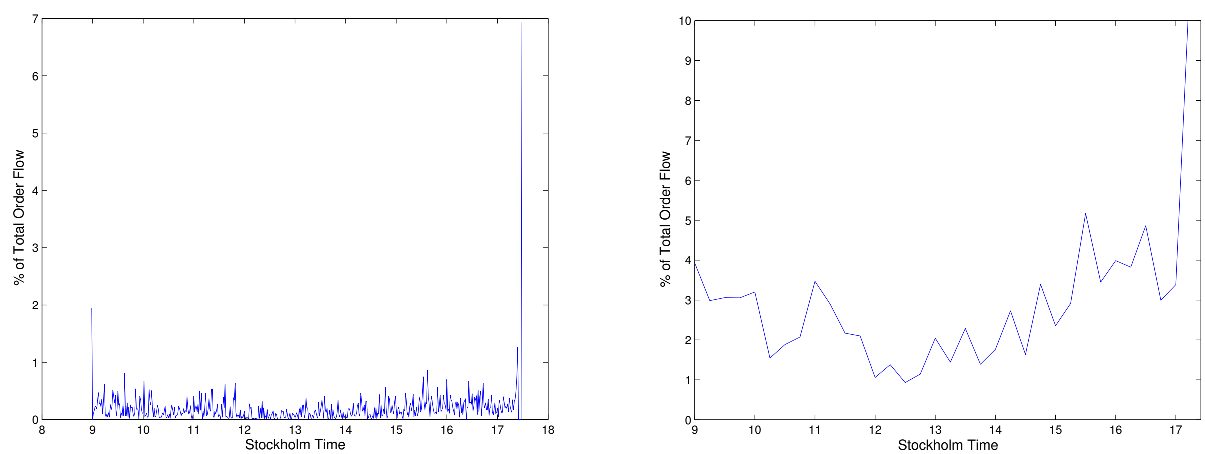
If interested in stock liquidity, one can turn to historical stock data to get a picture of the future order flow. Figures 1 and 2 below show the intraday liquidity cycle for two sample Swedish stocks as percentage of average daily volume (ADV) traded. The stocks are ABB and Rezidor Hotel Group (REZT). These stocks have different levels of liquidity, where ABB is a more frequently traded stock compared to REZT.



(a) Intraday liquidity cycle for ABB in February 2013, computed on 30-day historical data.

(b) Liquidity cycle for ABB, 9 am – 5:25 pm.

Figure 1



(a) Intraday liquidity cycle for Rezidor Hotel Group in February 2013, computed on 30-day historical data.

(b) Liquidity cycle for Rezidor Hotel Group, 9 am – 5:25 pm.

Figure 2

OMX Stockholm starts the day with a pre-open session where a call auction takes place. Buyers (sellers) submit a maximum (minimum) price at which they are willing to buy (sell). Their offers are matched with eligible sell (buy) orders in a process called uncrossing[3]. This process is carried out during a fraction of a second right before opening at 9:00 am. Uncertainty of stock price might have been raised overnight due to new information etc. and the morning call auction is conducted to decrease the instability of the opening stock price. At 9:00 the ordinary trade begins, when orders are automatically and continuously matched. The trade continues until 5:25 pm when the matching of orders is haltered. Orders submitted during the last 5 minutes of the day, i.e., the pre-close period, are not matched until the last 30 seconds of the day (5:29:30 - 5:30) when an uncrossing takes place again. This closing call is conducted to ensure a fair closing price for the stock (Nasdaq OMX [A]). Figures 1a and 2a show the order flow from the morning call auction finish at 8:59 am, until the closing at 5:30 pm. In these figures one can clearly see the peak of orders matched just before closing. To better understand the ordinary trade flow one can look at Figures 1b and 2b, which only display orders matched between 9:00 am to 5:25 pm in time buckets of 15 minutes. Looking at these figures one can see that the intraday liquidity cycle is somewhat convex for both stocks, meaning that most of the trade takes place in the beginning or at the end of the trading day. This pattern is according to Kolm et al. (2010) representable for most publicly traded stocks.

2.2 Costs Associated with Trading

Glanz & Kissel (2003) states that every trade generates a *transaction cost* which is defined as a cost paid by a trader without resulting in any value increment. These costs refer to costs associated with implementing an investment decision and facilitating the transactions, such as offering a price attractive to counterparties etc. To visualize transaction costs one can look at Figure 3. Transaction costs are described as the difference between an actual portfolio and its paper equivalent. The paper portfolio is a virtual portfolio, traded at benchmark prices and the actual portfolio is the portfolio where transaction costs are accounted for. The difference between the two portfolios was defined as *implementation shortfall* by André Perold (1988).

[3] Since all crossing prices are matched and removed

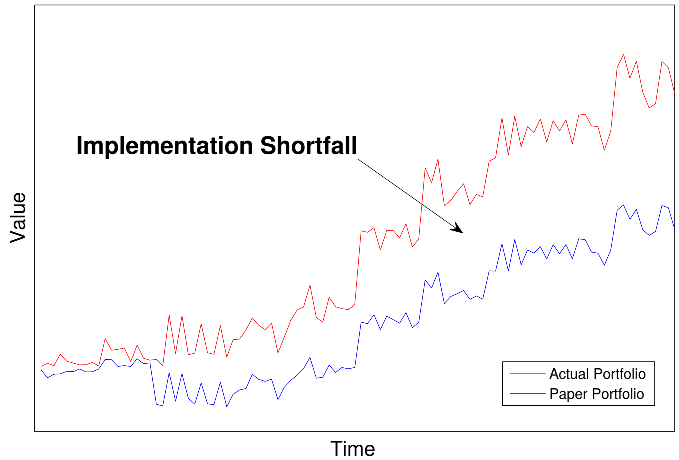


Figure 3: Implementation shortfall, defined by André Perold, is the difference between an actual portfolio and its paper equivalent.

Glanz et al. (2003) divides transaction costs into nine different cost components. These are shown in Figure 4. The costs are organized after visibility in a pyramid, where the most visible costs are closer to the top.

Almgren et al. (2005) states that if a transaction cost is visible, i.e., easily measured, it is also easily minimized. Commissions and fees are costs paid to brokers etc. These costs cannot be avoided altogether, though bargain with different brokers can minimize them[4]. Taxes vary depending on national monetary politics and can obviously not be avoided or negotiated. The bid-ask spread, defined in the previous section, compensates the liquidity providers on the market, e.g., market makers or brokers buying at bid prices and selling at ask price. Optimizing *trade times* and *participation rate*, i.e., the fraction between the traded order size and the total volume available at the chosen trade time, can minimize spread-related costs.

The visible costs do not contribute much to total transaction costs, instead Glanz et al. (2003) means that the hidden costs are those that account for the largest part. The five costs in the base of the cost pyramid are the ones generally described as hidden. Delay costs arise as there might be a time lag between the decision to trade and the actual trade, thus the price might have changed in an unfavorable direction. Price appreciation costs occur due to natural price movement of the stock; if buying stock in a rising market or vice

[4]For sales traders these costs are fairly low since they are high-frequency traders

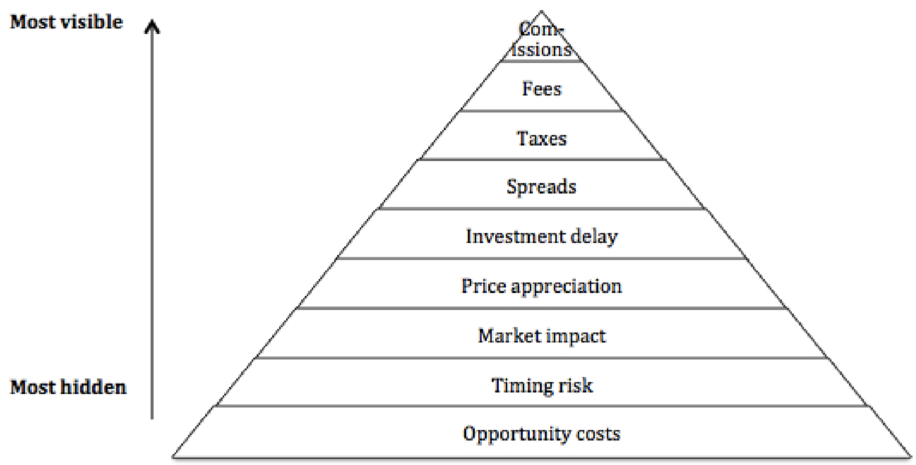


Figure 4: Visualization of transparent and hidden transaction costs defined by Glanz et al.

versa. The three most hidden components are: market impact; timing risk and opportunity costs. These are also the ones providing the greatest opportunity for cost reduction (Glanz & Kissel 2003), thus they are the most important to control. This thesis will focus on minimizing market impact under certain constraints on timing risk and opportunity cost. The characteristics of these costs are described in detail in section 3.3.1.

Implementation shortfall is sometimes referred to as a “unavoidable slippage”. This point of view is rejected by many, for example by Glanz et al. (2003) who suggests that if taking the right actions the costs can be considerably reduced. Perhaps transaction costs cannot fully be avoided, but since they can have a significant effect on investment returns it is important to manage them by implementing some kind of *transaction cost analysis* (TCA) for tracking and/or predicting future costs. Since transaction costs have many origins they can be complex and time demanding to control. According to Kissel (2006), the increased use of algorithmic trading has also increased the interest in TCA, maybe due to the fact that algorithms can be designed to manage and minimize transaction costs based on current market conditions. To ensure successful minimization one needs to have a good method for measuring transaction costs. The model used in this thesis is the PAR-model, presented by Rashkovich and Verma (2012), and is further described in section 3.5.

2.3 Investing in Stock Indexes

A stock index is an imagined portfolio composed of different stocks representing a specific part of the stock market. It can be constructed to capture the performance of a specific industry, e.g., telecommunications or mining, or the performance of companies with a certain market capitalization. indexes can also be constructed to track the overall performance of a national market. While one cannot actually invest directly in the index portfolio, there are many alternatives if one wants to achieve the same performance as an index. The most obvious one is full replication, i.e., creating a portfolio with portfolio stock weights corresponding to the index weights. Given that the index one wants to track is composed of a large number of different stocks, meaning that the index is high dimensional, this method could imply that one needs to create a very large portfolio and hold stocks with undesired characteristics. Atamtürk & Gollamudi (2013) means that this strategy usually is far too expensive to implement due to transaction costs that arise when trading and the cost of holding such a large number of securities. Hence it is not a preferred method.

Another method is to find a replicating portfolio composed by a smaller number of stocks than included in the index. This strategy for tracking the index can be viewed as making a dimension reduction of the index. However, to ensure that this method is successful both in the objective of tracking the index performance and avoiding extensive transaction costs one needs to choose stocks in a clever way. How this can be done is explained in the subsequent chapter.

3 Theory

This thesis will investigate how the performance of a portfolio, tracking a multidimensional index, is affected by certain measures to avoid high transaction costs. This problem can be approached in many ways. In the following sections the theory behind the methods used in this thesis are introduced. The selected multidimensional stock index is presented in the first section, followed by sections describing how a potential replicating portfolio can be constructed and how the transaction costs generated by trading this portfolio can be predicted and managed.

3.1 OMX Stockholm Benchmark Index

An index is essentially a list of stocks serving as a benchmark for a certain portion of the market. The most regularly quoted stock index in Sweden is probably OMXS30, which is an index composed of the 30 most traded stocks on OMX Stockholm. This is the index often used by the news to report how the Swedish market is doing. The included companies in this index all are large ones with high turnover of their stocks. In order to get a benchmark reflecting a larger part of the market movements one might want to turn to other indexes, such as OMX Stockholm Benchmark Index (OMXSB). This index is composed of stocks with top 10% turnover on OMX Stockholm. This results in the index portfolio comprising 70-100 stocks. The index is revised twice a year in order to mirror current market conditions[5], meaning that for a period of one half year the companies on the index stock list remains the same (Nasdaq OMX [B]).

The weighting of stocks included in an index can be done in different ways. One common method, which also is the one used for OMXSB, is to set weights according to the stocks' market capitalization[6]. When calculating market capitalization OMXSB use free float adjustment, which means that only those shares available[7] for daily trade are counted as shares outstanding (Nasdaq OMX [B]). The weight for each stock is calculated as the stock's market capitalization divided by the sum of market capitalization for all stocks.

Since OMXSB includes more stocks than OMXS30 one can draw the conclusion that some of the OMXSB-stocks are less liquid that the OMXS30-stocks, even though they have relatively high trading volume compared to the rest of the market. For that reason some stocks might be expensive to trade. Because of this characteristic OMXSB is a more interesting index for the purpose of this thesis and it is therefore selected for further investigation.

[5] I.e., the list of stocks included in the index is updated according to which stocks currently belong to the top 10% turnover companies on OMX Stockholm

[6] I.e., number of shares outstanding × price

[7] Stocks defined as non-available are shares held by the government or a controlling/company insider shareholder. Cross-held shares are also by definition non-available

The index will be dimension-reduced in order to get a more manageable portfolio where expensive, i.e., illiquid stocks, and stocks less important for index return will be excluded in order to minimize transaction costs. The distribution of capital weights for different industries in OMXSB, as of June 2013, is shown in Figure 5 (for a more detailed distribution of industries and sectors, please see Appendices A.1 and A.2). The classification of industries follows the *Industry Classification Benchmark* (ICB), a classification system used by OMX Stockholm since February 2012 (Nasdaq OMX [C]).

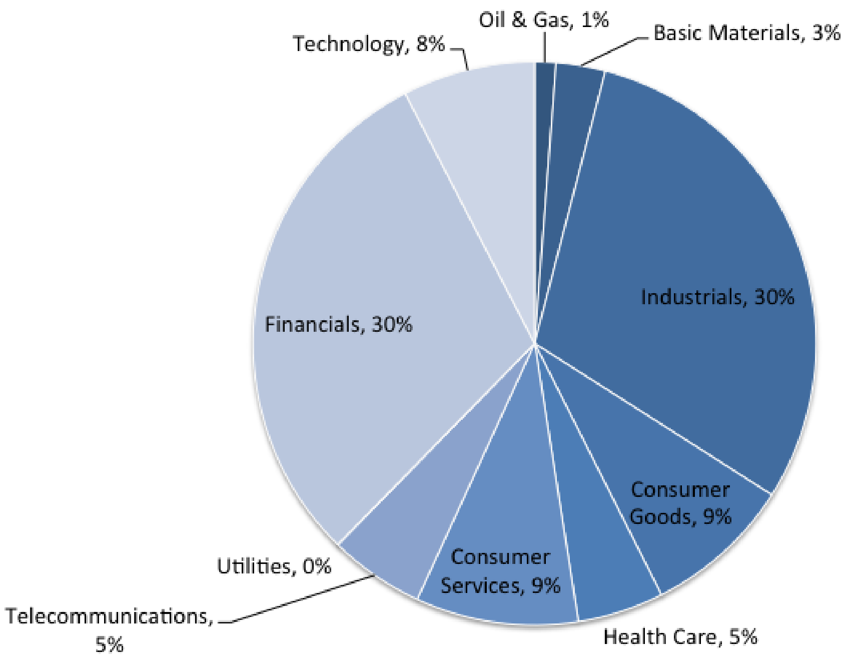


Figure 5: The distribution of capital weights for different industries in OMXSB, June 2013.

3.2 Portfolio Optimization

To track a specific index means to invest in a portfolio that follows the movements of the index to the best extent possible. As previously mentioned, full replication of an index do imply high cost, hence it is not best practice when tracking an index. A better method is to reduce the dimension of the index and create a portfolio that includes fewer stocks, but still follows the index movements resulting in a minimal tracking error. Atamtürk & Gollamudi (2013) means that the main problem faced for the investor is to decide which subset of securities to include and what capital weight should be assigned respectively. How these problems can be solved is presented in the subsequent subsections.

3.2.1 Tracking Error

First and foremost the term *tracking error* should be defined. The tracking error is some measure of the deviation between portfolio value and index value. One measurement could be absolute value deviation, i.e., *abs*(index value − portfolio value). A more comprehensible measure is the percentage difference in value, which is how tracking error will be interpreted in this thesis, defined in Equation (1). To ensure that the tracking error gets and remains low, the replicating portfolio holdings should be rebalanced continuously, e.g., daily, according to index movements.

$$\text{Tracking Error} = \left| \frac{\text{Portfolio Value}}{\text{Index Value}} - 1 \right|. \tag{1}$$

3.2.2 Quadratic Minimization

The basic method for portfolio optimization is the *mean-variance model*, which finds the optimal portfolio weights w minimizing the variance of the portfolio return for a given expected return R, i.e.,

$$\begin{aligned} \min_{w} \quad & w^\top Q w, \\ \text{s.t.} \quad & r^\top w = R, \end{aligned} \tag{2}$$

where Q is the covariance matrix for the security returns, r. In this model the investor can vary R and observe the trade-off between risk, i.e. variance in portfolio return, and expected return. However, the model ignores many considerations and possible constraints for an investor. As for the restriction on portfolio return set in this thesis, to track a multidimensional index, another portfolio optimization method is needed. The function optimized is, instead of Equation (2), the total active risk relative to a benchmark portfolio, e.g., an index, with weights w^b subject to some additional constraints on return, short positions etc., see Equation (3) below.

$$\begin{aligned} \min_{w} \quad & \sqrt{(w - w^b)^\top Q (w - w^b)}, && \text{(total active risk)} \\ \text{s.t.} \quad & r^\top w \geq R, && \text{(return constraint)} \\ & \sum w = 1, && \text{(budget constraint)} \\ & w \geq 0, && \text{(no short positions allowed)} \end{aligned} \tag{3}$$

where r is the exponentially weighted average logarithmic return for each stock in the portfolio and R is the return of the index portfolio

The covariance matrix Q for n securities can be constructed according to (4), where σ is the standard deviation for the stock returns and ρ is the correlation.

$$Q = \begin{bmatrix} \rho_{1,1}\sigma_1^2 & \rho_{1,2}\sigma_1\sigma_2 & \cdots & \rho_{1,n}\sigma_1\sigma_n \\ \rho_{2,1}\sigma_2\sigma_1 & \rho_{2,2}\sigma_2^2 & \cdots & \rho_{2,n}\sigma_2\sigma_n \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n,1}\sigma_n\sigma_1 & \rho_{n,2}\sigma_n\sigma_2 & \cdots & \rho_{n,n}\sigma_n^2 \end{bmatrix} \tag{4}$$

For the covariance matrix to be valid it must be based on a symmetric and *positive-semidefinite* correlation matrix, i.e., the correlation matrix must have eigenvalues larger or equal to zero. In Jäckel (2002) it is stated that slight inconsistencies in the historical data used increases the risk of obtaining an unvalid correlation matrix. This risk also increases as the number of assets grows. Hence, this is something one must pay attention to before continuing further analysis with the covariance matrix.

3.2.3 Principal Component Analysis

If having the attention of tracking an index with a portfolio of lower dimension than that of the index, one needs to select stocks in a clever way. The most logical approach is to include those index stocks that reflects most of the index performance. *Principal Component Analysis* (PCA) is a method widely used for extracting relevant information from noisy data sets. By orthogonal transformation the method converts a data set, with possibly correlated variables, into linearly uncorrelated variables, i.e., *principal components*, also called *factors*. If conducting a PCA on a covariance matrix for stock returns, such as the above described matrix Q, the resulting principal components should give a hint of which stocks explains most of the index return.

The procedure is based on the fact that a symmetric matrix can be expressed in terms of its eigenvalues and eigenvectors. Assume that the matrix considered is the covariance matrix Q above. The matrix can be expressed as $Q = \Gamma\Lambda\Gamma^\top$, where Λ is a diagonal matrix with the eigenvalues of Q, $\lambda_1, \ldots, \lambda_n$, in the diagonal. Γ is an orthogonal matrix with columns $\gamma_1, \ldots, \gamma_n$ corresponding to the standardized eigenvectors of Q. The principal components, P, can be expressed as:

$$P = \Gamma^\top \left(r - \mathbb{E}[r]\right), \tag{5}$$

where r is the data observations, in this case logarithmic stock return observations. The principal components have $\mathbb{E}[P] = 0$ and $Cov(P) = \Gamma^\top Q\Gamma = \Gamma^\top\Gamma\Lambda\Gamma^\top\Gamma = \Lambda$, which shows that the principal components are uncorrelated. Without loss of generality Λ and Γ can be ordered so that the eigenvalues are sorted in descending order. For sorted eigenvalues, the ratio expressed in Equation (6) represents the amount of variability explained by the first j principal components, when $j \leq n$.

$$\text{Lambda Ratio} = \frac{\sum_{k=1}^{j} \lambda_k}{\sum_{k=1}^{n} \lambda_k}, \tag{6}$$

The first principal component, with corresponding eigenvalue λ_1, explains the greatest amount of the total variation of the data, and the second explains the greatest amount of the remaining variation and so on. If a principal component has a corresponding low eigenvalue, the factor has little explanatory power of the data. Hult et al. (2012) states that for a good approximation of a data set one regularly only needs 2-3 factors. To conclude which original variables, in this case which stocks, that are of the greatest importance for each principal component one can turn to the *factor loading*, which is the correlation between the original variables and the principal component. The original variables with the largest correlation are those that are most important.

