A Scenario Based Allocation Model Using Entropy Pooling for Computing the Scenario Probabilities

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Abstract

We introduce a scenario based allocation model (SBAM) that uses entropy pooling for computing scenario probabilities. Compared to most other models that allow the investor to blend historical data with subjective views about the future, the SBAM does not require the investor to quantify a level of confidence in the subjective views.

A quantitative test is performed on a simulated systematic fund offered by the fund company Informed Portfolio Management in Stockholm, Sweden. The simulated fund under study consists of four individual systematic trading strategies and the test is simulated on a monthly basis during the years 1986-2010.

We study how the selection of views might affect the SBAM portfolios, creating three systematic views and combining them in different variations creating seven SBAM portfolios. We also compare how the size of sample data affects the results.

Furthermore, the SBAM is compared to more common allocation methods, namely an equally weighted portfolio and a portfolio optimization based only on historical data.

We find that the SBAM portfolios produced higher annual returns and information ratio than the equally weighted portfolio or the portfolio optimized only on historical data.

Keywords: Scenario Based Allocation Model, Entropy Pooling, Scenario Based Portfolio Allocation, Portfolio Allocation, Mixed Estimation, Systematic Fund
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1 Introduction

The financial markets have seen a tremendous increase of systematic fund companies over the past two decades. These funds use predefined algorithms in their investment processes. Most systematic funds apply more than one strategy. In general they have a set-up of trading signals which in turn, through different combinations, build up different strategies for trading. One major problem many systematic funds face is how to allocate their capital between the different strategies that are part of the investment structure.

Often fixed weights are implemented between the strategies. The funds then tend to either use equal weights or have an investment committee that decides how the capital should be allocated between the strategies. Both methodologies can be subject for criticism. The equally weighted portfolios will not target the highest risk adjusted return while portfolios influenced by an investment committee are criticized for the inclusion of human interaction and thus the fund is not fully systematic.

Classical portfolio optimizations such as the Markowitz model are of limited use since they can only handle historical data. The funds use trading signals in an attempt to predict future price movements and hence models only capable of handling historical data fall short.

Mixed estimation models, which use both historical and subjective data as input, should in theory be a good fit for the systematic funds aiming for a dynamic and systematic way for how to allocate between their strategies, since these models base their allocations on historical data combined with subjective views about the future. The most famous is the Black Litterman model which was the first model to apply mixed estimations to financial data.

All mixed estimation models known today suffer from the drawback that they require the investor to quantify a confidence level for the subjective view. For example; Asset A will go up 5% and this view has a 50% confidence level. Meucci (2008) suggests that the confidence level could be based on the investor’s track record but for most systematic trading strategies this does not offer an applicable solution.

In this Master Thesis we introduce the scenario based allocation model (SBAM) which uses the entropy pooling for computing the scenario probabilities. The SBAM presents a fully systematic method for dynamic weights between set-ups of systematic trading strategies and compared to mixed estimation models it eliminates the need to quantify a level of confidence for the subjective views about the future.

In this study we will present and describe the SBAM framework. Second we will simulate an implementation of the SBAM on a systematically simulated enhanced index product which uses four underlying trading strategies. We compare the SBAM portfolio with the two most common methods for portfolio allocation namely equally weighted and portfolio optimization based only on historical data.

The reminder of the thesis is structured as follows. In Chapter 2 we present previous research in the area of mixed estimation models applied to financial data. Chapter 3 intro-
duces the theoretical framework for the SBAM and for other methods implemented in the study. Chapter 4 is a study of the data used in the quantitative implementation. Chapter 5 presents the structure of our quantitative testing. In Chapter 6 we present the results and finally we will conclude in Chapter 7.
2 Previous Research

The first model based on mixed estimations was developed by Henri Theil in the early 1960s but the theory of mixed estimations was not applied to financial data until Black’s and Litterman’s 1990 model.