PCA is a commonly used data-reduction technique, mostly providing useful results. However, one should be careful before drawing definite conclusions. One pitfall could be that when applying PCA on a covariance matrix, where the original variables have very different sample variances, the variables with the highest variance will dominate the first principal component. The solution to this problem is to standardize the data and then apply PCA on the standardized data set's correlation matrix instead.

3.2.4 Bloomberg Performance Attribution Model

Evaluation of portfolio performance can give insight in potential improvements in portfolio formation or support future strategy decisions. Especially when trading a portfolio constructed as a dimension reduction of an index it would be useful to track relative performance versus the index performance, i.e., active return. Bloomberg Professional Services provides that kind of tool, presented by Gan (2013). The tool is called *Performance Attribution Model* and is based on the assumption that active return can be calculated by assessing return contribution to a set of factors, e.g., industries. Gan argues that active return can be decomposed into *Allocation* and *Selection Effects* as described in Equation (7).

$$\text{Active Return} = \underbrace{\sum_{s=1}^{S} (w_s^P - w_s^B)(R_s^B - \overline{R^B})}_{\text{Allocation}} + \underbrace{\sum_{s=1}^{S} w_s^P (R_s^P - R_s^B)}_{\text{Selection}}, \tag{7}$$

where w_s is the weight for certain industry s in the portfolio (P) and benchmark (B), R_s represents the return attributed to an industry and $\overline{R^B}$ is the weighted average return for all industries in the benchmark.

Allocation refers to the capital allocation assigned to different industries. To underweight an industry, i.e., $w_s^P < w_s^B$, with inferior return or overweight an industry with superior return, relative to the average benchmark return, gives positive contribution to active return. Selection effect origins from the selection of portfolio stocks. The term gives positive contribution to active return if the portfolio return attributed to a certain industry is higher than the benchmark return in the same industry. If tracking the two components of active return one can evaluate decisions about capital allocation and stock selection. Hence, it can give insight about if the dimension reduction has been done in an appropriate way.

3.3 Transaction Cost Analysis

3.3.1 Transaction Cost Overview

According to Glanz et al.(2003) portfolio managers claim that transaction costs account for around 1% of total trade costs when trading liquid assets, but can be as high as 2-3% for trades with illiquid assets or trades during adverse markets conditions. The ones generally described as the largest contributors to transaction costs are presented below.

Market impact cost is according to Almgren et al. (2005) the most important one to control in order to improve overall performance. It can be explained as the price change for a stock due to a particular trade or order. Kissel (2006) gives two reasons why this cost occurs, the first one being the order's liquidity demand and the second reason is the information leakage caused by placing the order. The liquidity demand forces investors to pay a premium (buy orders) or provide discounts (sell orders) to attract a counterpart. Glanz et al. (2003) states that information leakage occurs when the market interprets the trade as a signal that the stock is under- or overvalued. Market impact depends mostly on order size and participation rate, originated from chosen execution strategy, but also on price volatility and prevailing market conditions. Having a non-aggressive trading strategy and dividing large orders into small trades over a longer time period can, according to Spatt (2010), minimize market impact. For high liquid assets the market impact is small, implying low transaction costs even for substantial order sizes.

Another hidden transaction cost is *timing risk*. This refers to the uncertainty of the estimated transaction cost. One part of timing risk is price volatility and the other one is liquidity risk. Kissel (2006) states that price volatility can impose an unexpected change in the stock price independent of the presence of the order. Furthermore, liquidity risk is connected to unexpected low liquidity on the market that will impose high market impact if the order is completed. Having a short trade horizon, meaning trading in an aggressive manner, can minimize timing risk.

Opportunity cost is a hidden cost that represents the lost profits or the cost of not being able to fully complete an order. Glanz et al. (2003) means that the reason for this often is lack of liquidity in the market, adverse price movements, or both. For example, suppose that a trader decides to buy 200 000 shares of a stock, traded at a currently low price. However, throughout the day he only executes 150 000 shares due to a non-aggressive strategy originated from a desire to trade with minimal market impact. Then, if the price has increased the next day when he wants to execute the final 50 000 stocks, he has lost an opportunity to buy at a low price. An aggressive trading strategy, i.e., short trade horizon with potentially high participation, can minimize opportunity costs.

Obviously, these three costs are tightly connected to one another. A cost-reduction of one transaction cost can lead to an increase of another. For example, if a trader wants to reduce market impact by trading in a non-aggressive manner, the trader experience higher timing risk and opportunity costs since the trading horizon is prolonged. Glanz et al. (2003) refers to this trade-off between risk and market impact as “The Traders Dilemma”.

Market impact cost is, even though it is hidden on beforehand, fairly easy to measure post-trade. When it comes to timing risk and opportunity cost, much is depending upon the preferences of each individual trader. Therefore, market impact cost is the transaction cost that most TCA-models focus on.

3.3.2 TCA in the Investment Process

Madhavan (2002) refers to the investment process as a cycle, illustrated in Figure 6. He suggests that the first step is to decide an investment strategy, defining objective and horizon for the investment. When this is settled, one should make decisions about which stocks to invest in and what capital weight to assign to each stock. Before starting the trade, Madhavan means that a TCA should be implemented, predicting future transaction costs, allowing the trader to predict the best execution strategy. This pre-trade analysis could be based on historical data on price, liquidity and risk.

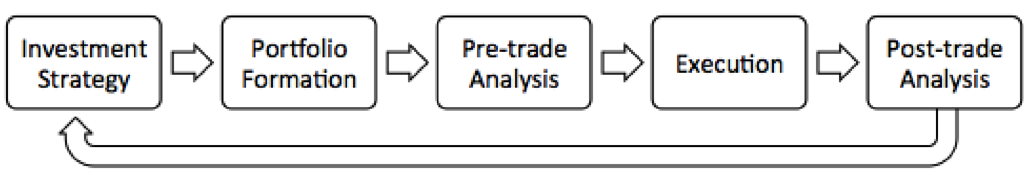


Figure 6: Scheme of Madhavan’s investment process where a pre-trade analysis should precede the execution.

There are many models eligible for predicting transaction costs. In the subsequent section 3.4 one of the most commonly used transaction cost models is introduced and in section 3.5 a modification of this model is presented and explained.

After the order is executed according to the determined strategy, the performance of the trade is evaluated in a post-trade analysis. In this stage the actual transaction cost can be measured. Information from the post-trade analysis can be used as feedback when deciding investment strategies for future trades.

3.4 The Almgren Model

A detailed study of market impact transaction cost estimates is provided by Almgren et al. 2005 which is based on previously published works by Almgren and Criss (2000) and Almgren (2003). The goal of this model is to calculate the *realized market impact costs* based on order size and duration. It is based on the separation of a trade's *temporary* and *permanent impac*t on the market where the first one dissipates over time and the second one remains. The concept behind Almgrens model is that the permanent impact can be measured, post-trade, as the price change from arrival price[8] 30 minutes after the end of an order. Almgren argues that by that time the temporary impact is gone, hence all that remains is the permanent impact. The permanent impact can then be used to calculate the temporary impact via Equation (8), where the market impact is estimated as the difference between arrival price and average execution price.

$$\text{Temporary Impact} = \text{Market Impact} - \frac{1}{2}\text{Permanent Impact}. \tag{8}$$

After an estimation process in several steps based on a large sample of data from Citigroup US, Almgren arrives at Equations (9) and (10) to predict the permanent impact I and the realized market impact J based on trade size and trade time. To simplify the model, Almgren states that the rate of trading is constant in volume time.

$$I = \gamma \times \sigma \times \frac{\text{size}}{ADV} \times \left(\frac{\Theta}{ADV}\right)^{\delta}, \tag{9}$$

$$J = \frac{I}{2} + \text{sgn}(\text{size}) \times \eta \times \sigma \times \left|\frac{size}{ADV \times T}\right|^{\beta}, \tag{10}$$

where size is total order size, ADV is average daily volume, T is the duration of the trade (in days) and σ represents the daily volatility. Furthermore, the factor $\left(\frac{\Theta}{ADV}\right)$ is a liquidity factor and γ, δ, η and β are model parameters estimated by regression on the data set.

For further reading about the Almgren model the reader is referred to the work by Almgren et al. 2005.

[8] Arrival price is the price at which trade is initiated

3.5 The PAR-model

3.5.1 Overview of the Model

Almgren's work has made a great contribution to the field of transaction cost analysis. However, his model has been accused of being too static. According to Rashkovich and Verma (2012), the fix amount of time Almgren waits to capture permanent impact is the major drawback of his model. Permanent impact of a trade with participation rate of only 1%, taking 2 minutes to execute, and a trade with participation rate of 30%, taking 2 hours to execute, are both measured after 30 minutes in the Almgren model. It is a reasonable assumption that these trades, with such different characteristics, will have different impact on the market. In 2012, Rachkovich et al. presented a more dynamic transaction cost model, based on the assumption that participation rate greatly affects the magnitude of the temporary impact. They introduced *Participation Arrival Reversion* (PAR), defined in Equation (11), as the time lag from order execution start until the temporary impact should be measured. This model is hereinafter referred to as the PAR-model.

$$\text{PAR} = \min(\text{participation \% minutes*}, 0.5 \times \text{duration}, 30 \text{ minutes}), \tag{11}$$

*For each 1% of participation, wait 1 minute to measure temporary impact

The PAR-model suggest that the post-trade measure for temporary impact is the price change from arrival price. For a trade with 1% participation one will wait one minute to capture the temporary impact and for a trade with 25% participation, one will wait 25 minutes. This is done in order to capture the impact as close to the source, i.e., the order execution, as possible. Two practical considerations with PAR are made: the first one being that the time one waits to capture temporary impact cannot be larger than half the duration of the trade; the second is that to ensure that the model includes enough trades close to the end of the day, trades with a higher participation rate than 30% will still be measured after 30 minutes. From the observed temporary impact, the permanent impact is calculated via Equation (12).

$$\text{Permanent Impact} = \text{Market Impact} - \frac{1}{2}\text{Temporary Impact}, \tag{12}$$

where market impact is the change from arrival price to average execution price.

One can distinguish two conceptual differences from the Almgren model. First; the *time lag* the two models wait to capture the impact, and second; *what kind* of impact being measured – Almgren measures permanent impact while the PAR-model measures the temporary impact. The authors find the PAR-model assumptions being more intuitive thanks to the dynamic approach of measuring transaction costs. For this reason, the PAR-model will be the basis for the TCA implemented in this thesis.

3.5.2 The Cost Components Reconsidered

When designing the formula for predicting market impact transaction costs using the PAR-model, data from more than 250 buy-side firms world wide were collected. Some filters were applied before including the orders in the data set[9]. After filtering 65 000 orders remained (all from the US market). These orders were used to calibrate the model. Rashkovich et al. divided the market impact transaction cost into three cost components: *instant impact*; *temporary impact*; and *permanent impact*, see Equation (13).

$$\text{Transaction Cost} = \text{Instant impact} + \text{Temporary impact} + \text{Permanent impact}. \quad (13)$$

Formulas for these components was found, which are further described below, and the model parameters used were obtained via regression. The parameter values are shown in Table 1.

Parameter	Value
α	0.023 ± 0.0014
β_1	0.76 ± 0.06
β_2	0.19 ± 0.04
γ	0.030 ± 0.0017
η	0.81 ± 0.08

Table 1: Parameter values in the PAR-model.

Rashkovich et al. (2012) states that instant impact cost occurs when trading through the bid-ask spread[10]. An aggressive execution strategy (with high participation rate) forces a trader to cross deeper into the spread than a non-aggressive strategy and will therefore suffer from higher transaction costs. Their research found that a participation of 5% would cross one quarter of the spread whereas a participation $\geq 30\%$ fully cross the spread. This is illustrated in Figure 7 in the case of a buy order. They concluded that the factor describing how much a trade would deviate from the mid price is linear and can be expressed as λ in Equation (14).

$$\lambda = [-0.25 + 3 \times (\max(\min(0.3, \frac{\text{participation}}{100}), 0.05) - 0.05)], \quad (14)$$

where participation is given in percent. Notice that a participation rate of 13.3% will cause $\lambda = 0$, and even lower participation will lead to $\lambda \leq 0$. This because a non-aggressive

[9] Order size $\leq$ 1000 shares, Market cap $\neq$ micro, Order duration $\geq$ 2 min and $\leq$ 1 day, 30-day volatility $\geq$ 8 and $\leq$ 100, Size/ADV $\geq$ 1% and $\leq$ 100%, Participation % $\geq$ 1% and $\leq$ 100%, Order life price momentum $< |3\%|$, Realized market impact $\leq |500|bp$, Country = United States, Dates = June 1, 2011, to May 31, 2012

[10] I.e., trade at a price deviating from the mid price $= \left(\frac{\text{ask price} - \text{bid price}}{2}\right)$

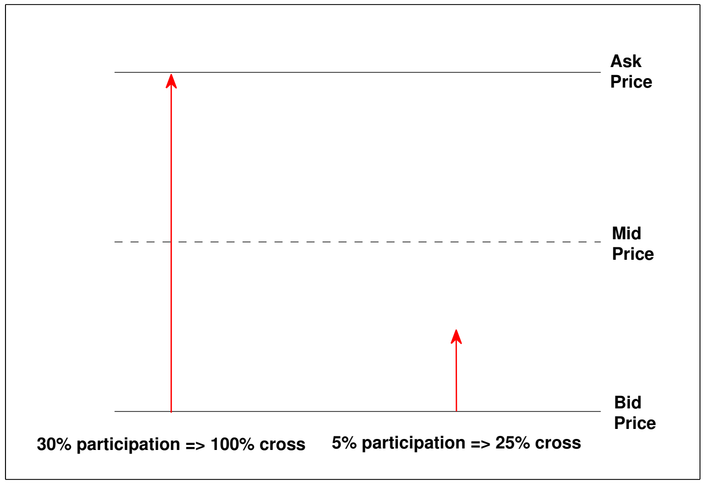


Figure 7: Rashkovich et al. suggest that a participation of 5% would cross one quarter of the spread whereas a participation $\geq 30\%$ fully cross the spread (buy order).

execution strategy allows the trader to wait until an eligible counterpart arrives, hence the trader do not have to cross over the mid-price. Rashkovich and Verma arrived to the conclusion that the instant impact factor could be estimated using the following formula:

$$\text{Instant Impact} = \lambda \times \text{bid-ask spread}, \tag{15}$$

where bid-ask spread is in percent. To ensure stability of the instant impact factor, Rashkovich et al. argues that one should use the average bid-ask spread over the last five trading days. Since λ can be negative this could cause a negative instant impact cost, and possibly a negative transaction cost. This is not practically possible, hence the instant impact factor is said to be zero if participation rate is lower than 13.3%.

In the previous subsection temporary impact was post-trade measured as the price change from arrival price after PAR, calibrated on participation rate alone, see Equation (11). However, Rashkovich et al. found that when predicting the temporary impact one could not only consider participation rate but also needed to add duration as a component in order to scale the cost with increasing order size[11]. Participation rate versus duration mirror the level of aggressiveness of an order. This because when decreasing duration for

[11] A large trade order with long duration is expected to imply a larger temporary impact than a small trade order with short duration and the same participation rate. Thus, duration seems to be an appropriate scale factor for the temporary impact

a fix order size, the participation rate is forced to increase, i.e., the strategy becomes more aggressive, if the order is to be fully executed. This represents the preferred strategy for a trader with low risk tolerance in terms of opportunity cost and timing risk. The opposite strategy, long duration and low participation, would represent a non-aggressive strategy with high risk tolerance. To fully capture this characteristic in the temporary impact, Rashkovich et al. found that it was not enough to use only participation and duration, but when adding the annualized volatility, σ, over the last 30 trading days, the temporary impact factor behaved as expected, resulting in Equation (16). The parameters α , β_1 and β_2 are obtained via regression and T is the duration of the trade (in days).

$$\text{Temporary Impact} = \alpha\sigma \times \text{participation}^{\beta_1}(T)^{\beta_2}. \tag{16}$$

When calibrating the formula for permanent impact, Rachkovich and Verma assumed that it would only depend upon the relation between order size and ADV. However, they found it appropriate to scale also this factor by the annualized 30-day volatility, see Equation (17). The variable ADV is calculated over a 30-day moving window and the parameters η and γ are obtained via regression.

$$\text{Permanent Impact} = \gamma\sigma \left(\frac{\text{size}}{ADV}\right)^{\eta}. \tag{17}$$

As previously stated, the total transaction cost is the sum of instant, temporary and permanent impact, see Equation (13), thus the resulting transaction cost equation can be written as follows:

$$\begin{aligned} \text{Transaction Cost} = \quad & \lambda \times \text{bid-ask spread} && \text{Instant Impact} \\ & + \alpha\sigma \left(\frac{\text{participation}}{100}\right)^{\beta_1} (T)^{\beta_2} && \text{Temporary Impact} \\ & + \gamma\sigma \left(\frac{\text{size}}{ADV}\right)^{\eta} && \text{Permanent Impact} \end{aligned} \tag{18}$$

where λ is given in Equation (14) and bid-ask spread and participation is given in percent. Equation (18) gives the transaction cost as fraction of the trade cost per share.

4 Methodology

This chapter will clarify how the previously described models and methods are implemented in this thesis. The work flow should be easy to follow and give the reader a scheme of how all different parts, such as PCA and TCA, are connected.

4.1 Terms for Analysis

4.1.1 Data Description

The basis for this thesis is OMXSB data from the first trading day in June 2013 to the last trading day in November 2013. This timeframe is chosen because it lies between two OMXSB rebalancing periods, hence the included stocks remain the same over the whole period, except for the stock 'HOGA B' which was delisted from OMX Stockholm in October 18 and excluded from OMXSB in September 25. To simplify calculations and programming problems, we chose to divide our data set in two; the first being a test period[12] which is defined as the time period before 'HOGA B' is removed; the second period, including the remaining data, is defined as run period[13]. We assume that an investor commissions us to construct a portfolio ready to trade from October 3 (five days into run phase data) and onwards. The data before this date is seen as historical data, and all sequent data is assumed to be unknown.

The test period data is used for calculating parameters and analyzing different models later used in the run phase. The data in the run period is used to simulate trading processes for different investment strategies, referred to as test cases (for clarification see Figure 8). The test cases are further described in the subsequent subsection.

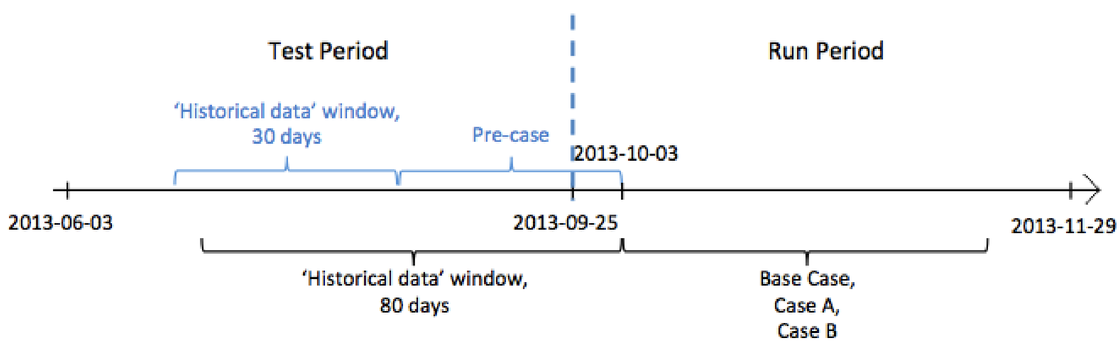


Figure 8: Decomposition of data.

[12] 2013-06-03 – 2013-09-24
[13] 2013-09-25 – 2013-11-29

The data we have available is comprised of daily stock data on trade size and volume-weighted mid-prices in one-minute ticks for all stocks included in OMXSB from June to November 2013 (68-69 stocks). We also have information on daily closing prices and average bid-ask spread for each stock. The bid-ask spread normally varies throughout the day depending on market liquidity conditions and the valuation of the underlying stock by sellers and buyers. The established assumption on the intraday pattern for bid-ask spread is a reversed 'J'-shape, presented by, among others, Groß-Klußmann et al. (2011). Thus, the bid-ask spread is largest at opening and decreases as the day passes. In the data used in this thesis, however, the bid-ask is fix for a window of one day, implying that the intraday dynamics are removed. For our results to be based on a more natural bid-ask spread we model it as a reversed 'J'-shaped curve with a mean equal to the average bid-ask spread given to us in the data.