One problem with classical portfolio theory is that it is difficult to include subjective views about the future and combine them with historical data. Black and Litterman (1990) allowed an investor to mix subjective views and combine them with historical data. The model’s distinct way of defining investor views and combining these with prior information makes the expected returns and covariance matrix produced by the model suitable input parameters for portfolio optimization. Meucci (2005) stated that the Black-Litterman model provides some path-breaking techniques, but it suffers from two major drawbacks. First, the model assumes that the prior market distribution (distribution of the historical data) and subjective views about the future are normally distributed. Second, the investor has to express views in terms of parameters that determine the market distribution. The second problem does not actually affect any results, but it might be difficult to express views about the market in this manner and more convenient for a manager to express views in the form of expected future realizations. Meucci (2008), presented a methodology that thanks to the use of scenarios and entropy pooling for setting scenario probabilities allowed the investor to express non-linear views in fully on non-normally distributed markets.

Since the very first mixed estimations model presented by Henri Theil in the 1960s until today all models suffer from the need to quantify a level of confidence. This is probably the main reason why they are not more common amongst professional investors. The new parameters that are used for portfolio optimization are a combination between historical data and subjective views about the future. How to mix these two parts and at which level is a common point for debate, see for example Black and Litterman (1992), He and Litterman (1999), Bevan and Winkelman (1998) and Satchell and Scowcroft (2000). The realized return can differ largely depending on this very sensible parameter.

Gosling (2010) suggests a scenario based approach to asset allocation designed to capture the complexity of relationships between fundamental factors and return outcomes. The article states that a scenario approach to asset allocation has the potential to increase long term risk adjusted returns but at the same time states that considerable resources is required to build a useful scenario set.

The SBAM presented in this paper could be described as a hybrid between a scenario based asset allocation model and a mixed estimation model. Although not being as flexible as for example Meucci (2008) in terms of possible areas of usage, it offers a fully systematic and dynamic allocation tool for algorithmic driven trading environments and compared to mixed estimation models it does not require the investor to quantify a level of confidence. Compared to Gosling (2010) scenario sets are much easier to construct since the model uses historical return as the scenario set. The main drawback with the model is that there are investment structures in which the model would be difficult to implement. Furthermore,
the model does not allow the investor to express views about future returns. Instead the SBAM uses a setup of input signals that are used to calculate a digital fingerprint for each historical scenario. When allocating for the future the model calculates a digital fingerprint and gives all historical scenarios probabilities of reoccurring based on how similar their digital fingerprints are to the current trading days.

In the quantitative testing the SBAM portfolio showed better performance compared to an equally weighted portfolio or a portfolio constructed by portfolio optimization based only on historical data. In the different tests the SBAM portfolio, with a set-up of systematic views as input, outperformed the other two portfolio allocation methods and produced higher annual returns and higher information ratio.
3 Methodology

This chapter will go through the theoretical methodology behind all processes used in this study.

3.1 Market Selection

The first step is to select an investment universe. According to Maginn, Tuttle, McLeavy and Pinto (2007) the criteria for specifying asset classes are that assets within an asset class should be homogeneous, asset classes should be mutually exclusive, be diversified, make up a significant fraction of the investors wealth and have the capacity to absorb a significant fraction of the investors capital.

Depending on the investor’s interests, the asset classes can be anywhere from very narrow to very broad. In our quantitative example we use a set-up of four simulated trading strategies as our market i.e. we see each trading strategy as an asset and the model allocates between these four assets. After a market universe is selected, time series for the returns of the assets in the market need to be calculated. Time series can be on a daily, weekly or monthly basis, to name a few examples.

3.2 Scenario Based Allocation Model

The SBAM is used to estimate input parameters for portfolio optimization. It is a scenario based allocation model that use entropy pooling for computing the scenario probabilities.

Instead of expressing views about future returns, we let a set-up of trading signals produce signals each trading day and then collect them in a combined vector. We call this combination of trading signals for the digital fingerprint. The next trading day we see what the return is for the assets we trade, and let the digital fingerprint calculated the prior trading day be linked to this return.

When the model trades it produces a digital fingerprint and then calculates the entropy between the current trading days fingerprint and all historical fingerprints. The historical returns are then given higher or lower probabilities of occurring based on how similar their linked fingerprints are to the current trading days. We then receive new parameters for portfolio optimization as we will get expected returns and correlations based on the signals from the current trading day.

3.2.1 Digital Fingerprints and Historical Scenarios

The first step in the SBAM is to construct a setup of trading signal functions $g_1, \ldots, g_K$, where $K$ is the number of trading signal functions. Each trading day, signals are calculated and the joint combination $V$ of these signals is what build up the digital fingerprint.
The trading signals are represented as generic functions of individual random variables

\[(g_1(Y_1), ..., g_K(Y_1)), (g_1(Y_2), ..., g_K(Y_2)), \ldots, (g_1(Y_M), ..., g_K(Y_M))\],

where \(Y = (Y_1, Y_2, \ldots, Y_M)\) and \(M\) is the number of random variables. When collecting all trading signals in a matrix this constitutes a \((K \cdot M) \times J\)-dimensional matrix (the digital fingerprints) where \(J\) is the number of trading days and whose joint distribution is represented by

\[V \equiv g(Y) \sim F_V.\]  

The generic function \(g\) could for example be a momentum strategy,

\[g_k = \begin{cases} 
1 & \text{if } Y > 0 \\
0 & \text{if } Y = 0 \\
-1 & \text{if } Y < 0 
\end{cases},\]  

that gives +1 for a buy signal and −1 for a sell signal and is based on the price data for a specific asset. It could be a function that calculate the current active share,

\[g_k = \frac{1}{2} \sum_{j=1}^{N} |w_{fund,j} - w_{index,j}|,\]  

where \(w_{fund,j}\) is the weight of the assets in the fund and \(w_{index,j}\) is the weight of the assets in the index. It could be a function that gives a signal based on external factors such as the interest rate or inflation.

For each digital fingerprint \(V\), calculated at time \(t\), realized asset returns are then calculated at time \(t + 1\) i.e. the next trading day or time for trading.

The distribution for realized asset returns is represented by

\[X \sim F_X,\]  

where \(X = (X_1, X_2, \ldots, X_N)\), \(N\) is the number of assets and the distribution \(F_X\) is represented by a set of scenario-probability pairs, \(J\) is the number of historical scenarios

\[F_X \text{ is specified by } \{(x_{1,j}, x_{2,j}, \ldots, x_{N,j}, p_j)\}_{j=1}^{J}\]  

### 3.2.2 Entropy Pooling

The Entropy Pooling Approach

Consider a market \(X\), this could be equity returns in the selected market. Denote the probabilities of \(X\) as \(p\). Then express some views, denoted \(V\), about the future i.e. scenarios, directional statements or stress tests which creates new estimated market probabilities. The new market probabilities \(\tilde{p}\) is as close as possible to the prior market probabilities \(p\) but satisfies the views \(V\). The new probabilities \(\tilde{p}\) is often referred to as the posterior probabilities.
3.2. SCENARIO BASED ALLOCATION MODEL

\[ \hat{p} \equiv \arg\min_{Vq=v} \{ \epsilon(q, p) \}, \quad (3.7) \]

and the relative entropy between the prior and posterior probabilities are given by

\[ \epsilon(q, p) = \sum_{j=1}^{J} q_{j} \ln \left( \frac{q_{j}}{p_{j}} \right). \quad (3.8) \]

Entropy Pooling covers highly non-linear markets such as derivatives markets and views on external factors that only influence realizations in a statistical manner. The input is an arbitrary market model and a set-up of arbitrarily distributed views. The output is a distribution that incorporates all inputs and can be used for risk management and portfolio optimization.

**Numerical Entropy Minimization**

The entropy minimization problem in (3.7) can be expressed as

\[ \tilde{q} \equiv \arg\min_{Vq=v} \{ \sum_{j=1}^{J} q_{j}(ln(q_{j}) - ln(p_{j})) \}, \quad (3.9) \]

where the equality constraints satisfies \( V = \{ q_{j}, \ Vq = v \}, \quad j = 1, \ldots, J \)

The Lagrangian for (3.9) is defined by

\[ L(q, \lambda) = \sum_{j=1}^{J} q_{j}(ln \left( \frac{q_{j}}{p_{j}} \right)) + \sum_{i=1}^{K \cdot M} \lambda_{i}(Vq, i - v_{i}). \quad (3.10) \]