Furthermore, we also have OMXSB index data, comprised of the daily stock weights in the index and index closing value. The index value is calculated so that the closing value on day t is equal to the index opening value day $t + 1$.

4.1.2 Cases to be Investigated

Four test cases are run on our data set. These will be referred to as Base Case, Case A, Case B and Pre-case, further described below.

The first case to be investigated is the **Base Case**, in which we fully replicate OMXSB. This case is used as a basis against which the other case results are compared. The Base Case is simulated in the run period, using an 80-day rolling data window, starting in the test period, to calculate parameters such as historical average daily volume and volatility. The trading strategy chosen in this case is the commonly used *volume-weighted* strategy. This strategy aims to trade with a constant participation throughout the day, hence the trade sizes will vary with the available trade volume. If trading with a constant relatively low participation, this strategy can be viewed as a non-aggressive market impact minimizing strategy. The volume-weighted trading strategy will predict how the intraday volume pattern will evolve and decide which order size to trade at what time during the day based on historical data.

The second case, **Case A**, is the first step towards trying to minimize transaction costs and improve portfolio performance. In this case we aim to trade a dimension reduced portfolio with the same volume-weighted trading strategy as in the Base Case. It is run on the same data as the Base Case, using the same historical parameters. However, since we have excluded stocks with undesired characteristics we expect that the transaction costs in Case A will be lower than in the Base Case. The dimension reduction is made based on results from a PCA, together with knowledge about which stocks are expensive to trade in terms of transaction cost as fraction of total trade cost. This will ensure that we include the stocks most important for index return as well as those being least expensive to trade. Because of the dimension reduction we also expect that this case will have some active return against OMXSB due to allocation and selection effect.

A potential improvement in minimizing transaction costs is to trade the same dimension reduced portfolio on the same data as in Case A, but to use another trading strategy. This case, **Case B**, uses a trading strategy based on predictions about which times during the day that are the least expensive to trade at. For this objective we have developed three transaction cost optimizing versions, referred to as TC-optimizers. From testing these versions in a **Pre-case** study we decide which one to implement for Case B. The Pre-case tests the TC-optimizers by trading a portfolio being a full replication of OMXSB in the test period (+ five days of run phase data) since we want to simulate a real situation where a customer commissions us to create a portfolio ready to start trade at October 3. Thus, the only data available at this time would be previous data. The TC-optimizers are described further in section 4.2. Case B follows the investment cycle described by Madhavan: a TCA is conducted before trading and based on its result, trade is executed (see Figure 6).

All cases are post-trade analyzed in terms of transaction cost, active return and tracking error during a trading period of 10 trading days (2013-10-03 – 2013-10-16). Since we do not actually trade, only simulate trading on historical data for each case, we cannot post-trade measure the realized transaction cost as in the PAR-model[14]. Instead we use the formula for predicting transaction costs with real-time input parameters as approximation[15], see Equation (18). This implies that we cannot rely on the calculated transaction cost's absolute value. However it reflects the size of the transaction cost paid, hence this gives us comparable test case results. One can also argue that the transaction cost prediction is reliable enough if measured over a longer period of time. An overestimation one day will probably be compensated by an underestimation another day. Both Case A and B are initiated to investigate trade with a dimension reduced portfolio and these two cases are also evaluated on their active return against benchmark.

To conclude the most important characteristics of the test cases:

Base Case: Full replication of OMXSB index, volume-weighted trading strategy

Case A: Trade with dimension reduced portfolio, volume-weighted trading strategy

Case B: Trade with dimension reduced portfolio, transaction cost optimizing trading strategy selected via a Pre-case study

[14]Market impact costs arise due to a certain order being disclosed to the market. Our historical data is not affected by our simulated trades, hence no market impact arise

[15]Such as available volume, actual trade size, bid-ask spread etc.

In order to run the above described test cases, we first need to decide some input variables such as maximal allowed participation, how many index instruments we want to track, i.e., how much money we initially want to invest in the portfolio, and acceptable tracking error. These variables are usually determined by the investor, but in order for him/her to make these decisions we need to provide information on how these two variables are connected to how many days it takes to reach an acceptable tracking error. We obtain this information by calculating the 30-day average ADV for each stock in the index as well as the 30-day average stock holding needed to fully replicate the index, based on the 30 last days before October 3. Based on these results we approximate the number of days it would take to obtain a tracking error of less than a certain limit for different values on maximal participation.

4.1.3 Assumptions for the Transaction Cost Model

As mentioned earlier, the market impact transaction cost prediction method used in this thesis is the PAR-model. The model requires the following assumptions on model parameters and variables:

Model parameters: The fixed parameters in Table 1, obtained via regression on US market data, are used without consideration of the confidence intervals.

Volatility: In this model, σ is the annualized average 30 day volatility. It is calculated on the logarithmic returns r_t based on the stocks' closing prices p_t, for each day in our historical data window of 80 days, $t = 1, 2, ..., 80$, see (19). σ_{daily} for each stock is obtained through Equation (20). This is converted to yearly standard deviation, σ_{yearly}, by multiplication of a factor $\sqrt{252}$[16].

$$r_t = \log\left(\frac{p_{\text{t+1}}}{p_{\text{t}}}\right), \tag{19}$$

$$\sigma_{\text{daily}} = \sqrt{\frac{1}{80-1}\sum_{t=1}^{80}(r_t - \bar{r})^2}, \tag{20}$$

$$\sigma_{\text{yearly}} = \sigma_{\text{daily}} \times \sqrt{252} \tag{21}$$

where $\bar{r}$ is the mean of the stock's logarithmic returns.

[16] We assume 252 trading days per year

Average Daily Volume: ADV is calculated as an exponentially weighted moving average over 30 days.

Bid-ask spread: We approximate the bid-ask spread to a reversed 'J'-shaped curve with an average equal to actual daily average bid-ask spread. The bid-ask used in the PAR-formula is a five-day average.

Size, Duration and Participation: The size is the order size one wants to trade and the time T is the duration of its execution. Participation is calculated as the fraction between the trade size and the available volume during T, see Equation (22).

$$\frac{\text{Size}}{\text{Available Volume}} = \text{Participation} \tag{22}$$

4.2 Preparations

4.2.1 Constructing the Dimension Reduced Portfolio

The first step towards constructing the dimension reduced portfolio, used in Case A and B, is to conduct a PCA on the stock return covariance matrix. For this objective we create a data set containing the stocks' logarithmic returns for an 80-day window of historical data, ending just before the portfolio trade period starts at October 3. The eigenvectors, $\gamma_1, \ldots, \gamma_n$, and eigenvalues, $\lambda_1, \ldots, \lambda_n$, for the data set's covariance matrix are obtained. The λ:s are used to calculate the lambda ratio, described in Equation (6). The result supports the decision of how many of the first principal components (PC) that are needed to accurately mirror the data. To determine which stocks are the most important for the chosen PC:s, we look at their factor loadings for each stock respectively. The factor loading can be obtained by looking at the value attributed to each stock in the eigenvector.

The second step is to obtain information on which stocks that are expensive to trade. We measure this in terms of fraction of the daily trade cost attributed to transaction costs. This variable will be referred to as TC_{frac}[17]. TC_{frac} for one day is obtained by predicting transaction costs when trying to trade a certain amount of each stock, equal to the fraction of the stock's ADV corresponding to trading with maximal participation throughout the whole day. To get a fair value on this variable we take the five day average TC_{frac}

Via a scoring formula, including results form both the PCA and the five day average TC_{frac}, we determine which stocks to include in our dimension reduced portfolio. The

[17] TC_{frac} = transaction cost/total cost. Total cost refers to the cost of trading the stock, i.e., stock price paid + transaction cost

results are weighted according to relative importance for our investigation. The skeleton for the scoring formula is displayed in Equation (23).

$$\text{Score}_i = \Omega_1 \times \underbrace{\sum_{k=1}^{N_{\text{PC}}} e_k f_{(i,k)}}_{\text{PCA results}} - \Omega_2 \times \underbrace{\text{TC}_{\text{frac}}}_{\text{TC-prediction}} \tag{23}$$

where Ω is a vector containing weighting factors for the PCA results and the TC-prediction, N_{PC} is the number of PC:s taken into consideration, e_k is the fraction between how much of the variance is explained by PC_k and the cumulative sum of variance explained by the N_{PC} PC:s. $f_{(i,k)}$ is the factor loading for PC_k assigned to stock i.

4.2.2 Transaction Cost Optimizing Trading Strategies

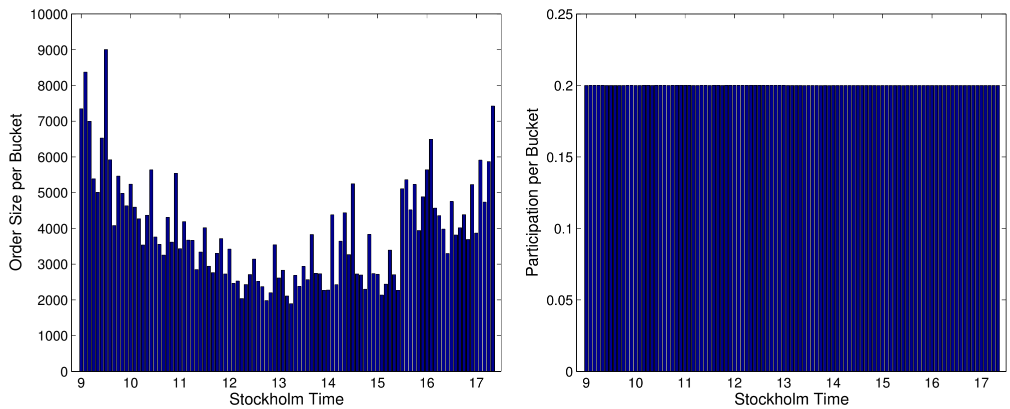
We have developed three versions of TC-optimizers with objective to predict time and size for optimal order execution in terms of transaction cost, given that we have a desired goal size which we want to trade each day. The prediction is based on the PAR-model formulas for calculating transaction costs. The versions are tested in a Pre-case study from which we are able to select the best TC-optimizer.

Of the PAR-model variables: volatility; ADV; and bid-ask spread are fix for each individual stock and day in the trade period, since they all are historical averages. Hence, these variables cannot be optimized. We also fix the duration to a specified fraction of the trading day in order to simplify the calculations. Thus, the remaining variables for our PAR-model are size and participation, where the relation between the two are described in Equation (22). Looking at Equation (18), we can see that transaction cost will increase with increased participation, i.e., larger order size, over some time period T. Evidently, finding optimal participation rate, and corresponding trade size, is key to minimizing transaction costs. For this objective the historical intraday liquidity curves, i.e., volume curves, are used to predict future volume patterns and finding optimal trading times where participation and trade size results in minimal transaction costs.

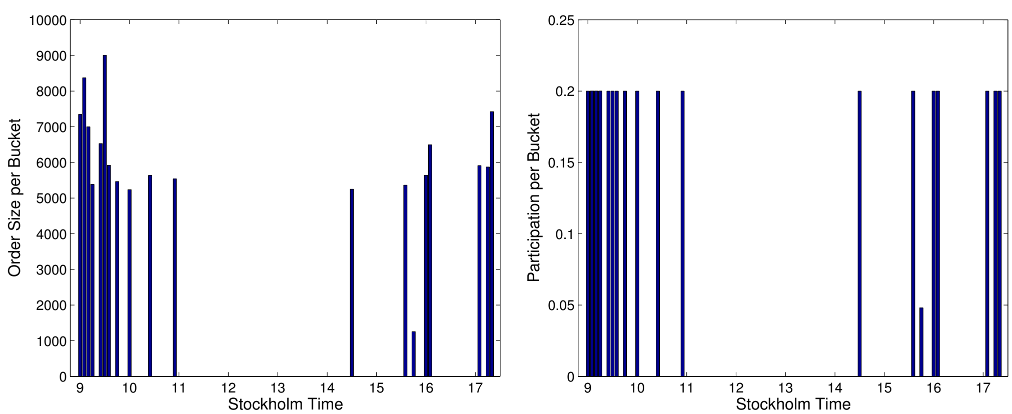
The different TC-optimizing versions tested in this thesis are described below. The input variables are volatility, ADV and bid-ask spread, as well as historical volume curves divided into five-minute buckets, meaning that the duration is fixed to five minutes[18]. Based on this data, together with a desired trade size, $\text{size}_{\text{desired}}$, and a constraint on maximal participation, referred to as part_{max}, the following methods optimizes execution time and order size. All three versions differentiate two scenarios. Scenario 1: desired size *is not* tradable during one day, i.e., $\text{size}_{\text{desired}} \geq \text{part}_{\text{max}} \times \text{ADV}$. Scenario 2: desired size *is* tradable during one day

[18] Hence, order size and participation are optimized based on $T = 5$ minutes/minutes in one trading day

Version 1: This method suggest trade with part_{max} throughout the whole day if Scenario 1 applies (see Figure 9a) which is equal to a volume-weighted strategy. In the opposite case, however, this model calculates predicted transaction cost per bucket under the assumption that the size to execute in each bucket is equal[19]. The five-minute buckets are ordered from lowest to highest transaction cost and trade is conducted, with part_{max}, in the in buckets with lowest predicted transaction cost until size is fully executed (see Figure 9a).



(a) Version 1, $\text{part}_{\text{max}} = 20\%$: Trade size and participation for Scenario 1 (desired size is not tradable during one day). Notice that the order size follows the same pattern as the intraday liquidity curve in Figure 1b.



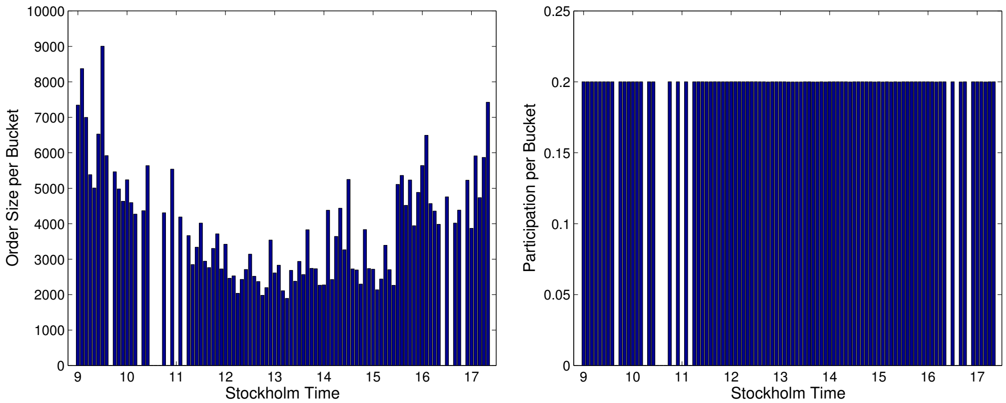
(b) Version 1, $\text{part}_{\text{max}} = 20\%$: Trade size and participation for Scenario 2 (desired size is tradable during one day). Trade is conducted only in buckets with the lowest predicted transaction costs.

Figure 9

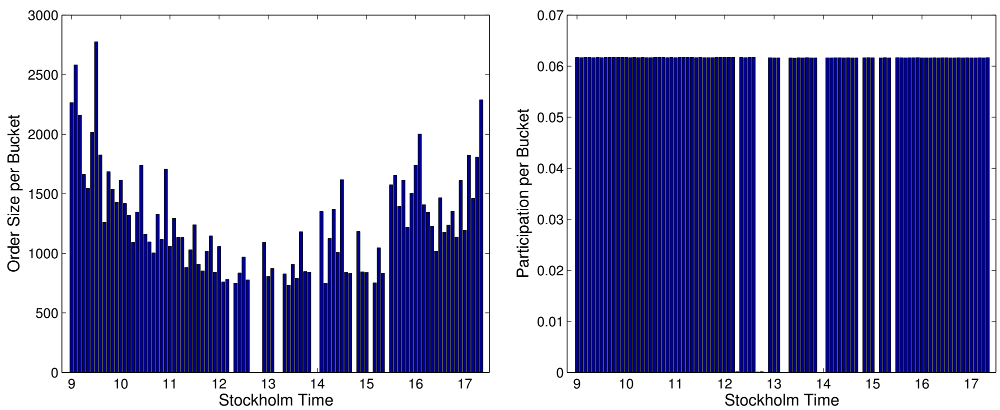
[19] $\text{size}_{\text{bucket}} = \text{size}_{\text{desired}}/\text{nbr of buckets}$

Version 2: This TC-optimizer start by predicting the transaction costs in each time bucket under the same assumption on equally sized orders as in Version 1. The buckets with higher transaction cost than a certain limit are excluded from the set of possible trade times. Version 2 has a limit that excludes the top 10% of the most expensive time buckets. In Scenario 1 this version suggests trading a size equal to $\text{part}_{\text{max}} \times$ available volume in the buckets with predicted transaction cost below the limit (see Figure 10a). When Scenario 2 applies, this method trades in the less expensive buckets using a volume-weighted strategy, i.e., constant participation equal to $\frac{\text{size}_{\text{desired}}}{\text{ADV}}$ (see Figure 10b).

Version 3: The only difference in this version compared to Version 2 is the way we calculate the limit for transaction costs. The limit in Version 3 is set to be the mean plus the standard deviation of all of the buckets' transaction costs. Apart from that this version suggests trading in the same manner as Version 2. For clarification on how this version predicts optimal trade look at the Figures 10a and 10b.



(a) Version 2, $\text{part}_{\text{max}} = 20\%$: Trade size and participation for Scenario 1 (desired size is not tradable during one day). Trade is excluded in buckets where predicted transaction costs exceeds a certain limit.



(b) Version 2, $\text{part}_{\text{max}} = 20\%$: Trade size and participation for Scenario 2 (trade size is tradable during one day). Notice that the participation in this case is only around 6%, hence we never trade through the bid ask spread. This implies that no instant impact factor is added to the predicted transaction cost

Figure 10

4.3 Trading Algorithm

The trading algorithm will be quite similar for all test cases, only differing in the way we calculate the portfolio weights and how trade times are chosen. Our trading algorithm will operate between 9:00 am and 5:25 pm since we do not want to participate in the pre-open and pre-close auctions because of the uncertainty of the price movements in the beginning and the end of the day.

The trading algorithm's objective is to trade stocks to obtain a portfolio that tracks OMXSB. The first step in the trading algorithm is to find the weights that we want to use as goal weights. If we want to preform a full replication of the index, as in the Base Case and Pre-case, we use the index weights as goal weights. However, if we want to exclude some stocks and create a dimension reduced portfolio, as in Case A and B, we use quadratic programming to find our weights. In these cases we decide the capital weights for each stock by optimizing the total active risk according to Equation (3). To do this we use the inbuilt Matlab function *quadprog* which returns a vector w that minimizes Equation (24).

$$\min(\frac{1}{2}w^\top Hw + f^\top w). \tag{24}$$

Here H must be a positive semidefinite matrix for the problem to have a finite minimum. We have to adjust the input variables to the inbuilt function in order for it to assemble Equation (3) and therefore we create H and f according to Equations (25) and (26) (see Appendix B for a more detailed explanation).

$$H = 2Q, \tag{25}$$

$$f = -2w^b Q. \tag{26}$$

By rewriting the problem this way we can use the ready-made Matlab function to find the optimal weights. Note that the optimal solution for Equation (24) also solves the squared root problem in Equation (3). To construct the covariance matrix Q, given in Equation (4), we need the standard deviation σ and the correlation ρ. σ is calculated as in Equations (19)-(21) and ρ is obtained via the log-returns calculated in (19). We control that the resulting covariance matrix is positive semidefinite which is a constraint for the optimization to work.

The constraints under which Equation (24) is minimized are those presented in Equation (3). The two last constraints, the budget and short position constraint, can easily be implemented in our quadratic programming tool. The return constraint, on the other hand, demands some calculations. We need this constraint to make sure that even though we trade a dimension reduced portfolio, the return will be at least that of the index. We use the logarithmic returns obtained from the closing prices for each stock and calculate a

30-day exponentially weighted moving average. The sum of our optimized portfolio weights times the exponentially weighted log-returns for each stock should be greater or equal to the total return of the index, i.e.,

$$\sum w_i r_i \geq R, \tag{27}$$

where r_i is the exponentially weighted log-return for stock i, w_i is the optimized weight and R is index return. Since the calculations are based on historical data and desired portfolio weights, we cannot fully ensure that the actual portfolio return a certain day is higher than index return. However, having this constraint increases the probability of the outcome being as desired.