We have

\[ \frac{\delta L}{\delta q_{j}} = \frac{\delta}{\delta q_{j}} \left( q_{j}(ln \left( \frac{q_{j}}{p_{j}} \right)) \right) + \frac{\delta}{\delta q_{j}} \left( \sum_{i=1}^{K \cdot M} \lambda_{i}(Vq, i - v_{i}) \right) \]

\[ = 1 + ln \left( \frac{q_{j}}{p_{j}} \right) + \sum_{i=1}^{K \cdot M} \lambda_{i} \frac{\delta}{\delta q_{j}} (Vq, i), \quad j = 1, \ldots, J, \quad (3.11) \]

where

\[ \frac{\delta}{\delta q_{j}} (Vq, i) = \frac{\delta}{\delta q_{j}} \left( \sum_{l=1}^{K \cdot M} (V_{ij} q_{j}) \right) = \delta_{ij} (V_{ij} q_{j}) = V_{ij}, \quad (3.12) \]

which gives

\[ \frac{\delta L}{\delta q_{j}} = 1 + ln \left( \frac{q_{j}}{p_{j}} \right) + \sum_{i=1}^{K \cdot M} \lambda_{i} V_{ij} \]

\[ = 1 + ln \left( \frac{q_{j}}{p_{j}} \right) + (V^{T} \lambda) = 0, \quad j = 1, \ldots, J. \quad (3.13) \]

The first order conditions for \( q_{j} \) yield

\[ q_{j}(\lambda) = e^{\ln(p_{j})-1-(V^{T} \lambda)_{j}}, \quad j = 1, \ldots, J, \quad (3.14) \]
The multipliers $\lambda$ are determined using the equality constraint $Vq = v$, or

$$\sum_{j=1}^{J} V_{ij}q_j = v_i, \quad i = 1, \ldots, K \cdot M.$$  \hspace{1cm} (3.15)

Inserting $q_j$ in (3.14), yields that $\lambda$ solves the non-linear equation

$$v_i = \sum_{j=1}^{J} V_{ij}e^{ln(p_j) - 1 - \sum_{l=1}^{K \cdot M} V_{jl}\lambda_l}, \quad i = 1, \ldots, K \cdot M.$$  \hspace{1cm} (3.16)

We solve the equation numerically.

**SBAM Adjustments of Entropy Pooling**

We first consider the set-up of digital fingerprints in (3.2), then express all the historical digital fingerprints as a set of scenario-probability pairs of the same form as (3.6).

$$F_v \text{ is specified by } \{(g_{1,j}, g_{2,j}, \ldots, g_{K \cdot M,j}, p_j)\}_{j=1}^{J}. \hspace{1cm} (3.17)$$

This is the prior distribution, where $g$ are the view functions. Compared to the entropy pooling approach the SBAM does not consider the distribution of the market. Instead it uses the distribution of the historical views. Then by the same calculations as in (3.8) and (3.7) we get a posterior distribution of the views which has the same scenarios but new probabilities

$$\tilde{F}_v \text{ is specified by } \{(g_{1,j}, g_{2,j}, \ldots, g_{K \cdot M,j}, \tilde{p}_j)\}_{j=1}^{J}. \hspace{1cm} (3.18)$$

The prior market distribution is described as in (3.6)

$$F_x \text{ is specified by } \{((x_{1,j}, x_{2,j}, \ldots, x_{N,j}), p_j)\}_{j=1}^{J}. \hspace{1cm} (3.19)$$

Hence, we get the posterior distribution by switching the probabilities in (3.19) with the probabilities in (3.18)

$$\tilde{F}_x \text{ is specified by } \{((x_{1,j}, x_{2,j}, \ldots, x_{N,j}, \tilde{p}_j)\}_{j=1}^{J}. \hspace{1cm} (3.20)$$