After deciding goal weights w, we calculate the goal sizes, size^G, which represent how many stocks we need to have in our portfolio in order to obtain minimal tracking error. A portfolio with zero tracking error is a portfolio with a value equal to that of the index value multiplied by the number of index instruments the portfolio should track, i.e., Equation (28) is equal to Equation (29). When that equality holds, the desired holding for each stock, size_i^G, is given via Equation (30).

$$\text{Portfolio Value} = \sum_{i=1}^{n} \text{size}_i^G \times \text{price}_i \tag{28}$$

$$\text{Index Portfolio Value} = \text{Index Value} \times N \tag{29}$$

$$\text{size}_i^G = \frac{\text{Index Value} \times N \times w_i}{\text{price}_i}, \tag{30}$$

where N is the number of instruments and w_i is the stock i's weight in the portfolio.

When we have found the goal weights and corresponding desired portfolio holdings we start to simulate trade according to the different trading strategies' predictions on what quantity to trade at what time. The simulated orders assemble market orders since we submit a quantity which we want to execute, and trade is conducted if there is available volume meeting our demand. Placing market orders imply that we cannot control what stock price we have to pay, as can be done when placing limit orders. Since we are interested in comparing our test cases' trading strategies in terms of transaction cost, rather than total trade cost, we make the simplification that we always accept trading at the volume-weighted mid-price observed in our data set. This means that we never trade at the best available price, but not at the worst observed price either.

Each day we update size^G according to index price movements and check with our current portfolio holdings how many shares need to be traded to track the potential change. The Base Case and Case A trade according to a volume-weighted prediction, whereas Case B trades based on the results from the selected TC-optimizer's prediction. When simulating on 'new' data, however, the predictions cannot always be fulfilled because of lack of available volume, resulting in deviations from the pre-set strategy. Three different situations may arise when placing the orders. First, if available volume is equal to, or higher than historical volume at a certain time, the predicted size can be fully executed. Second, if available volume is lower than expected, we can only execute a fraction of the predicted size corresponding to $\text{part}_{\text{max}} \times$ available volume. Third and last situation: if there is no available volume then no trade is conducted. The transaction costs are calculated based on the actual outcome. As previously mentioned, we cannot measure the actual market impact from our trades since we only simulate trading on our data set. Instead we approximate the realized transaction costs by using the PAR-prediction formula with real input parameters for available volume etc.

To clarify the steps in the trading algorithm we have summarized the process below. The process is repeated every day in the trading period.

1. Find portfolio stock weights

   Base Case & Pre-case: Portfolio weights = Index weights

   Case A & Case B: Portfolio weights = optimal solution to Equation (24) subject to constraints described in (3)

2. Find the desired holding, i.e., goal size, for each stock via Equation (30)

3. Check with current portfolio holdings how many shares of each stock need to be traded, i.e., find the total order size

4. Decide trading strategy for executing the total order size. The decisions are based on historical data such as: volume curves; ADV; volatility and bid-ask spread

   Base Case & Case A: Divide the total order size into smaller orders so that the pre-set trading strategy equals trading with a volume-weighted trading strategy

   Case B: Use the TC-optimizer selected via the Pre-case. Predict which time buckets are the most expensive to trade in according to historical data. Exclude these buckets from possible trade times and distribute the total order size in the remaining time buckets according to historical volume

5. Simulate trade! Place market orders according to the different test cases trading strategies and trade if enough volume is available

6. Calculate the resulting transaction costs

5 Results

Results obtained from test data commence this chapter. These results serves as basis for decisions made by the imagined customer. Also, the Pre-case study conducted in the test period, supporting the selection of the best TC-optimizer for Case B, is presented. Furthermore the construction of the dimension reduced portfolio, based on PCA results and transaction cost predictions, is described. The remainder of the chapter is dedicated to present the results from the test cases, and ends with a summary of the obtained results.

5.1 Test Period Results

5.1.1 Investor Decisions

Maximal participation limits the volumes we can trade every day, defining the shortest trading horizon. The number of instruments (N) we want to track determines how much money to invest. Calculations providing support for the decisions about part_{max} and N are shown in Table 2. Usually an investor would decide these variables according to preferences. We assume that our imagined investor chooses to make an investment corresponding to 3 million index instruments[20] and that he/she accepts a tracking error of 1%. For a maximal allowed participation of 20-25%, calculations from test period data show that it would take approximately 4 and 2 days respectively to get a tracking error less than 1% when trading a full replication of the index. Our investor decides that a maximal participation of 20% suits his/her preferences in terms of timing risk and opportunity cost, i.e., level of aggressiveness. Subsequent test case results are based on these decisions.

	$\text{part}^1_{\text{max}}$	$\text{part}^2_{\text{max}}$	$\text{part}^3_{\text{max}}$	$\text{part}^4_{\text{max}}$
N	**10%**	**15%**	**20%**	**25%**
1×10^6	5	2	1	1
2×10^6	10	4	2	2
3×10^6	15	7	4	2

Table 2: Approximation for how many days it takes until tracking error for full replication of OMXSB is less than 1% depending on number of index instruments traded and maximal participation. Our imagined investor decides that he/she wants to invest in 3 million index instruments with a maximal participation of 20%.

5.1.2 Transaction Cost Optimizer Selection

In Case B we want to trade in a less expensive way compared to the volume-weighted method used in Base Case and Case A. We want to investigate whether predicting trans-

[20]This equals an investment of $624.3 \times 3,000,000$ SEK, where 624.3 is the value of OMXSB as of Oct 3

action costs and optimizing order size and trade time can improve performance.

From running the Pre-case with the three different TC-optimizing versions we could analyze and compare their results. In Figure 11 we can see that by trading based on Version 2 (V.2) and Version 3 (V.3) predictions, we reach a low tracking error quicker than for Version 1 (V.1). However, after five days of trade all three versions have reached approximately the same tracking error and in the end of the Pre-case period all tracking errors are close to the acceptable range of 1%. The reason why V.1 is a bit slower can be explained by the fact that when $\text{size}_{\text{desired}} \leq \text{part}_{\text{max}} \times \text{ADV}$ (Scenario 2) V.1 suggests that all day's trading can be conducted in a few buckets. If, however, the volume in those buckets this day is less than the historical volume, then the resulting trade size will be much lower than predicted. V.2 and V.3 will not suffer as much from this since they trade in nearly all buckets anyway. Furthermore, Figure 12 show that V.2 and V.3 are outperforming V.1 in terms of transaction cost per day and per share. This result is not surprising since even though V.1 predicts and excludes expensive buckets, it suggests trading with maximal participation in a few number of buckets instead of trading with a constant low participation in all remaining buckets. Hence, V.1 suggests a more aggressive trading strategy compared to V.2 and V.3. This implies both a high average transaction cost per share and total transaction cost per day due to market impact. From Figure 13 we can see that for the whole Pre-case trading period (10 days), V.2 and V.3 ends up with a total transaction cost being less than 1.25% of total trade costs while V.1 results in almost 1.5%. From these results we reject V.1 as TC-optimizer. Looking at transaction cost as part of total trade cost we can see that V.2 is slightly better than V.3, which is why we select V.2 as the TC-optimizer used in Case B.

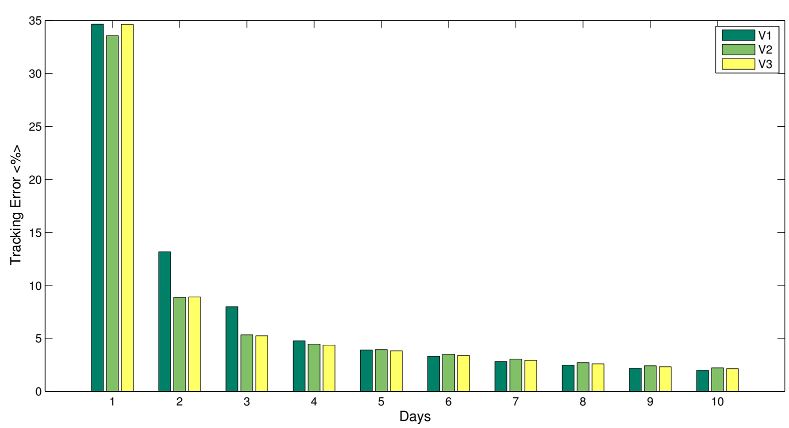


Figure 11: Tracking Error for the different versions during 10 days of trade ($N = 3 \times 10^6$, $\text{part}_{\text{max}} = 20\%$. Version 2 and 3 reaches a lower tracking error faster than Version 1.

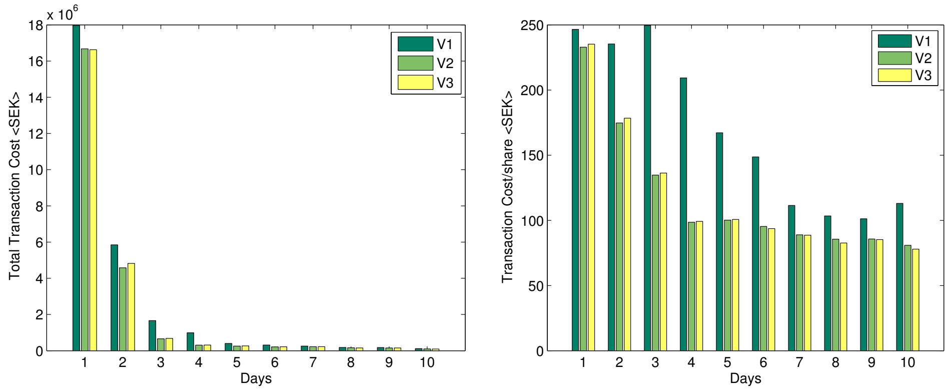


Figure 12: Transaction cost per day and version (left) and average transaction cost per share (right). Version 1 is more expensive than Version 2 and 3, both in terms of total transaction costs and in terms of transaction cost per share.

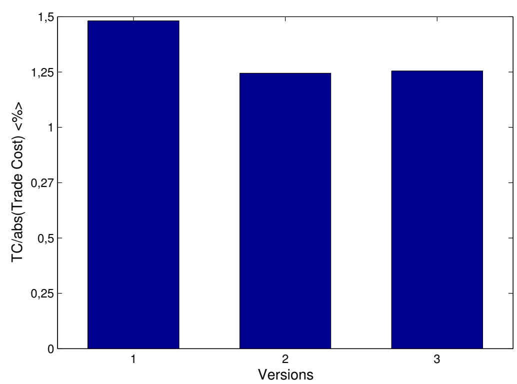


Figure 13: TC as % of Total Cost for the different versions. The result is obtained during 10 days of trade ($N = 3 \times 10^6$, $\text{part}_{\text{max}} = 20\%$). Version 2 is the least expensive version and will be selected as TC-optimizer in Case B.

5.2 Dimension Reduced Portfolio Construction

From the eigenvalues of the covariance matrix we calculate the lambda ratio. Figure 14 shows which explanatory power each principal component has on the variance in index return (bars) and their cumulative explanatory power (line). The first principal component explains more than 30% and has a correlation with the index portfolio of 97%. PC_1 together with PC_2 and PC_3 explains approximately 50% of the index return variation. We therefore conclude that these three PC:s are enough to include when scoring the stocks. To find which stocks that are of most importance for the PC:s we look at the stocks' individual factor loadings, i.e., correlation with PC_k ($k = 1, 2, 3$). Figure 15 show the distribution of the factor loadings for PC_1. Factor loadings for PC_2 and PC_3 are shown in Appendix C.2.

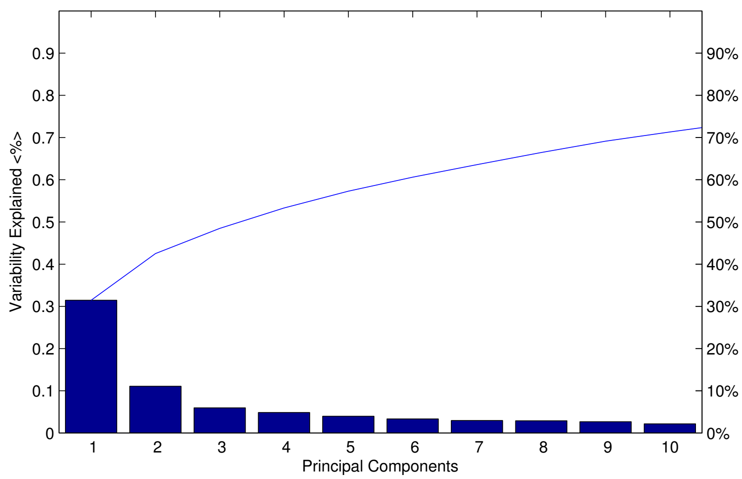


Figure 14: Lambda ratio for the first 10 principal components. PC_1 together with PC_2 and PC_3 explains approximately 50% of the index return variation.

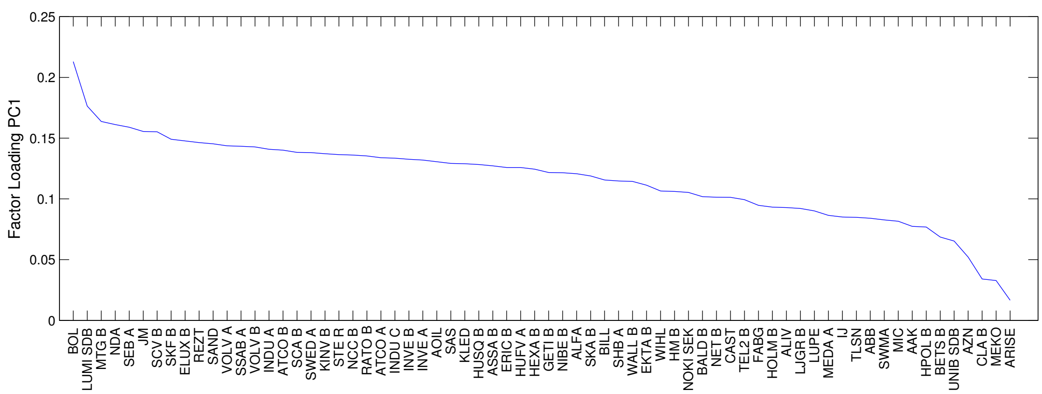


Figure 15: Factor loadings for the first principal component. Boliden has the highest and Arise Windpower has the lowest factor loading in the first principal component.

To see if our PCA result is reliable, we compare the stocks most important for PC_1 with the stocks that have the largest variance (see Appendix C.1). Since these are not consistent we can draw the conclusion that it was fine to conduct the PCA on the covariance matrix instead of on the standardized correlation matrix.

As shown in Figure 15, the first two stocks, being most important for PC_1, are Boliden ('BOL') and Lundin Mining ('LUMI SDB'). These companies are both in the Basic Materials industry, in the sector of Basic Resources (see Appendix A.1). Their primary market is Europe. From these similarities one would like to draw the conclusion that PC_1 mostly depends upon European-based Basic Material companies. But looking at the sequent companies: Modern Times Group ('MTG B'); Nordea ('NDA'); and SEB ('SEB A'), this conclusion seems unreasonable. MTG is an international media conglomerate and the last two are large Nordic banks. To find the scarlet thread defining what factor PC_1 stands for is not easy. This is one drawback with PCA: one can determine which the main drivers are but not what they actually stand for. For the purpose of this thesis, however, we confine ourselves with the result as it is and use the stocks' factor loadings in PC_{1-3} as one part of our dimension reduction scoring.

The second part of the scoring is the five day average TC_{frac}. We decide that we want more weight for the TC-prediction than for the PCA-result. This because we are most concerned with having minimal transaction costs. We therefore set the weighting factor in the scoring formula in Equation (23) to be $\Omega = [100; 200]$. Figure 16 below shows the stocks' scores in descending order. We decide to conduct a dimension reduction of 50%, thus we will include all stocks with score equal to, or higher, than 'HEXA B' (34 stocks). We find it reasonable not to reduce the dimension too much since we still want some differentiation for our portfolio risk. Furthermore we believe that reducing the dimension by less than 50% would not display the differences between the Base Case and the other cases with desired clarity.

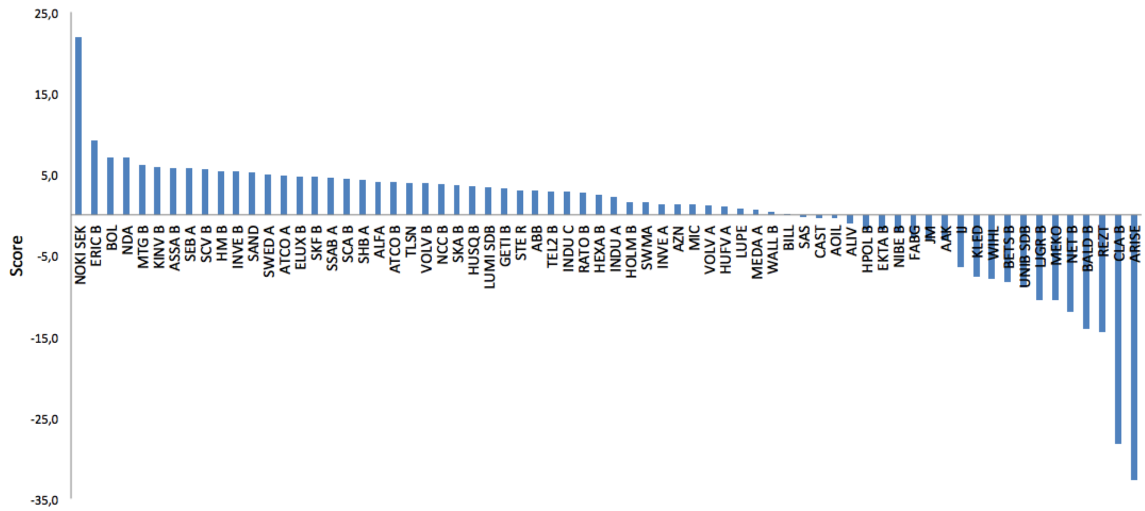


Figure 16: Resulting score for each stock. Stocks with score equal to, or higher than 'HEXA B' will be included in the 50% dimensioned reduced portfolio (34 stocks).

A full table displaying PCA results, TC-prediction and score for the stocks included in the dimension reduced portfolio is found in Appendix C.3 and a table for those excluded is found in Appendix C.4. The average TC_{frac} for all OMXSB stocks is 3.7%. This figure is reduced to 2.0% when taking the average TC_{frac} for the 34 stocks included in the portfolio, while it for the excluded stocks raise to 5.5%. Hence, we can conclude that via our scoring formula we have been able to exclude some of the most expensive stocks in terms of transaction cost.

5.3 Base Case Result

In this case we preform a full replication of the index and trade with a volume-weighted strategy over 10 trading days (2013-10-03 – 2013-10-16). Each day we get output data on stock- and industry level. Since the data on stock level is very detailed, we only show the results on industry level. The output is comprised of: portfolio weights; net cost (i.e., total cost excl. TC); net income (i.e., total income excl. TC); transaction cost and TC as fraction of total cash flow in and out of the portfolio[21], see Appendix D.2. These result tables could be shown to an interested customer on a daily basis, and give him/her support for suggesting changes in the portfolio strategy. Below, we display a summary of these results on day 10 plus the active return in each industry (Figure 17). In Figure 18 a day by day summary of the performance measures and the active risk against OMXSB are displayed.

Industry	Total Net Cost <SEK>	Total Net Income <SEK>	Total TC <SEK>	TC/abs(Trade Cost) <%>	Portfolio Weight <%>	Active Return <%>
Oil and Gas	22 192 127	0	338 517	1.5	1.22	0.00
Basic Materials	48 075 740	0	824 269	1.69	2.66	0.00
Industrials	539 324 454	628	6 195 887	1.14	29.03	0.06
Consumer Goods	150 600 384	164	2 252 815	1.47	8.16	0.01
Health Care	90 630 706	0	1 160 091	1.26	4.69	0.00
Consumer Services	202 800 645	272	2 118 888	1.03	10.91	0.02
Telecommunications	105 279 592	128	785 906	0.74	5.78	0,00
Utilities	1 075	0	16	1.44	0.00	0.00
Financials	527 275 183	627	6 668 101	1.25	29.44	0.14
Technology	152 458 471	128	1 552 196	1.01	8.12	0.00
Total	**1 838 638 378**	**1 947**	**21 896 687**	**1.18**	**100.00**	**0.24**

Figure 17: Base Case: performance summary after 10 days. Results are on sector level where one can see how different sectors varies in performance and weights.