### 3.3 Portfolio Optimization

The parameters produced from the SBAM are good input parameters for portfolio optimization. Each trading day new parameters are calculated and an investor can use the new expected return and correlation matrix in an optimization of their own preference. In this study we optimize the portfolio by finding the portfolio with the highest risk adjusted expected return. No transaction costs are taken into consideration. Furthermore, the risk free interest rate (traditionally included when calculating the Sharpe Ratio) is assumed to be 0.
3.3. PORTFOLIO OPTIMIZATION

3.3.1 Maximum Sharpe Portfolio

In 1966, William Sharpe developed what is now called the Sharpe Ratio. The classic definition is

\[ \text{SharpeRatio} = \frac{E[R] - r_f}{\sqrt{\text{Var}(R)}}, \]  

(3.21)

where \( E[R] \) is the expected asset return, \( r_f \) is the risk free rate of return and \( \text{Var}(R) \) is the assets variance. In this paper we will assume \( r_f = 0 \) since it is of no importance for this study. Hence when referring to the Sharpe ratio it is on the reduced form (often called the information ratio)

\[ \text{SharpeRatio} = \frac{E[R]}{\sqrt{\text{Var}(R)}}. \]  

(3.22)

To be able to compare the portfolios created by different models we will create the maximum sharpe portfolio when optimizing. The maximum sharpe portfolio is retrieved by maximizing the below expression

\[ \text{SharpePortfolio}(w) = \frac{w^T \mu}{\sqrt{w^T \Sigma w}}, \quad w \in \mathbb{R}. \]  

(3.23)

3.3.2 Portfolio Construction

In this paper three different portfolios will be compared namely an equally weighted portfolio, an optimized maximum Sharpe portfolio and the SBAM portfolio. The first is used to symbolize a multi-strategy fund that weights equally between the funds underlying strategies. For the optimized maximum Sharpe portfolio we run a classic portfolio optimization on historic data. The SBAM portfolio is also built by the same optimization method as the optimized maximum Sharpe portfolio but the input parameters are created using the framework presented in the section "Scenario Based Allocation Model" in Chapter 3.

Equally Weighted Portfolio (EQ)

The EQ portfolio is equally weighted and rebalanced each trading day to fulfill the equal weights condition.

Maximum Sharpe Portfolio (MS)

The MS portfolio is recalculated every trading day and the weights are calculated by maximizing (3.23) using historical data as input i.e. the prior market distribution described in (3.6) where all probabilities are equal and sum up to 1.
CHAPTER 3. METHODOLOGY

SBAM Portfolio

The SBAM portfolio is recalculated every trading day and the weights are calculated by maximizing (3.23) using the posterior distribution (3.20) as input. All probabilities sum up to one.
4 The Data Set

In this section the data set used in the quantitative implementation is introduced. All data in this study was delivered by Informed Portfolio Management (IPM).

The product under study is an enhanced equity index product. The benchmark index is the FTSE All World Developed Large Cap TR Index which is an index consisting of approximately 1000 global equities. The enhancement consist of four simulated systematic trading strategies that all are modified versions of the benchmark index.

The data range consists of monthly data from January 1970 until December 2010. For this period we received six matrices. The first matrix represents the benchmark index, and consists of the market cap weights for all assets. The second matrix consists of price data for all assets in the benchmark between January 1975 and December 2010. The last four matrices represent the four systematic strategies and consist of alpha weights for all assets i.e. the difference in the allocation weight in an asset compared to the market cap weight. During the time period 3562 assets have at some time been included in the benchmark index and we have a total of 431 date points.

Matrix Presentation

The data set is represented in six matrices all built by the same structure.

\[
\begin{array}{c|cccccc}
\text{Asset} \backslash \text{Date} & t & t+1 & t+2 & \cdots & t+n \\
\hline
Asset_1 & \omega_1^t & \omega_1^{t+1} & \omega_1^{t+2} & \cdots & \omega_1^{t+n} \\
Asset_2 & \omega_2^t & \omega_2^{t+1} & \omega_2^{t+2} & \cdots & \omega_2^{t+n} \\
\vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
Asset_i & \omega_i^t & \omega_i^{t+1} & \omega_i^{t+2} & \cdots & \omega_i^{t+n} \\
\end{array}
\]

Table 4.1. Matrix Layout. The table displays the layout of data matrices. For the market cap matrix and the four strategies \(\omega\) represent the asset allocation weight and for the price data matrix \(\omega\) would represent the historical prices.