Day	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
TC/abs(Trade Cost) <%>	1.22	1.14	1.14	1.15	1.16	1.16	1.17	1.17	1.17	1.18
Active Return <%>	0.00	33.51	3.57	0.8	0.67	0.58	0.42	0.32	0.27	0.24
Active Risk <%>	0.54	0.32	0.25	0.21	0.19	0.16	0.14	0.13	0.13	0.12
Tracking Error <%>	31.11	8.14	4.87	4.13	3.49	2.94	2.54	2.24	1.99	1.76

Figure 18: Base Case: performance results where TC/abs(Trade cost) is cumulative and the other measurements are day by day. Acceptable tracking error ($\geq 1\%$) is not reached during the 10 day period.

[21] TC/(TC + Net Cost + Net Income)

5.4 Case A Result

In Case A we trade our dimension reduced portfolio, comprised of the 34 stocks with highest scores. The same volume-weighted trading strategy as in the Base Case is used. The portfolio is equal to a dimension reduction of OMXSB of 50%. Apart from getting the same output data as in the Base Case (shown in Appendix D.3), we also calculate the components of active return from the Bloomberg Performance Attribution Model: allocation and selection effect. These components are calculated from day 2 and onwards since their formulas demand portfolio return which can only be obtained by comparing portfolio value on day t and $t-1$. Figure 21 shows the Performance Attribution results for day 10, for all days' results see Appendix D.4.

Industry	Total Net Cost <SEK>	Total Net Income <SEK>	Total TC <SEK>	TC/abs(Trade Cost) <%>	Portfolio Weight <%>	Active Return <%>
Oil and Gas	0	0	0	0.00	0.00	0.01
Basic Materials	39 396 456	6 426 317	608 669	1.31	1.82	-0.06
Industrials	731 581 845	22 461 014	8 503 085	1.12	37.5	0.36
Consumer Goods	116 279 283	2 222 322	1 542 432	1.28	6.02	-0.01
Health Care	22 961 362	1 138 191	238 940	0.98	1.04	0.01
Consumer Services	204 396 903	4 844 620	1 735 853	0.82	10.55	-0.01
Telecommunications	182 979 096	8 106 920	1 274 138	0.66	9.45	0.09
Utilities	0	0	0	0.00	0.00	0.00
Financials	486 796 943	15 916 943	5 135 596	1.01	25.81	-0.18
Technology	151 154 105	1 502 493	1 507 005	0.98	7.82	-0.06
Total	**1 935 545 993**	**62 618 819**	**20 545 718**	**1.02**	**100.00**	**0.14**

Figure 19: Case A: performance summary after 10 days on sector level. Total TC/abs(Trade cost) is lower than for Base Case.

Day	1	2	3	4	5	6	7	8	9	10
TC/abs(Trade Cost) <%>	1.14	1.07	1.05	1.05	1.04	1.04	1.03	1.03	1.02	1.02
Active Return <%>	0.00	46.19	6.94	1.77	0.66	0.41	-0.01	-0.11	-0.04	0.14
Active Risk <%>	0.96	0.69	0.64	0.62	0.61	0.62	0.62	0.62	0.63	0.64
Tracking Error <%>	37.39	8.86	2.66	0.97	0.34	0.06	0.04	0.07	0.13	0.01

Figure 20: Case A: performance results where TC/abs(Trade cost) is cumulative and the other measurements are day by day. Acceptable tracking error is reached day 4.

Industry	Portfolio Return <%>	Allocation <bps>	Selection <bps>	Active Return <%>
Oil and Gas	0.00	0.55	0.00	0.01
Basic Materials	-2.66	-0.21	-5.35	-0.06
Industrials	0.68	-3,00	39.01	0.36
Consumer Goods	-0.4	0.4	-1.38	-0.01
Health Care	-1.18	1.56	-0.79	0.01
Consumer Services	-0.46	0.09	-1.19	-0.01
Telecommunications	1.25	2.01	6.7	0.09
Utilities	0.00	0.00	0.00	0.00
Financials	-0.19	-1.63	-16.7	-0.18
Technology	-0.42	-0.04	-5.75	-0.06
Total	**0.15**	**-0.26**	**14.57**	**0.14**

Figure 21: Case A: Active Return (day 10) is positive and mostly generated by stock selection.

5.5 Case B Result

Case B trades the dimension reduced portfolio with the selected TC-optimizing trading strategy V.2. Same result tables as for Case A are obtained and the full results are shown in Appendix D.5. All active return results are shown in Appendix D.6. For active return components on day 10, see Figure 24.

Industry	Total Net Cost <SEK>	Total Net Income <SEK>	Total TC <SEK>	TC/abs(Trade Cost) <%>	Portfolio Weight <%>	Active Return <%>
Oil and Gas	0	0	0	0.00	0.00	0.01
Basic Materials	39 394 886	6 435 823	626 536	1.35	1.82	-0.06
Industrials	729 394 831	20 656 798	8 507 122	1.12	37.5	0.36
Consumer Goods	116 224 916	2 213 571	1 542 832	1.29	6.02	-0.01
Health Care	22 950 145	1 133 783	241 822	0.99	1.04	0.01
Consumer Services	204 322 799	4 830 330	1 789 091	0.85	10.55	-0.01
Telecommunications	181 873 612	7 156 524	1 234 926	0.65	9.45	0.09
Utilities	0	0	0	0.00	0.00	0.00
Financials	486 687 010	15 852 720	5 201 111	1.02	25.81	-0.18
Technology	151 118 113	1 522 485	1 557 039	1.01	7.82	-0.06
Total	**1 931 966 312**	**59 802 034**	**20 700 479**	**1.03**	**100.00**	**0.14**

Figure 22: Case B: performance summary on sector level after 10 days. Case B is less expensive than Base Case but slightly more expensive than Case A.

Day	1	2	3	4	5	6	7	8	9	10
TC/abs(Trade Cost) <%>	1.14	1.08	1.06	1.06	1.06	1.05	1.04	1.04	1.04	1.03
Active Return <%>	0.00	51.21	8.25	2.05	0.78	0.58	0.03	-0.11	-0.04	0.14
Active Risk <%>	1.07	0.72	0.64	0.62	0.61	0.62	0.62	0.62	0.63	0.64
Tracking Error <%>	40.37	10.49	3.24	1.29	0.54	0.01	0.04	0.07	0.13	0.01

Figure 23: Case B: performance results where TC/abs(Trade cost) is cumulative and the other measurements are day by day. Acceptable tracking error is reached day 5.

Industry	Portfolio Return <%>	Allocation <bps>	Selection <bps>	Active Return <%>
Oil and Gas	0.00	0.55	0.00	0.01
Basic Materials	-2.69	-0.21	-5.39	-0.06
Industrials	0.68	-3,00	38.97	0.36
Consumer Goods	-0.4	0.4	-1.39	-0.01
Health Care	-1.18	1.56	-0.79	0.01
Consumer Services	-0.46	0.09	-1.19	-0.01
Telecommunications	1.25	2.01	6.69	0.09
Utilities	0.00	0.00	0.00	0.00
Financials	-0.19	-1.63	-16.72	-0.18
Technology	-0.43	-0.04	-5.81	-0.06
Total	**0.15**	**-0.26**	**14.39**	**0.14**

Figure 24: Case B: Active Return (day 10) is positive and mostly generated by stock selection.

5.6 Summary of Results

To get a better overview of the results we compile the most important performance measures for the three different cases in a summary for the 10 trading days, see Figure 25. As shown in this table we do achieve a reduction of transaction costs in Case A and Case B compared to Base Case as expected. Looking at TC/abs(Trade Cost) we can see that for Case A this figure is 1.02%, slightly higher for Case B, and 1.18% for the Base Case. This result can also be seen in Figure 26 and Figure 27 which show the transaction cost performance over the 10 day trading period. A surprising result is the fact that Base Case has a non-zero active return, in fact it is larger than for both A and B. This can be explained by looking at the tracking error. Throughout the 10 trading days the Base Case does not manage to reach the acceptable range of 1% of tracking error, whilst both A and B are close to zero. This result can also be seen in Figure 28. However, by looking at active return over the whole trading period we can see that it is diminishing over time, see Figure 18.

Performance Measure	Total Net Cost <SEK>	Total Net Income <SEK>	Total TC <SEK>	TC/abs(Trade Cost) <%>	Active Return <%>	Tracking Error <%>
Base Case	1 838 638 378	1 947	21 896 687	1.18	0.24	1.76
Case A	1 935 545 993	62 618 819	20 545 718	1.02	0.14	0.01
Case B	1 931 966 312	59 802 034	20 700 479	1.03	0.14	0.01

Figure 25: Performance comparison for Base Case, Case A and Case B (10 days). Case A has the best performance in terms of transaction cost and tracking error. Active return is higher for Base Case than for Case A and B since acceptable tracking error is not yet reached.

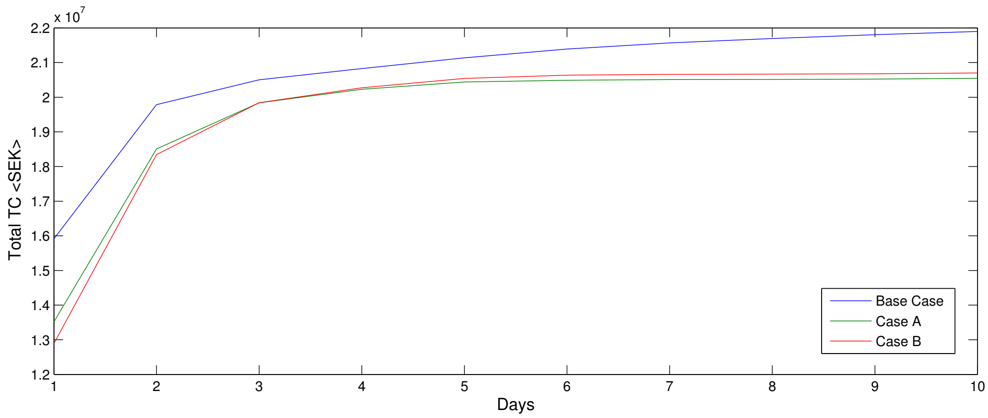


Figure 26: Accumulated transaction cost per day for the three test cases. One can see that Base Case is the most expensive case during the whole trading period.

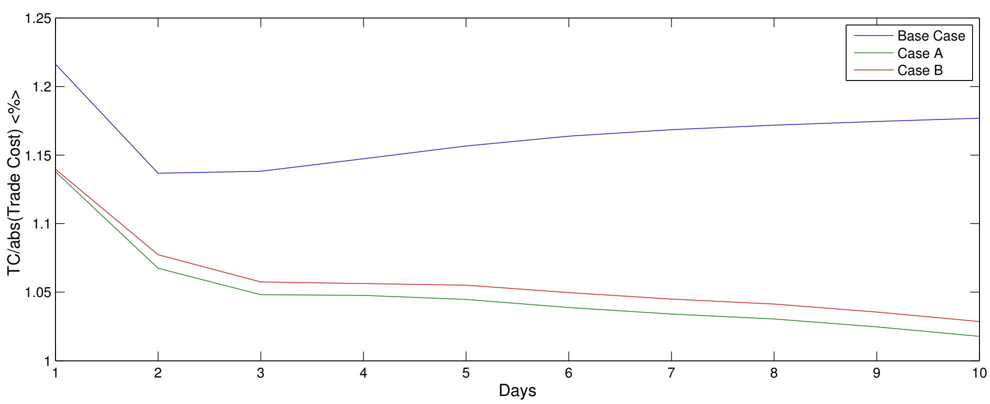


Figure 27: Accumulated transaction cost divided by total trade cost per day for the three test cases. One can see that by this measure Case A represents the best strategy during the whole trading period.

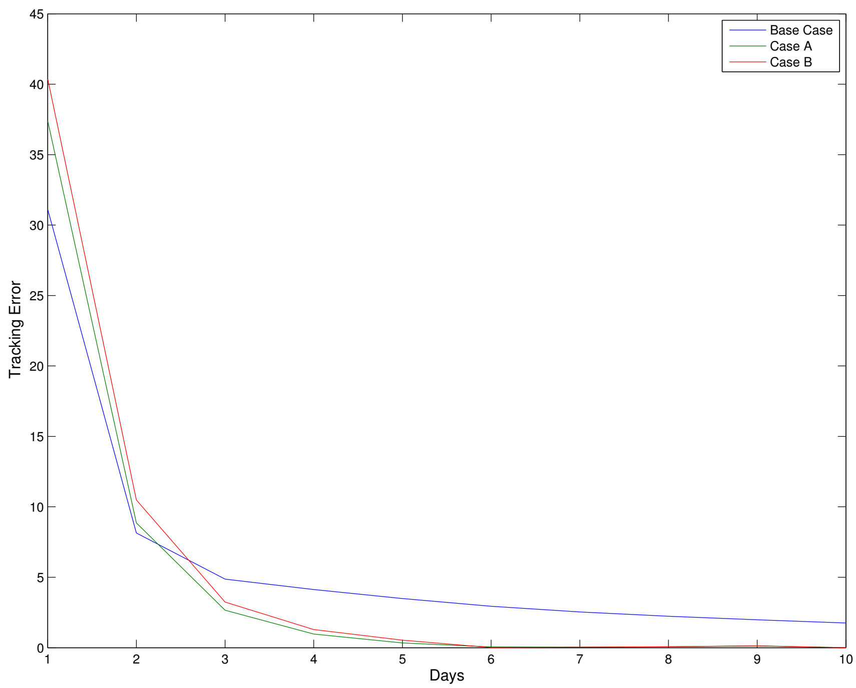


Figure 28: Tracking error comparison for Base Case, Case A and Case B. Case A reaches acceptable tracking error day 4, Case B in day 5 and Base Case does not reach the acceptable range over the whole period

6 Discussion

6.1 Performance Results

As mentioned in the beginning of this thesis, performance will primarily be measured in terms of transaction cost, but also in terms of tracking error and active return against OMXSB. The three test cases are evaluated and compared based on these measures.

6.1.1 Tracking Error

If we start to look at the resulting tracking error after 10 days of trade we can see that Case A reaches the acceptable range of 1% in 4 days and Case B in 5 days. The reason why it takes longer time for Case B could be the fact that its trading strategy prohibits trade in certain time buckets because they have a high predicted transaction cost. Instead it suggests that all trade should be conducted in a subset of all available time buckets. If the actual volumes during the trading day in the accepted time buckets deviates from historical volume and is lower than expected, the Case B strategy might not be able to be fulfilled, resulting in a lower traded volume than suggested pre-trade.

The Base Case, however, does not manage to reach the acceptable range throughout the whole trading period, instead it ends up at an error of 1.76%. Thus, it takes more than double the time approximated beforehand. The explanation for this is that we in the Base Case aim to trade with all OMXSB stocks, even those being relatively illiquid, implying that it is hard to trade a potential large order size quickly. This would most probably also lead to the Base Case giving high transaction costs in terms of timing risk and opportunity cost if measured.

6.1.2 Active Return

Active return, calculated according to the Performance Attribution Model, ends up around 0.14% for both Case A and B on day 10. For the Base Case the active return is 0.24 on day 10 which is surprising since it should be almost zero. Yet again this is explained by the fact that the Base Case has not managed to reach an acceptable tracking error, resulting in its portfolio weights differing from the index weights which lead to some active return. This figure will decrease as the days pass and the Base Case portfolio becomes the full replication of OMXSB as being its objective[22].

Studying the active return on a daily basis for Case A and B, see Figures 20 and 23, we can conclude that the portfolio's active returns sometimes are negative, meaning that the constraint on equal or better return than benchmark is not always fulfilled. As previously

[22] The Base Case reaches the acceptable tracking error on day 15 with an active return on 0.10. These results were obtained by running the test case for a period of 16 days

discussed, we had knowledge of this possibility since the constraint is based on historical data. However, if we compare total portfolio return from the day when tracking error is reached (day 4 for Case A and day 5 for Case B) we see that Case A has a return equal to 2.92% from day 4 to day 10, whilst the index return over the same period is 1.91%. Case B has a return of 3.03% from day 5 to day 10 and corresponding index return is 2.47% (See Appendix E.1 for more details). From this we can conclude that we have fulfilled the pre-determined constraint on portfolio return.

6.1.3 Transaction Cost

Looking at the total transaction cost during the 10 days of trade for each test case, we can conclude that the Base Case have the largest amount of transaction costs. This is not surprising since we in this case include all OMXSB-stocks, even those that are expensive to trade. In Figure 17 we can see that the industries being most expensive in terms of TC as percent of absolute trade cost are Oil & Gas, Basic Materials and Consumer Goods. The portfolio weights for these industries are 1.22, 2.66 and 8.16% respectively. This is close to the goal weights, i.e., the index weights (cf. Appendix D.1). When comparing this to the dimension reduced portfolio traded in Case A and B, we can see that these industries are underweighted (0.00, 1.82 and 6.02 respectively) and the measure TC as percent of absolute trade cost has decreased. This is a sign that the dimension reduction successfully excluded expensive stocks, resulting in lower transaction costs. The industry with lowest TC/abs(Trade Cost) is Telecommunications, which is overweighted in the dimension reduced portfolio.

One unexpected result is that Case B gets higher transaction cost than Case A, even though the Case B trading strategy is to predict which times during the day that are least expensive to trade at. When comparing the prediction of transaction cost for the two cases, however, Case B do fulfill its purpose and returns order sizes and trade times that would, based on historical data, cause lower transaction costs than Case A. From this result we can conclude that making predictions based on historical input parameters can be hard and that the volume-weighted trading strategy used in Case A already gives attractive transaction cost in terms of market impact. A potential improvement for Case B could be to continuously update the transaction cost predictions as the day passes, e.g., hourly. By doing this, the trading strategy would be more adapted to current market conditions and actual portfolio holdings which could imply more accurate predictions. This, however, demands more frequent data on index value than available in our data set. In addition, to decrease the amount of transaction cost spent in Case B, one could increase the limit for excluding time buckets from 10% as used in our analysis. This action would imply a trade-off between how quickly the acceptable tracking error is reached and acceptable range for transaction costs which must be taken into consideration.

Furthermore we can see that the total flow of capital in and out of the portfolio, i.e., abs(Trade Cost), is higher for the dimension reduced portfolio than for the full replication portfolio in the Base Case. Hence, we draw the conclusion that Case A and B conducts more transactions. This is also supported by the result tables in Appendices D.3 and D.5 where we can see that these cases alters between selling and buying more frequently than the Base Case. The reason why is that since we have excluded some stocks and overweighted others, the goal weights become more sensitive to index movements. However, both Case A and B have managed to achieve a higher portfolio value than Base Case with lower amount of transaction costs. Thus, we can see that the transactions made has been cheaper than those made in the Base Case and have resulted in a lower tracking error.

6.1.4 Transaction Cost Performance Reconsidered

Above we have made references to the total realized transaction cost for all test cases and to the measure TC as percentage of absolute trade cost. From this point of view the Case A and B strategies, with lowest total transaction costs and 1.02 and 1.03% respectively in TC/abs(Trade Cost), would be chosen over the simple full replication strategy. One could argue that this is misleading because Case A and B have a larger amount of absolute trade cost, hence TC/abs(Trade Cost) gets smaller. Instead one could suggest that it would be better to look at the total amount of money actually spent on the portfolio (net cost + TC) and to measure transaction cost performance as percent of this cost. These measures are presented in Appendix E.2. The actual net cost (excl. TC) is approximately 30×10^6 SEK lower for the Base Case compared to Case A and B. This might be due to the fact that the goal weights are not yet completely achieved and that this difference would decrease if prolonging the trade period. However, TC as percentage of actual cost (incl. TC) is still better for Case A and B why we can conclude that the dimension reduced portfolio performs better than full replication in terms of transaction cost also when measuring it this way.

Since transaction costs occur both when buying and selling we find it more reasonable to display the fraction between transaction cost and total cash flow as presented in the result tables in Chapter 5. The conclusion drawn from those results, that the dimension reduced portfolio performs better than full replication in terms of transaction cost, remains unchanged.

6.2 Error Sources and Suggested Improvements

6.2.1 The Transaction Cost Model

When calculating transaction costs, following the formulas from the PAR-model, we use parameters estimated from US stock market data, which were presented by Rashkovich et al. 2012. One adjustment implying potential improvement for the results of this thesis could be to preform a new regression based on Swedish stock data and use these parameters instead. However, this procedure is time demanding and since we are more interested in comparing performance of different test cases than of the exact size of the transaction costs, these US-market parameters are used since they provide sufficiently good results for comparative purposes.

Furthermore, as an input to the transaction cost model one needs the intraday bid-ask spread. In our data we have an *average daily* bid-ask spread. When comparing the different TC-optimizers, having a fix bid-ask throughout a whole day provides difficulties in finding the best optimizer, since the PAR-model is very sensitive to bid-ask fluctuations. As mentioned in the Methodology chapter we model a reversed J-shaped spread in order to obtain a clearer intraday transaction cost pattern. Even if this assumption provides a result based on a more natural behavior of the bid-ask spread, it may affect the absolute size of the transaction cost. The modeling of the bid-ask also provides additional uncertainty since we have applied the same reversed J-shape on all the stocks (but with individual daily means) which is a simplification of the actual behavior of each stock's spread. Hence, to improve the results of this study we suggest that one should use actual intraday bid-ask spread data instead.

6.2.2 Dimension Reduction of OMXSB

In this thesis we assume that our investor wants to track 3 million OMXSB instruments ($N = 3 \times 10^6$). N affects both the amount of money put in the investment and the number of days it takes to reach an acceptable tracking error. In addition, N affects the significance of the improvements due to dimension reduction. If only investing in a small number of index instruments, the holding of relatively illiquid and/or expensive stocks decrease, hence the difference in transaction cost effect on performance between full replication and a dimension reduced portfolio would diminish. We can therefore conclude that the dimension reduction effect on portfolio performance increases with the value of the desired portfolio.

The dimension reduction of OMXSB is in this thesis based on transactions cost predictions and a PCA. The portfolio is constructed to track OMXSB and the weights are obtained by minimizing total active risk against this benchmark. This implies that the resulting active return is quite low (around 0.14 % on day 10 for Case A and B). If more interested in getting a higher active return than tracking benchmark performance, one could base the dimension reduction on a deeper knowledge in future stock/industry returns and overweight those stocks/industries predicted to have superior return compared to others and underweight those with predicted inferior return. Industry or stock weight constraints are easily implemented in our weight optimizer based upon the Matlab function quadprog.

The selection of portfolio stocks in the dimension reduction of OMXSB are in this thesis constrained to be a subset of those included in the index. Another way to potentially improve performance could be to replace illiquid and/or expensive stocks with stocks not belonging to the OMXSB set. To successfully pursue this strategy deeper analysis of the index stocks are needed.

6.3 Remarks

The trading period chosen in this thesis is 10 days in October 2013. For our investment proposal to be seen as attractive, the tracking error had to decrease quickly so that the investment strategy's objective – to track OMXSB – was fulfilled in a reasonable period of time. Hence, 10 days should be enough for an attractive investment strategy to reach the acceptable tracking error range of 1% and to reach a state of maintenance. One might argue that the sampling period used in this thesis is short and decreases the strength of our results. However, to empower our results and following conclusions we have tested that our results are replicable. We repeated our simulations over two other 10 day time periods[23] in our data and obtained similar results. Thus, we argue that our results presented in the previous chapter are representable and gives sufficient support for our conclusions.

OMXSB, constructed out of the companies with top 10 % turnover on their stocks, is a relatively liquid stock index. This, together with the fact that trading with a market impact minimizing volume-weighted strategy, which is the transaction cost measured in this thesis, implies that the Base Case can achieve quite good results. If the same two-step improvement method used on OMXSB would be applied on an index of even higher dimension, constructed out of more illiquid stocks, the test case results might have differed more. An example of such an index could be some small-cap stock index or the index OMX Stockholm[24].

[23] 2013-10-31 – 2013-11-13 and 2013-11-14 – 2013-11-27

[24] Also called Stockholm all-share index since it includes all stocks listed on the Stockholm Stock Exchange

7 Conclusion

An investment decision should be preceded by determining strategy and objective for the investment. The pre-set objective for the investment alternative investigated in this thesis was a constraint on the return being higher than, or equal to, that of the OMXSB index. The overall strategy was to track OMXSB with a portfolio constructed of the same set, or a subset, of the stocks included in the index. The goal was to investigate the effects on portfolio performance from tracking OMXSB with a dimension reduced portfolio and from implementing a TCA-step in the trading process. From running three different test cases on our data set we were able to draw the following conclusions about how to improve performance in terms of transaction cost, active return and tracking error.

7.1 Dimension Reduction

When reducing the dimension of a multidimensional index, such as OMXSB, it is possible to obtain diverse portfolio characteristics by using different criteria for excluding/including stocks. The dimension reduction in this thesis was based on results from a Principal Component Analysis together with predictions on transaction costs related to trading a certain stock. The PCA was conducted to ensure that the stocks most important for index return was included. The second part, predicting transaction costs, made it possible to exclude stocks that were expensive to trade in order to investigate how minimizing transaction costs affected overall performance. The results gave input to a scoring formula in which the stocks got positive score contribution if explaining much of index return and were penalized if being expensive to trade. When constructing the dimension reduced portfolio we chose to include the index stocks with top 50% scores. This portfolio's performance was tested in a test case (Case A) and was compared against trading a full replication of the index (Base Case). The results obtained showed that we got lower transaction costs and reached a low tracking error quicker in Case A compared to the Base Case. Hence, the reference to transaction costs being *unavoidable slippage* can be rejected by these results. When comparing active return we could conclude that we achieved higher return than index in both cases, but since the Base Case did not reach an acceptable tracking error during the 10-day trading period, we did not get any comparable results. Thus, no conclusions about how dimension reduction affected this performance measure could be drawn. However, since the Base Case strived to become a full replication of OMXSB, the active return in this case would approach zero if prolonging the trade period, while Case A most probably would continue to have some active return against the benchmark.

7.2 Transaction Cost Prediction

When looking at improving performance additionally by adding a TCA-step in the trading process we used historical data and PAR-model transaction cost predictions for optimizing trade times and order sizes to trade each day (Case B). The portfolio traded in Case

B was the same dimension reduced portfolio as in Case A. However, when comparing Case A and B results we could conclude that Case B got higher transaction costs and reached the acceptable tracking error range slower than Case A. As for active return both cases had similar performance. This comparison lead to the conclusion that the attempt to minimize transaction costs by predicting them did not give positive contribution to portfolio performance. This highlights a drawback when trying to act based on predictions: the future patterns are seldom fully captured in historical data. Especially in the stock market, where the intraday dynamics can be greatly affected by macro events, statements from insiders or journalists etc., it is hard to make accurate predictions.

7.3 Empirical Findings

From running our test cases and analyzing their results we have support for answering the main problem to be solved in this thesis. The best strategy investigated in this thesis to construct a portfolio, having a return constraint corresponding to that of a multidimensional index, is to reduce the dimension and exclude stocks with undesired features. Furthermore, the best way to maintain it is to use a volume-weighted trading strategy which is similar to minimizing market impact leading to low transaction costs[25]. From our empirical studies this course of action results in superior performance in terms of transaction cost and tracking error. In addition, it gives a satisfactory level of active return against benchmark.

[25] Note that there are fixed fees for trading which implies that this strategy might not be optimal for a private trader. For professional traders, as sales traders, the fixed fees are quite low.

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A OMXSB Classification and Capital Weights

A.1 Industry Classification

Oil & Gas (0001)	Basic Materials (1000)		Industrials (2000)		Consumer Goods (3000)			Health Care (4000)
Oil & Gas (0500)	Chemicals (1300)	Basic Resources (1700)	Construction & Materials (2300)	Industrial Goods & Services (2700)	Automobiles & Parts (3300)	Food & Beverage (3500)	Personal & Household Goods (3700)	Health Care (4500)
AOIL SDB	HPOL B	BILL	ASSA B	HEXA B	ALIV SDB	AAK	ELUX B	EKTA B
LUPE		HOLM B	NIBE B	SCV B	MEKO	CLA B	HUSQ B	GETI B
		STE R	NCC B	VOLV A			SCA B	AZN
		LUMI SDB	SKA B	VOLV B			SWMA	MEDA A
		HOGA B		ABB				
		SSAB A		ALFA				
		BOL		ATCO A				
				ATCO B				
				SAND				
				SKF B				

Consumer Services (5000)			Telecommunications (6000)	Utilities (7000)	Financials (8000)			Technology (9000)
Retail (5300)	Media (5500)	Travel & Leisure (5700)	Telecommunications (6500)	Utilities (7500)	Banks (8300)	Real Estate (8600)	Financial Services (8700)	Technology (9500)
HM B	MTG B	BETS B	MIC SDB	ARISE	NDA SEK	BALD B	IJ	ERIC B
		NET B	TEL2 B		SEB A	CAST	INDU A	NOKI SEK
		UNIB SDB	TLSN		SHB A	FABG	INDU C	
		REZT			SWED A	HUFV A	INVE A	
		SAS				JM	INVE B	
						KLED	KINV B	
						LJGR B	RATO B	
						WIHL		
						WALL B		

Figure 29: Classification according to Industry Classification Benchmark (2014)

A.2 Capital Weights

Company	OMX Ticker	Capital Weight	Company	OMX Ticker	Capital Weight
AarhusKarlshamn AB	AAK	0,28%	Kungsleden AB	KLED	0,17%
ABB Ltd	ABB	2,81%	Atrium Ljungberg AB	LJGR B	0,12%
Alfa Laval AB	ALFA	1,51%	Lundin Mining Corporation SDB	LUMI SDB	0,19%
Autoliv Inc. SDB	ALIV SDB	1,27%	Lundin Petroleum AB	LUPE	1,02%
Alliance Oil Company Ltd. SDB	AOIL SDB	0,20%	Meda AB	MEDA A	0,64%
ASSA ABLOY AB	ASSA B	2,81%	Mekonomen AB	MEKO	0,18%
Atlas Copco AB	ATCO A	3,93%	Millicom International Cellular S.A. SDB	MIC SDB	1,09%
Atlas Copco AB	ATCO B	1,94%	Modern Times Group MTG AB	MTG B	0,48%
Arise Windpower AB	ARISE*	0,02%	NCC AB ser. B	NCC B	0,41%
AstraZeneca PLC	AZN	1,76%	Nordea Bank AB	NDA SEK	7,16%
Balder	BALD B	0,15%	Net Entertainment NE AB	NET B	0,10%
Betsson AB	BETS B	0,17%	NIBE Industrier AB	NIBE B	0,30%
BillerudKorsnäs AB	BILL	0,26%	Nokia Corporation	NOKI SEK	0,12%
Boliden AB	BOL	0,87%	Ratos AB	RATO B	0,41%
Castellum AB	CAST	0,57%	Rezidor Hotel Group AB	REZT	0,07%
Cloetta AB	CLA B	0,07%	Sandvik AB	SAND	3,31%
Elekta AB	EKTA B	1,23%	SAS Scandinavian Airlines	SAS	0,07%
Electrolux, AB	ELUX B	1,61%	Svenska Cellulosa AB	SCA B	3,03%
Ericsson, Telefonab. L M	ERIC B	7,49%	SCANIA AB	SCV B	1,48%
Fabege AB	FABG	0,32%	Skandinaviska Enskilda Banken	SEB A	4,00%
Getinge AB	GETI B	1,32%	Svenska Handelsbanken	SHB A	4,43%
Hexagon AB	HEXA B	1,63%	Skanska AB	SKA B	1,49%
Hennes & Mauritz AB	HM B	8,27%	SKF, AB	SKF B	1,99%
Höganäs AB	HOGA B**	0,24%	SSAB AB	SSAB A	0,30%
Holmen AB	HOLM B	0,30%	Stora Enso Oyj	STE R	0,31%
HEXPOL AB	HPOL B	0,36%	Swedbank AB	SWED A	4,77%
Hufvudstaden AB	HUFV A	0,35%	Swedish Match AB	SWMA	1,57%
Husqvarna AB	HUSQ B	0,51%	Tele2 AB	TEL2 B	0,87%
Intrum Justitia AB	IJ	0,35%	TeliaSonera AB	TLSN	3,51%
Industrivärden, AB	INDU A	0,83%	Unibet Group plc	UNIB SDB	0,18%
Industrivärden, AB	INDU C	0,45%	Volvo, AB	VOLV A	1,21%
Investor AB	INVE A	0,77%	Volvo, AB	VOLV B	5,16%
Investor AB	INVE B	2,90%	Wallenstam AB	WALL B	0,30%
JM AB	JM	0,40%	Wihlborgs Fastigheter AB	WIHL	0,25%
Kinnevik, Investment AB	KINV B	1,34%			

*Previously 'AWP' ** Delisted 2013-10-18

Figure 30: Capital weights for stocks included in OMXSB at 2013-06-03

B Construction of H and f

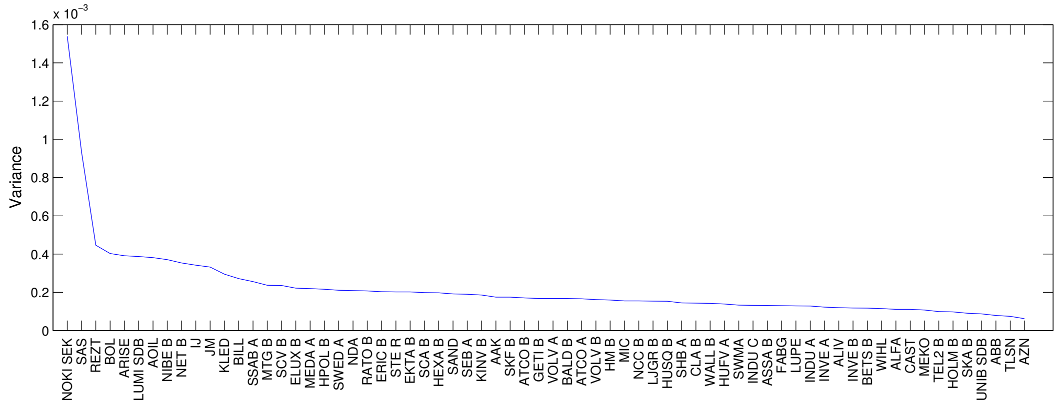
In order to minimize Equation (3) by using the inbuilt Matlab function quadprog we have to find f and H in Equation (24). In the two dimensional case, one can express Equation (3) as

$$\begin{aligned}
\begin{bmatrix} w_1 - w_1^b & w_2 - w_2^b \end{bmatrix} \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} \begin{bmatrix} w_1 - w_1^b \\ w_2 - w_2^b \end{bmatrix} = \\
w_1^2 Q_{11} + w_1 w_2 Q_{21} + w_1 w_2 Q_{12} + w_2^2 Q_{22} - 2w_1 w_1^b Q_{11} - 2w_2 w_2^b Q_{22} \\
- w_1 w_2^b (Q_{21} + Q_{12}) - w_2 w_1^b (Q_{21} + Q_{12}) + (w_1^b)^2 Q_{11} + w_1^b w_2^b Q_{21} + w_1^b w_2^b Q_{12} + (w_2^2)^b Q_{22} = \\
\begin{bmatrix} w_1 & w_2 \end{bmatrix} \underbrace{\begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix}}_{A} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \underbrace{-2 \begin{bmatrix} w_1^b & w_2^b \end{bmatrix} \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix}}_{B} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} + \underbrace{\begin{bmatrix} w_1^b & w_2^b \end{bmatrix} \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix} \begin{bmatrix} w_1^b \\ w_2^b \end{bmatrix}}_{C}.
\end{aligned}$$

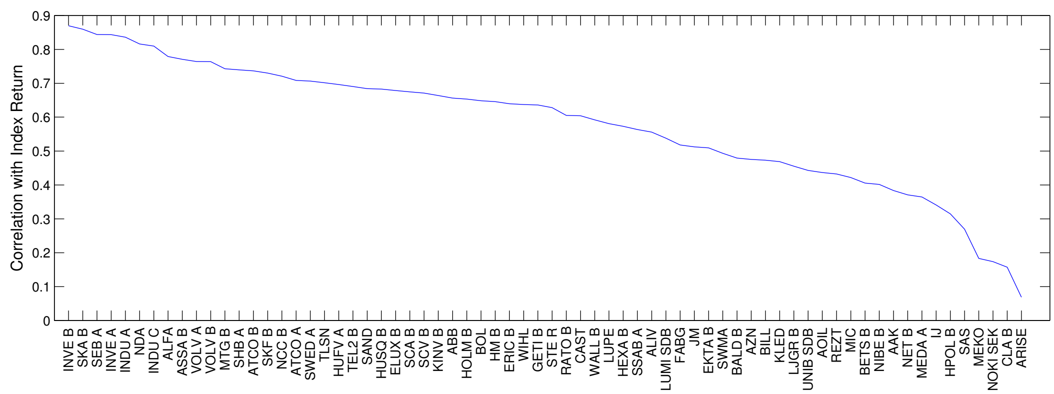
When comparing this result to Equation (24) we can see that $H = 2A$, $B = f$ and C=*constant*. The constant term can be neglected in the optimization. This two dimensional result can be applied to higher dimensional problems as well. In thesis, the dimension will be the number of stocks included in our portfolio tracking OMXSB.

C PCA Results

C.1 Stock Return Variance and Correlation with Index



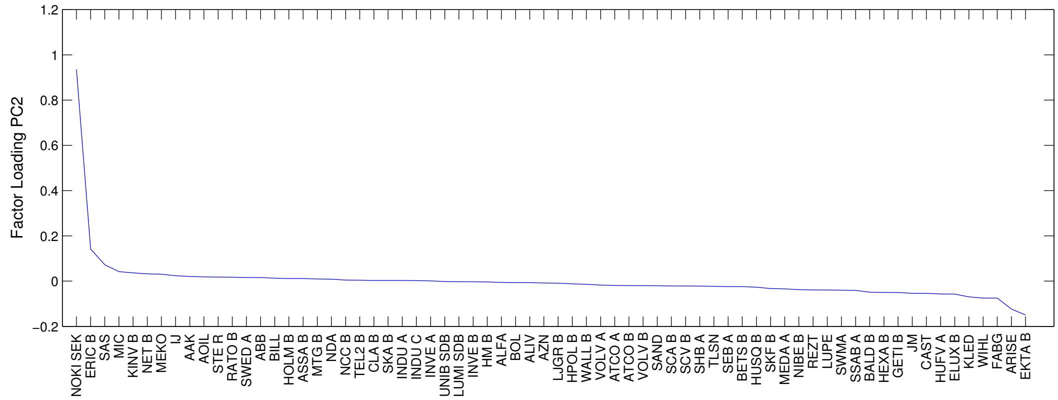
(a) Variance in Stock Return



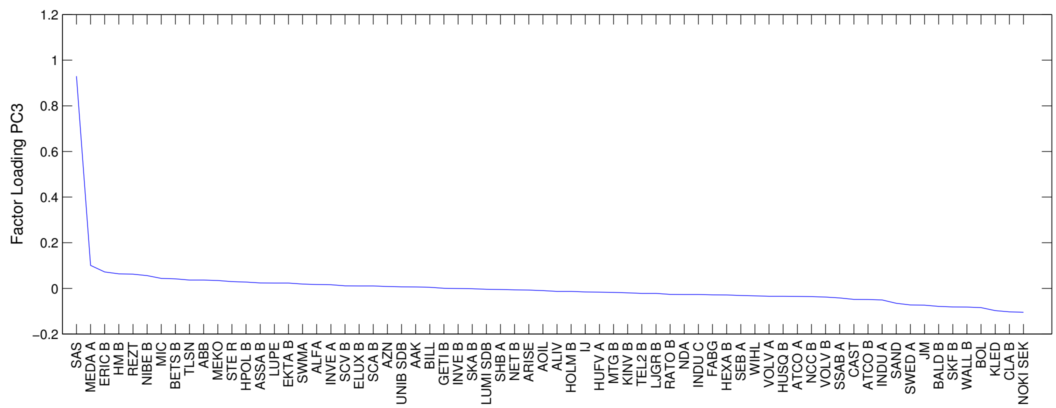
(b) Stock Correlation with Index Return

Figure 31

C.2 Factor Loadings



(a) Factor loadings for second principal component



(b) Factor loadings for third principal component

Figure 32

C.3 Stocks Included in the Dimension Reduced Portfolio

Stock	Days to Buy	Relative Liquidity	TC/share <SEK>	TC as % of Daily Cost	Factor Loading in PC1	Factor Loading in PC2	Factor Loading in PC3	Score
NOKI SEK	1	0,06%	1,08	2,49%	0,11	0,94	-0,10	21,93
ERIC B	1	8,96%	1,40	1,55%	0,13	0,14	0,07	9,18
BOL	1	2,19%	2,92	2,77%	0,21	-0,01	-0,08	7,09
NDA	1	0,36%	1,31	1,64%	0,16	0,01	-0,03	7,04
MTG B	2	0,15%	7,61	2,27%	0,16	0,01	-0,02	6,10
KINV B	1	0,26%	4,25	1,84%	0,14	0,04	-0,02	5,82
ASSA B	1	0,81%	4,63	1,51%	0,13	0,01	0,02	5,78
SEB A	2	1,37%	1,30	1,80%	0,16	-0,02	-0,03	5,77
SCV B	2	1,76%	3,01	2,08%	0,16	-0,02	0,01	5,57
HM B	2	2,37%	2,99	1,11%	0,11	0,00	0,06	5,36
INVE B	2	0,04%	3,25	1,59%	0,13	0,00	0,00	5,36
SAND	1	0,06%	1,41	1,48%	0,15	-0,02	-0,07	5,20
SWED A	1	0,77%	2,70	1,71%	0,14	0,02	-0,07	5,01
ATCO A	1	3,12%	2,89	1,50%	0,13	-0,02	-0,04	4,83
ELUX B	2	1,40%	3,36	1,83%	0,15	-0,06	0,01	4,76
SKF B	1	1,19%	2,96	1,59%	0,15	-0,03	-0,08	4,75
SSAB A	1	1,93%	0,74	1,65%	0,14	-0,04	-0,04	4,54
SCA B	2	1,36%	3,59	2,11%	0,14	-0,02	0,01	4,40
SHB A	1	4,83%	3,68	1,27%	0,11	-0,02	-0,01	4,34
ALFA	1	0,99%	3,00	1,90%	0,12	-0,01	0,02	4,10
ATCO B	1	1,03%	3,51	1,99%	0,14	-0,02	-0,05	4,06
TLSN	1	2,61%	0,37	0,76%	0,08	-0,02	0,04	3,91
VOLV B	1	0,08%	2,33	2,23%	0,14	-0,02	-0,04	3,88
NCC B	1	0,22%	4,55	2,32%	0,14	0,00	-0,04	3,85
SKA B	2	1,15%	2,66	2,05%	0,12	0,00	0,00	3,66
HUSQ B	2	0,24%	0,80	1,86%	0,13	-0,03	-0,03	3,58
LUMI SDB	1	0,02%	1,22	3,97%	0,18	0,00	0,00	3,39
GETI B	2	0,50%	4,18	1,75%	0,12	-0,05	0,00	3,26
STE R	2	2,89%	1,99	3,32%	0,14	0,02	0,03	2,99
ABB	1	1,86%	2,53	1,64%	0,08	0,02	0,04	2,98
TEL2 B	1	0,60%	1,44	1,68%	0,10	0,00	-0,02	2,90
INDU C	2	0,09%	3,42	2,75%	0,13	0,00	-0,03	2,89
RATO B	2	10,88%	1,95	3,03%	0,14	0,02	-0,03	2,80
HEXA B	2	0,58%	4,20	2,09%	0,12	-0,05	-0,03	2,41

Figure 33: OMXSB-stocks included in dimension reduced portfolio

Days to Buy: Number of days until the difference in the portfolio market value compared to index market value is less than 5% when trading with a volume-weighted strategy ($\text{part}_{\text{max}} = 20\%$)
Relative Liquidity: Stock's average daily volume as percentage of total average daily volume for all index stocks
TC/share: 5-day average transaction cost per share
TC as % of Daily Cost: 5-day average TC_{frac} (= transaction cost as percentage of daily trade cost for stock)
Factor Loading: Stock's correlation with principal component
Score: Calculated according to Equation (23) with $\Omega = [100; 200]$

C.4 Stocks Excluded from the Dimension Reduced Portfolio

Stock	Days to Buy	Relative Liquidity	TC/share <SEK>	TC as % of Daily Cost	Factor Loading in PC1	Factor Loading in PC2	Factor Loading in PC3	Score
INDU A	6	0,14%	4,22	3,18%	0,14	0,00	-0,05	2,22
HOLM B	2	0,01%	4,81	2,30%	0,09	0,01	-0,01	1,55
SWMA	2	3,15%	3,74	1,58%	0,08	-0,04	0,02	1,51
INVE A	9	0,31%	7,61	3,75%	0,13	0,00	0,02	1,30
AZN	1	1,02%	3,35	1,00%	0,05	-0,01	0,01	1,29
MIC	3	0,02%	16,58	2,77%	0,08	0,04	0,04	1,26
VOLV A	0	0,03%	3,89	3,67%	0,14	-0,02	-0,03	1,16
HUFV A	2	0,02%	2,44	2,84%	0,13	-0,06	-0,02	0,98
LUPE	1	1,33%	3,22	2,23%	0,09	-0,04	0,02	0,79
MEDA A	2	0,89%	2,13	2,70%	0,09	-0,03	0,10	0,66
WALL B	5	5,79%	2,62	2,88%	0,11	-0,01	-0,08	0,32
BILL	2	0,18%	2,68	3,87%	0,12	0,01	0,01	0,12
SAS	2	6,03%	2,50	10,89%	0,13	0,07	0,93	-0,33
CAST	3	0,28%	2,42	2,56%	0,10	-0,05	-0,05	-0,37
AOIL	2	0,48%	2,50	4,61%	0,13	0,02	-0,01	-0,44
ALIV	2	0,19%	19,79	3,39%	0,09	-0,01	-0,01	-1,07
HPOL B	4	0,17%	16,90	3,47%	0,08	-0,01	0,03	-1,90
EKTA B	2	1,39%	3,30	3,01%	0,11	-0,15	0,02	-1,91
NIBE B	6	0,02%	6,42	4,95%	0,12	-0,04	0,06	-2,19
FABG	4	0,13%	2,60	3,52%	0,09	-0,08	-0,03	-2,96
JM	1	0,96%	10,93	5,48%	0,16	-0,05	-0,07	-3,00
AAK	5	0,02%	18,20	4,35%	0,08	0,02	0,01	-3,12
IJ	3	1,27%	11,37	6,18%	0,09	0,02	-0,02	-6,48
KLED	4	0,80%	3,18	6,64%	0,13	-0,07	-0,10	-7,70
WIHL	7	0,08%	7,06	6,32%	0,11	-0,08	-0,03	-7,85
BETS B	2	0,08%	12,40	6,32%	0,07	-0,02	0,04	-8,24
UNIB SDB	6	8,33%	18,87	6,65%	0,07	0,00	0,01	-9,01
LIGR B	0	0,12%	7,60	8,02%	0,09	-0,01	-0,02	-10,54
MEKO	6	0,90%	16,91	6,91%	0,03	0,03	0,03	-10,57
NET B	7	8,38%	11,94	9,62%	0,10	0,03	-0,01	-12,00
BALD B	5	0,15%	5,27	9,27%	0,10	-0,05	-0,08	-14,02
REZT	9	0,47%	5,11	11,94%	0,15	-0,04	0,06	-14,51
CLA B	0	0,08%	3,26	14,66%	0,03	0,00	-0,10	-28,29
ARISE	0	0,02%	4,38	15,44%	0,02	-0,12	-0,01	-32,71

Figure 34: OMXSB-stocks excluded from dimension reduced portfolio

Days to Buy: Number of days until the difference in the portfolio market value compared to index market value is less than 5% when trading with a volume-weighted strategy ($\text{part}_{\max} = 20\%$)
Relative Liquidity: Stock's average daily volume as percentage of total average daily volume for all index stocks
TC/share: 5-day average transaction cost per share
TC as % of Daily Cost: 5-day average TC_{frac} (= transaction cost as percentage of daily trade cost for stock)
Factor Loading: Stock's correlation with principal component
Score: Calculated according to Equation (23) with $\Omega = [100; 200]$

D Case Results

This Appendix shows how day to day performance results could be presented for an interested customer. These *daily* result tables could be seen as redundant for the problem to be solved but are requested by Handelsbanken and therefore included in this thesis.

D.1 Index Data

Below are figures showing index weights and index return during the period October 3 – October 16 (10 trading days). Since the index is not depending upon which test case we run, these tables are the same for all cases.

Day	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Oil and Gas	1,19	1,18	1,18	1,20	1,21	1,21	1,20	1,20	1,20	1,20
Basic Materials	2,59	2,56	2,57	2,54	2,54	2,53	2,56	2,55	2,57	2,60
Industrials	29,73	29,68	29,57	29,50	29,62	29,48	29,66	29,73	29,78	29,48
Consumer Goods	8,17	8,19	8,22	8,17	8,23	8,21	8,22	8,14	8,14	8,16
Health Care	4,86	4,86	4,77	4,78	4,60	4,64	4,58	4,62	4,63	4,63
Consumer Services	10,92	10,85	10,90	10,93	10,87	10,93	10,90	10,88	10,78	10,80
Telecommunications	5,65	5,61	5,62	5,62	5,63	5,67	5,63	5,62	5,67	5,65
Utilities	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02	0,02
Financials	28,74	28,91	29,01	29,09	29,19	29,22	29,14	29,24	29,32	29,50
Technology	8,15	8,15	8,13	8,14	8,09	8,07	8,09	8,00	7,89	7,95

Figure 35: Index weights during October 3 (trading day 1) – October 16 (trading day 10)

Day	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Oil and Gas	0,00	-0,17	1,58	-0,32	-0,03	0,84	0,30	-0,03	0,61	-0,45
Basic Materials	0,00	-0,21	-1,65	-0,42	-0,82	3,09	0,02	0,20	1,93	0,28
Industrials	0,00	-0,71	-0,65	-0,10	-1,01	2,59	0,69	-0,42	-0,42	-0,36
Consumer Goods	0,00	0,01	-0,99	0,24	-0,80	2,05	-0,46	-0,69	0,89	-0,17
Health Care	0,00	-2,15	-0,25	-4,17	0,38	0,48	1,32	-0,39	0,74	-0,42
Consumer Services	0,00	0,14	-0,14	-1,07	0,03	1,68	0,28	-1,51	0,75	-0,35
Telecommunications	0,00	-0,09	-0,37	-0,33	0,03	1,28	0,28	0,37	0,21	0,54
Utilities	0,00	-0,82	-1,66	2,11	-0,83	0,00	0,00	0,00	0,00	0,00
Financials	0,00	0,01	-0,17	-0,15	-0,42	1,69	0,80	-0,32	1,23	0,45
Technology	0,00	-0,54	-0,36	-1,12	-0,75	2,27	-0,64	-2,05	1,43	0,32
Total	**0,00**	**-0,35**	**-0,43**	**-0,49**	**-0,55**	**1,98**	**0,46**	**-0,59**	**0,60**	**0,01**

Figure 36: Index return during October 3 (trading day 1) – October 16 (trading day 10)

D.2 Base Case Results

'Net' refers to cost/income without consideration of transaction costs. 'TC/abs(Trade Cost)' is the fraction between TC + Net Cost + Net Income and TC.

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,33	17303565	0	281668	1,60
Basic Materials	2,32	30102625	0	464198	1,52
Industrials	30,04	388806011	0	4839927	1,23
Consumer Goods	7,72	99690920	0	1629353	1,61
Health Care	4,88	63259227	0	910723	1,42
Consumer Services	10,63	137701840	0	1460841	1,05
Telecommunications	6,89	89192755	0	686358	0,76
Utilities	0,00	0	0	0	0,00
Financials	27,79	357956350	0	4391396	1,21
Technology	8,40	108546538	0	1251034	1,14
Total	**100,00**	**1292559832**	**0**	**15915498**	**1,22**

(a) Base Case results day 1

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,22	3814809	0	45995	1,19
Basic Materials	2,14	6884121	0	123442	1,76
Industrials	29,73	124763106	0	1072622	0,85
Consumer Goods	8,12	39387278	0	394505	0,99
Health Care	5,10	25812285	0	243113	0,93
Consumer Services	11,24	55280457	0	434320	0,78
Telecommunications	6,04	14769542	0	89441	0,60
Utilities	0,00	0	0	0	0,00
Financials	27,63	114834180	0	1167207	1,01
Technology	8,77	42519946	0	298758	0,70
Total	**100,00**	**428065723**	**0**	**3869403**	**0,90**

(b) Base Case results day 2

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,26	1041247	0	10819	1,03
Basic Materials	2,23	3532763	0	80864	2,24
Industrials	29,63	17286117	0	114083	0,66
Consumer Goods	8,18	6816819	0	64898	0,94
Health Care	5,02	1558324	0	6256	0,40
Consumer Services	11,13	4337494	0	68120	1,55
Telecommunications	5,90	1186139	0	9780	0,82
Utilities	0,00	333	0	11	3,07
Financials	28,08	23089838	0	361176	1,54
Technology	8,55	1391987	43	2404	0,17
Total	**100,00**	**60241061**	**43**	**718410**	**1,18**

(c) Base Case results day 3

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,26	31869	0	35	0,11
Basic Materials	2,35	2293412	0	47471	2,03
Industrials	29,62	1707373	358	25593	1,48
Consumer Goods	8,24	1041347	164	29068	2,72
Health Care	4,80	799	0	0	0,00
Consumer Services	11,05	1292565	272	41224	3,09
Telecommunications	5,87	115266	128	327	0,28
Utilities	0,00	0	0	0	0,00
Financials	28,37	7230275	157	181145	2,44
Technology	8,43	0	85	0	0,00
Total	**100,00**	**13712906**	**1164**	**324864**	**2,31**

(d) Base Case results day 4

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,26	637	0	0	0,00
Basic Materials	2,43	1742768	0	43248	2,42
Industrials	29,35	1115744	270	23663	2,08
Consumer Goods	8,23	1177499	0	39571	3,25
Health Care	4,81	71	0	0	0,00
Consumer Services	11,11	1115168	0	34536	3,00
Telecommunications	5,87	13686	0	0	0,00
Utilities	0,00	24	0	0	0,00
Financials	28,58	6673330	470	169421	2,48
Technology	8,36	0	0	0	0,00
Total	**100,00**	**11838926**	**740**	**310440**	**2,56**

(e) Base Case results day 5

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,24	0	0	0	0,00
Basic Materials	2,54	1730170	0	37307	2,11
Industrials	29,43	1297570	0	27308	2,06
Consumer Goods	8,25	982467	0	29630	2,93
Health Care	4,72	0	0	0	0,00
Consumer Services	11,08	1053791	0	24673	2,29
Telecommunications	5,80	2205	0	0	0,01
Utilities	0,00	0	0	0	0,00
Financials	28,62	4971011	0	132208	2,59
Technology	8,34	0	0	0	0,00
Total	**100,00**	**10037213**	**0**	**251126**	**2,44**

(f) Base Case results day 6

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,23	0	0	0	0,00
Basic Materials	2,56	868192	0	16125	1,82
Industrials	29,46	1304917	0	26608	2,00
Consumer Goods	8,18	674946	0	21911	3,14
Health Care	4,74	0	0	0	0,00
Consumer Services	11,06	825763	0	27175	3,19
Telecommunications	5,76	0	0	0	0,00
Utilities	0,00	120	0	0	0,00
Financials	28,80	3939038	0	85085	2,11
Technology	8,21	0	0	0	0,00
Total	**100,00**	**7612975**	**0**	**176905**	**2,27**

(g) Base Case results day 7

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,23	0	0	0	0,00
Basic Materials	2,62	713862	0	10226	1,41
Industrials	29,47	867959	0	18692	2,11
Consumer Goods	8,16	344445	0	16109	4,47
Health Care	4,73	0	0	0	0,00
Consumer Services	10,95	475622	0	10669	2,19
Telecommunications	5,80	0	0	0	0,00
Utilities	0,00	0	0	0	0,00
Financials	28,97	3276093	0	73233	2,19
Technology	8,07	0	0	0	0,00
Total	**100,00**	**5677981**	**0**	**128928**	**2,22**

(h) Base Case results day 8

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,23	0	0	0	0,00
Basic Materials	2,65	170381	0	1328	0,77
Industrials	29,15	1138304	0	23048	1,98
Consumer Goods	8,18	264300	0	9980	3,64
Health Care	4,73	0	0	0	0,00
Consumer Services	10,96	377367	0	11942	3,07
Telecommunications	5,76	0	0	0	0,00
Utilities	0,00	167	0	0	0,01
Financials	29,23	2850259	0	61270	2,10
Technology	8,11	0	0	0	0,00
Total	**100,00**	**4800778**	**0**	**107569**	**2,19**

(i) Base Case results day 9

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	1,22	0	0	0	0,00
Basic Materials	2,66	37445	0	60	0,16
Industrials	29,03	1037355	0	24343	2,29
Consumer Goods	8,16	220362	0	17790	7,47
Health Care	4,69	0	0	0	0,00
Consumer Services	10,91	340579	0	5387	1,56
Telecommunications	5,78	0	0	0	0,00
Utilities	0,00	431	0	5	1,17
Financials	29,44	2454810	0	45959	1,84
Technology	8,12	0	0	0	0,00
Total	**100,00**	**4090982**	**0**	**93544**	**2,24**

(j) Base Case results day 10

Figure 37

D.3 Case A Cost Results

'Net' refers to cost/income without consideration of transaction costs. 'TC/abs(Trade Cost)' is the fraction between TC + Net Cost + Net Income and TC.

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	2,22	26146952	0	363693	1,37
Industrials	36,95	434548243	0	5531100	1,26
Consumer Goods	4,92	57859751	0	867491	1,48
Health Care	1,26	14812633	0	211974	1,41
Consumer Services	10,87	128065021	0	1194032	0,92
Telecommunications	8,60	101155407	0	781516	0,77
Utilities	0,00	0	0	0	0,00
Financials	26,37	308766333	0	3352563	1,07
Technology	8,81	103507590	0	1219240	1,16
Total	**100,00**	**1174861930**	**0**	**13521610**	**1,14**

(a) Case A results day 1

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,69	6339780	3448670	174224	1,75
Industrials	37,64	209648166	0	2089559	0,99
Consumer Goods	5,15	30314526	434774	397600	1,28
Health Care	1,16	5810655	0	23804	0,41
Consumer Services	11,41	66317368	0	494998	0,74
Telecommunications	9,97	69124001	0	436344	0,63
Utilities	0,00	0	0	0	0,00
Financials	24,55	108205371	0	1090949	1,00
Technology	8,44	40830446	0	279261	0,68
Total	**100,00**	**536590313**	**3883444**	**4986739**	**0,91**

(b) Case A results day 2

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,75	4391328	605370	52171	1,03
Industrials	37,35	48092345	8634860	579721	1,01
Consumer Goods	5,60	15060674	0	136587	0,90
Health Care	1,09	0	289395	377	0,13
Consumer Services	10,91	6335510	2653808	43204	0,48
Telecommunications	9,63	10314831	4631989	52377	0,35
Utilities	0,00	0	0	0	0,00
Financials	25,65	50456548	4102432	461378	0,84
Technology	8,01	1841314	0	3460	0,19
Total	**100,00**	**136492550**	**20917853**	**1329276**	**0,84**

(c) Case A results day 3

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,83	1696252	0	12009	0,70
Industrials	37,68	16296279	1027068	170908	0,98
Consumer Goods	5,83	6149687	0	86890	1,39
Health Care	0,95	0	248993	5	0,00
Consumer Services	10,64	31836	624078	53	0,01
Telecommunications	9,51	338314	86741	312	0,07
Utilities	0,00	0	0	0	0,00
Financials	25,75	9472372	1915158	122302	1,06
Technology	7,82	0	109742	19	0,02
Total	**100,00**	**33984740**	**4011779**	**392498**	**1,02**

(d) Case A results day 4

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,81	323564	171329	356	0,07
Industrials	37,47	6932375	3271647	92606	0,90
Consumer Goods	5,99	3604710	207830	39146	1,02
Health Care	1,06	1925679	0	2438	0,13
Consumer Services	10,71	989650	337	460	0,05
Telecommunications	9,48	0	455313	66	0,01
Utilities	0,00	0	0	0	0,00
Financials	25,66	4165560	2384718	74471	1,12
Technology	7,81	981258	0	901	0,09
Total	**100,00**	**18922794**	**6491175**	**210444**	**0,82**

(e) Case A results day 5

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,86	279382	106426	110	0,03
Industrials	37,80	5659302	375167	15032	0,25
Consumer Goods	6,03	1587286	707839	10376	0,45
Health Care	1,02	0	300914	113	0,04
Consumer Services	10,56	0	1448268	1254	0,09
Telecommunications	9,34	64893	1175463	245	0,02
Utilities	0,00	0	0	0	0,00
Financials	25,58	3071770	981717	23305	0,57
Technology	7,81	159830	0	32	0,02
Total	**100,00**	**10822463**	**5095795**	**50467**	**0,32**

(f) Case A results day 6

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,81	0	747695	2268	0,30
Industrials	37,68	681479	4190150	6177	0,13
Consumer Goods	6,02	451658	594648	2150	0,21
Health Care	1,05	343132	0	194	0,06
Consumer Services	10,57	388951	0	172	0,04
Telecommunications	9,38	891406	14716	485	0,05
Utilities	0,00	0	0	0	0,00
Financials	25,78	1986452	52684	5587	0,27
Technology	7,71	0	340510	78	0,02
Total	**100,00**	**4743078**	**5940403**	**17111**	**0,16**

(g) Case A results day 7

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,83	219197	126345	421	0,12
Industrials	37,72	915381	2066145	2621	0,09
Consumer Goods	5,98	172744	37805	179	0,08
Health Care	1,04	0	124443	18	0,01
Consumer Services	10,50	332838	0	35	0,01
Telecommunications	9,49	121193	71550	35	0,02
Utilities	0,00	0	0	0	0,00
Financials	25,77	10061	1721136	1008	0,06
Technology	7,68	1572864	0	1088	0,07
Total	**100,00**	**3344279**	**4147424**	**5404**	**0,07**

(h) Case A results day 8

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,87	0	265634	82	0,03
Industrials	37,31	865213	1973700	1226	0,04
Consumer Goods	6,05	1078247	0	1873	0,17
Health Care	1,05	69262	0	3	0,00
Consumer Services	10,61	1935730	0	1643	0,08
Telecommunications	9,35	0	1671148	1903	0,11
Utilities	0,00	0	0	0	0,00
Financials	25,90	493955	1455728	963	0,05
Technology	7,86	2260803	0	1685	0,07
Total	**100,00**	**6703211**	**5366210**	**9378**	**0,08**

(i) Case A results day 9

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,82	0	954848	3335	0,35
Industrials	37,50	7943063	922277	14135	0,16
Consumer Goods	6,02	0	239426	138	0,06
Health Care	1,04	0	174446	14	0,01
Consumer Services	10,55	0	118129	3	0,00
Telecommunications	9,45	969052	0	855	0,09
Utilities	0,00	0	0	0	0,00
Financials	25,81	168521	3303370	3070	0,09
Technology	7,82	0	1052241	1241	0,12
Total	**100,00**	**9080636**	**6764737**	**22792**	**0,14**

(j) Case A results day 10

Figure 38

D.4 Case A Performance Attribution Results

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0021	0,0000	-0,0021
Basic Materials	10,5201	-0,0013	0,1813	0,1800
Industrials	47,7601	-0,0285	18,2432	18,2148
Consumer Goods	51,5697	-0,0110	2,6531	2,6421
Health Care	33,8306	0,0665	0,4175	0,4841
Consumer Services	52,1552	0,0027	5,9329	5,9357
Telecommunications	68,1217	0,0115	6,8001	6,8116
Utilities	0,0000	0,0001	0,0000	0,0001
Financials	35,0267	-0,0159	8,5953	8,5794
Technology	39,0307	-0,0006	3,3411	3,3405
Total	**45,0491**	**0,0215**	**46,1644**	**46,1860**

(a) Case A active return components day 2

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0237	0,0000	-0,0237
Basic Materials	10,2757	0,0100	0,2089	0,2189
Industrials	5,5216	-0,0176	2,3059	2,2883
Consumer Goods	15,7844	0,0148	0,9398	0,9546
Health Care	-0,4643	-0,0063	-0,0023	-0,0086
Consumer Services	1,7575	0,0000	0,2066	0,2067
Telecommunications	2,7607	0,0022	0,3018	0,3040
Utilities	0,0000	0,0003	0,0000	0,0003
Financials	11,1396	-0,0085	2,9022	2,8937
Technology	0,9373	-0,0001	0,1039	0,1038
Total	**6,3481**	**-0,0290**	**6,9669**	**6,9379**

(b) Case A active return components day 3

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0021	0,0000	-0,0021
Basic Materials	5,5848	-0,0005	0,1098	0,1093
Industrials	2,1504	0,0323	0,8473	0,8796
Consumer Goods	5,3201	-0,0172	0,2960	0,2788
Health Care	-11,6087	0,1408	-0,0705	0,0703
Consumer Services	-1,2928	0,0017	-0,0232	-0,0216
Telecommunications	-0,0885	0,0062	0,0233	0,0295
Utilities	0,0000	-0,0006	0,0000	-0,0006
Financials	1,5933	-0,0115	0,4485	0,4370
Technology	-1,2518	0,0020	-0,0104	-0,0084
total	**1,2317**	**0,1512**	**1,6207**	**1,7720**

(c) Case A active return components day 4

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0063	0,0000	-0,0063
Basic Materials	-0,6128	0,0020	0,0037	0,0057
Industrials	-0,4730	-0,0362	0,2008	0,1646
Consumer Goods	2,9009	0,0057	0,2219	0,2275
Health Care	12,1137	-0,0329	0,1246	0,0917
Consumer Services	0,6941	-0,0009	0,0709	0,0699
Telecommunications	-0,1926	0,0222	-0,0210	0,0012
Utilities	0,0000	0,0001	0,0000	0,0001
Financials	-0,2451	-0,0044	0,0461	0,0418
Technology	0,0308	0,0006	0,0612	0,0618
Total	**0,0893**	**-0,0501**	**0,7082**	**0,6580**

(d) Case A active return components day 5

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	0,0138	0,0000	0,0138
Basic Materials	4,6944	-0,0075	0,0298	0,0223
Industrials	3,2724	0,0509	0,2580	0,3089
Consumer Goods	3,0624	-0,0016	0,0611	0,0595
Health Care	-1,3521	0,0541	-0,0188	0,0353
Consumer Services	1,0317	0,0011	-0,0684	-0,0673
Telecommunications	0,8451	-0,0256	-0,0406	-0,0662
Utilities	0,0000	0,0004	0,0000	0,0004
Financials	2,0631	0,0103	0,0942	0,1045
Technology	2,3294	-0,0008	0,0044	0,0036
Total	**2,3825**	**0,0951**	**0,3197**	**0,4148**

(e) Case A active return components day 6

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	0,0020	0,0000	0,0020
Basic Materials	-1,9274	0,0033	-0,0352	-0,0319
Industrials	0,1324	0,0186	-0,2115	-0,1928
Consumer Goods	0,2346	0,0202	0,0416	0,0618
Health Care	2,8970	-0,0303	0,0165	-0,0138
Consumer Services	0,4886	0,0006	0,0215	0,0221
Telecommunications	0,9353	-0,0068	0,0614	0,0546
Utilities	0,0000	0,0001	0,0000	0,0001
Financials	1,2299	-0,0114	0,1105	0,0990
Technology	-0,8774	0,0043	-0,0186	-0,0143
Total	**0,4431**	**0,0005**	**-0,0137**	**-0,0132**

(f) Case A active return components day 7

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0067	0,0000	-0,0067
Basic Materials	0,4288	-0,0057	0,0042	-0,0014
Industrials	-0,5982	0,0141	-0,0678	-0,0537
Consumer Goods	-1,4156	0,0020	-0,0436	-0,0416
Health Care	-1,5699	-0,0074	-0,0123	-0,0197
Consumer Services	-1,3945	0,0035	0,0121	0,0156
Telecommunications	0,3738	0,0375	0,0000	0,0375
Utilities	0,0000	-0,0001	0,0000	-0,0001
Financials	-0,7530	-0,0095	-0,1114	-0,1209
Technology	-1,0340	0,0047	0,0783	0,0830
Total	**-0,7054**	**0,0324**	**-0,1405**	**-0,1081**

(g) Case A active return components day 8

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0001	0,0000	-0,0001
Basic Materials	2,6529	-0,0093	0,0135	0,0042
Industrials	-0,5642	-0,0771	-0,0536	-0,1307
Consumer Goods	1,7856	-0,0059	0,0543	0,0484
Health Care	1,8562	-0,0049	0,0117	0,0068
Consumer Services	1,6523	-0,0003	0,0953	0,0951
Telecommunications	-0,8876	-0,0146	-0,1024	-0,1170
Utilities	0,0000	0,0001	0,0000	0,0001
Financials	1,0559	-0,0213	-0,0440	-0,0653
Technology	2,9090	-0,0002	0,1161	0,1158
Total	**0,5465**	**-0,1335**	**0,0910**	**-0,0426**

(h) Case A active return components day 9

Figure 39

D.5 Case B Cost Results

'Net' refers to cost/income without consideration of transaction costs. 'TC/abs(Trade Cost)' is the fraction between TC + Net Cost + Net Income and TC.

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	2,31	25969840	0	375739	1,43
Industrials	37,28	417516614	0	5281503	1,25
Consumer Goods	4,95	55364427	0	811597	1,44
Health Care	1,31	14651821	0	211716	1,42
Consumer Services	10,54	118275331	0	1118067	0,94
Telecommunications	8,08	90408858	0	645030	0,71
Utilities	0,00	0	0	0	0,00
Financials	26,56	296187830	0	3243582	1,08
Technology	8,97	100315701	0	1209291	1,19
Total	100,00	**1118690422**	**0**	**12896524**	**1,14**

(a) Case B results day 1

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,70	6241593	3454952	172501	1,75
Industrials	37,65	215136857	0	2186187	1,01
Consumer Goods	5,11	30683281	424471	425450	1,35
Health Care	1,18	5961230	0	26722	0,45
Consumer Services	11,42	72915166	0	610973	0,83
Telecommunications	9,90	75576123	0	525941	0,69
Utilities	0,00	0	0	0	0,00
Financials	24,42	111260769	0	1160882	1,03
Technology	8,61	44126212	0	339173	0,76
Total	100,00	**561901233**	**3879423**	**5447828**	**0,95**

(b) Case B results day 2

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,75	4432243	605146	55376	1,09
Industrials	37,26	52269882	7114190	650375	1,08
Consumer Goods	5,57	15899988	0	140634	0,88
Health Care	1,09	0	283967	397	0,14
Consumer Services	10,98	9471694	2637934	56222	0,46
Telecommunications	9,68	13462124	3770518	59670	0,35
Utilities	0,00	0	0	0	0,00
Financials	25,60	56297359	4123092	532447	0,87
Technology	8,06	1692759	0	3038	0,18
Total	100,00	**153526050**	**18534847**	**1498160**	**0,86**

(c) Case B results day 3

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,83	1863962	0	15352	0,82
Industrials	37,65	18778638	996997	203943	1,02
Consumer Goods	5,78	6074512	0	89898	1,46
Health Care	0,95	0	250382	5	0,00
Consumer Services	10,68	11915	623842	53	0,01
Telecommunications	9,54	381786	0	319	0,08
Utilities	0,00	0	0	0	0,00
Financials	25,74	11431985	1845118	120709	0,90
Technology	7,84	0	109655	19	0,02
Total	100,00	**38542798**	**3825994**	**430299**	**1,01**

(d) Case B results day 4

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,82	392207	171511	586	0,10
Industrials	37,45	8107759	3265732	122364	1,06
Consumer Goods	5,96	4107724	207783	52239	1,20
Health Care	1,06	1924884	0	2610	0,14
Consumer Services	10,73	989156	0	430	0,04
Telecommunications	9,50	0	464543	71	0,02
Utilities	0,00	0	0	0	0,00
Financials	25,65	4652246	2384410	92053	1,29
Technology	7,83	985463	0	901	0,09
Total	100,00	**21159438**	**6493979**	**271254**	**0,97**

(e) Case B results day 5

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,86	279440	106094	111	0,03
Industrials	37,80	7113437	374188	37008	0,49
Consumer Goods	6,03	2233877	700300	17742	0,60
Health Care	1,02	0	300156	133	0,04
Consumer Services	10,57	0	1450146	1355	0,09
Telecommunications	9,34	64651	1165110	280	0,02
Utilities	0,00	0	0	0	0,00
Financials	25,57	3888036	980941	37227	0,76
Technology	7,81	155439	0	22	0,01
Total	100,00	**13734880**	**5076935**	**93878**	**0,50**

(f) Case B results day 6

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,81	0	744689	2356	0,32
Industrials	37,68	742665	3919129	6140	0,13
Consumer Goods	6,02	606748	597388	3085	0,26
Health Care	1,05	342746	0	195	0,06
Consumer Services	10,57	390884	0	142	0,04
Telecommunications	9,38	890623	14798	481	0,05
Utilities	0,00	0	0	0	0,00
Financials	25,78	2291203	49290	8851	0,38
Technology	7,71	0	350123	79	0,02
Total	100,00	**5264869**	**5675417**	**21330**	**0,19**

(g) Case B results day 7

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,83	215601	123920	425	0,13
Industrials	37,72	922020	2106380	3075	0,10
Consumer Goods	5,98	175436	42578	181	0,08
Health Care	1,04	0	124642	20	0,02
Consumer Services	10,50	333374	0	44	0,01
Telecommunications	9,49	121267	71456	39	0,02
Utilities	0,00	0	0	0	0,00
Financials	25,77	10139	1699162	1009	0,06
Technology	7,68	1582358	0	1125	0,07
Total	100,00	**3360195**	**4168137**	**5917**	**0,08**

(h) Case B results day 8

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,87	0	266522	86	0,03
Industrials	37,31	865428	1956278	1285	0,05
Consumer Goods	6,05	1078923	0	1829	0,17
Health Care	1,05	69464	0	3	0,00
Consumer Services	10,61	1935278	0	1797	0,09
Telecommunications	9,35	0	1670099	2160	0,13
Utilities	0,00	0	0	0	0,00
Financials	25,90	497957	1461973	1226	0,06
Technology	7,86	2260181	0	1728	0,08
Total	100,00	**6707231**	**5354871**	**10115**	**0,08**

(i) Case B results day 9

Industry	Portfolio Weight <%>	Net Cost <SEK>	Net Income <SEK>	TC <SEK>	TC/abs(Trade Cost) <%>
Oil and Gas	0,00	0	0	0	0,00
Basic Materials	1,82	0	962989	4004	0,41
Industrials	37,50	7941532	923904	15242	0,17
Consumer Goods	6,02	0	241050	177	0,07
Health Care	1,04	0	174637	19	0,01
Consumer Services	10,55	0	118409	7	0,01
Telecommunications	9,45	968179	0	935	0,10
Utilities	0,00	0	0	0	0,00
Financials	25,81	169487	3308734	3126	0,09
Technology	7,82	0	1062707	1663	0,16
Total	100,00	**9079197**	**6792429**	**25174**	**0,16**

(j) Case B results day 10

Figure 40

D.6 Case B Performance Attribution Results

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0021	0,0000	-0,0021
Basic Materials	10,1613	-0,0013	0,1766	0,1754
Industrials	51,0376	-0,0285	19,4814	19,4529
Consumer Goods	54,5719	-0,0111	2,7899	2,7788
Health Care	35,2715	0,0662	0,4420	0,5082
Consumer Services	62,0596	0,0028	7,0742	7,0770
Telecommunications	83,3215	0,0113	8,2574	8,2687
Utilities	0,0000	0,0001	0,0000	0,0001
Financials	37,5483	-0,0164	9,1679	9,1515
Technology	43,5874	-0,0009	3,7976	3,7967
Total	**49,5802**	**0,0202**	**51,1870**	**51,2072**

(a) Case B active return components day 2

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0237	0,0000	-0,0237
Basic Materials	10,5340	0,0100	0,2131	0,2231
Industrials	6,5471	-0,0175	2,6830	2,6656
Consumer Goods	17,1804	0,0150	1,0115	1,0265
Health Care	-0,4377	-0,0063	-0,0020	-0,0083
Consumer Services	3,4458	0,0002	0,3932	0,3935
Telecommunications	5,2873	0,0022	0,5480	0,5502
Utilities	0,0000	0,0003	0,0000	0,0003
Financials	12,8414	-0,0086	3,3323	3,3237
Technology	0,8318	0,0000	0,0960	0,0960
Total	**7,6427**	**-0,0284**	**8,2752**	**8,2468**

(b) Case B active return components day 3

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0021	0,0000	-0,0021
Basic Materials	6,1624	-0,0005	0,1205	0,1200
Industrials	2,5501	0,0322	0,9969	1,0291
Consumer Goods	5,3156	-0,0176	0,2931	0,2755
Health Care	-11,6156	0,1407	-0,0708	0,0699
Consumer Services	-1,3026	0,0015	-0,0244	-0,0229
Telecommunications	-0,0137	0,0062	0,0305	0,0368
Utilities	0,0000	-0,0006	0,0000	-0,0006
Financials	2,0456	-0,0115	0,5648	0,5533
Technology	-1,2518	0,0018	-0,0104	-0,0086
total	**1,5055**	**0,1503**	**1,9002**	**2,0504**

(c) Case B active return components day 4

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0063	0,0000	-0,0063
Basic Materials	-0,4120	0,0019	0,0074	0,0093
Industrials	-0,3018	-0,0361	0,2648	0,2287
Consumer Goods	3,4252	0,0058	0,2519	0,2577
Health Care	12,1112	-0,0329	0,1248	0,0919
Consumer Services	0,6941	-0,0008	0,0710	0,0702
Telecommunications	-0,1980	0,0223	-0,0216	0,0007
Utilities	0,0000	0,0001	0,0000	0,0001
Financials	-0,1428	-0,0044	0,0723	0,0680
Technology	0,0339	0,0005	0,0616	0,0621
Total	**0,2130**	**-0,0498**	**0,8323**	**0,7826**

(d) Case B active return components day 5

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	0,0138	0,0000	0,0138
Basic Materials	4,6956	-0,0075	0,0298	0,0223
Industrials	3,4862	0,0509	0,3388	0,3897
Consumer Goods	3,6805	-0,0016	0,0983	0,0967
Health Care	-1,3480	0,0541	-0,0188	0,0353
Consumer Services	1,0307	0,0011	-0,0685	-0,0674
Telecommunications	0,8510	-0,0257	-0,0401	-0,0657
Utilities	0,0000	0,0004	0,0000	0,0004
Financials	2,2395	0,0103	0,1393	0,1496
Technology	2,3263	-0,0008	0,0042	0,0034
Total	**2,5440**	**0,0951**	**0,4830**	**0,5780**

(e) Case B active return components day 6

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	0,0020	0,0000	0,0020
Basic Materials	-1,9193	0,0033	-0,0351	-0,0318
Industrials	0,1791	0,0186	-0,1938	-0,1752
Consumer Goods	0,3703	0,0202	0,0498	0,0700
Health Care	2,8948	-0,0303	0,0165	-0,0138
Consumer Services	0,4896	0,0006	0,0216	0,0222
Telecommunications	0,9348	-0,0068	0,0614	0,0546
Utilities	0,0000	0,0001	0,0000	0,0001
Financials	1,2947	-0,0114	0,1272	0,1157
Technology	-0,8839	0,0043	-0,0191	-0,0148
Total	**0,4851**	**0,0005**	**0,0285**	**0,0290**

(f) Case B active return components day 7

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0067	0,0000	-0,0067
Basic Materials	0,4253	-0,0057	0,0042	-0,0015
Industrials	-0,6031	0,0141	-0,0696	-0,0555
Consumer Goods	-1,4175	0,0020	-0,0437	-0,0418
Health Care	-1,5709	-0,0074	-0,0123	-0,0197
Consumer Services	-1,3942	0,0035	0,0121	0,0157
Telecommunications	0,3739	0,0375	0,0000	0,0375
Utilities	0,0000	-0,0001	0,0000	-0,0001
Financials	-0,7485	-0,0095	-0,1102	-0,1197
Technology	-1,0275	0,0047	0,0788	0,0835
Total	**-0,7057**	**0,0323**	**-0,1408**	**-0,1084**

(g) Case B active return components day 8

Industry	Portfolio Return <%>	Allocation	Selection	Active Return <%>
Oil and Gas	0,0000	-0,0001	0,0000	-0,0001
Basic Materials	2,6503	-0,0093	0,0134	0,0041
Industrials	-0,5617	-0,0771	-0,0527	-0,1297
Consumer Goods	1,7862	-0,0059	0,0544	0,0484
Health Care	1,8573	-0,0049	0,0117	0,0068
Consumer Services	1,6521	-0,0003	0,0953	0,0951
Telecommunications	-0,8875	-0,0146	-0,1024	-0,1170
Utilities	0,0000	0,0001	0,0000	0,0001
Financials	1,0553	-0,0213	-0,0441	-0,0654
Technology	2,9089	-0,0002	0,1161	0,1158
Total	**0,5473**	**-0,1335**	**0,0917**	**-0,0418**

(h) Case B active return components day 9

Figure 41

E Test Case Comparison

E.1 Portfolio Return vs Index Return

	Case A	Case B
Day TE < 1%	4	5
Portfolio (Index) Value	1826175505 (1844133735)	1824158064 (1834020738)
Portfolio (Index) Value Day 10	1879449418 (1879290389)	1879416000 (1879290389)
Portfolio (Index) Return	2.92% (1.91%)	3.03% (2.47%)

Table 3: Case A and B portfolio return compared to index portfolio return from day 4 -10 and 5-10 respectively. Portfolio Value and Index Value in the table are measured at the day when tracking error is less than 1%.

E.2 Alternative Transaction Cost Measures

Case	Actual Net Cost <SEK>	TC/ (Actual Cost) <%>
Base Case	1.8386×10^9	1.18
Case A	1.8729×10^9	1.09
Case B	1.8722×10^9	1.09

Table 4: Table displaying alternative transaction cost measures. Actual Net Cost = Net Cost − Net Income and TC/(Actual Cost) = TC/(Actual Net Cost + TC)