4.1 Raw Data Statistics

We calculate the return for the benchmark index and the four strategies by first calculating the asset return and then multiplying the return by the asset weight

\[
Return(t) = \sum_{i=1}^{3562} \left( \frac{\text{price}_i(t)}{\text{price}_i(t-1)} - 1 \right) w_i(t),
\]

where \(Return(t)\) represents the benchmarks or a strategy’s return at time \(t\), \(\text{price}_i(t)\) is the asset price at time \(t\) and \(w_i(t)\) is the allocation weight to the specific asset. We then create
CHAPTER 4. THE DATA SET

return series for the benchmark index (BI) and the four strategies (S1, S2, S3 and S4). The summary statistics for the returns are presented in Table 4.2. The trading strategies are all, except for S2, more volatile than the benchmark index. S3 has the highest volatility and also the largest gain and loss along with the highest average gain.

<table>
<thead>
<tr>
<th>Measure</th>
<th>BI</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>S4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean(%)</td>
<td>1.05</td>
<td>1.22</td>
<td>1.11</td>
<td>1.48</td>
<td>1.43</td>
</tr>
<tr>
<td>Median(%)</td>
<td>1.25</td>
<td>1.47</td>
<td>1.18</td>
<td>1.82</td>
<td>1.49</td>
</tr>
<tr>
<td>Max(%)</td>
<td>13.00</td>
<td>18.88</td>
<td>13.60</td>
<td>25.46</td>
<td>23.95</td>
</tr>
<tr>
<td>Min(%)</td>
<td>-22.51</td>
<td>-21.47</td>
<td>-22.58</td>
<td>-32.36</td>
<td>-24.43</td>
</tr>
<tr>
<td>StD(%)</td>
<td>4.32</td>
<td>4.59</td>
<td>4.32</td>
<td>6.10</td>
<td>4.97</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.6693</td>
<td>-0.5440</td>
<td>-0.6013</td>
<td>-0.6268</td>
<td>-0.4369</td>
</tr>
</tbody>
</table>

Table 4.2. Return Series Summary Statistics. Return series summary statistics are calculated for the benchmark indices and the four strategies from January 1975 until December 2010.

In Figure 4.1 we present equity curves and in Figure 4.2 we show the monthly returns and histograms for the same returns.
Figure 4.1. Equity Curves. Equity curves for the benchmark indices and the four strategies from January 1975 until December 2010.
Figure 4.2. Monthly Returns and Histograms. Monthly returns (left) and histograms (right) for the benchmark indices and the four strategies from January 1975 until December 2010.
5 Implementation

In this chapter the set up for the quantitative testing is presented. The SBAM methodology is tested on four systematic strategies with the aim to create a fund with dynamic weights between the different strategies. As comparison an equally weighted portfolio and a portfolio that use traditional portfolio optimization based purely on historical data are used. The test can be seen as three different managers managing a fund using different investment principles for how to allocate the capital between four systematic trading strategies.

The study simulates portfolio management for these three portfolios over a period of 24 years from January 1987 until December 2010. The portfolios are rebalanced on a monthly basis.

Some important facts should be noted. First, we do not consider transaction costs. Second, four simulated systematic trading strategies are used as our investment universe. These strategies create individual portfolios by investing in the equities that are included in the benchmark index. Third, we will not consider liquidity. Positions are assumed to always be possible to execute at current prices.

We are not allowed to in detail describe investment strategies. This surely is of interest for the reader but it is of no importance for the study. The main scope of this study is to test if the SBAM can be implemented at an actual hedge fund and if it can offer an asset allocation tool based on mixed estimation theory but without the requirement to quantify a level of confidence for the subjective views about the future.

5.1 Prior Market

For the four systematic trading strategies monthly data from January 1975 until December 2010 are used. Our investment universe consists of these four possible investments. Portfolio optimization models require some historical data to be able to produce portfolios. The initial prior market consists of twelve years of monthly returns for these four strategies.

Two different methods are used with respect to the length of the sample data. First, all data is kept in the sample and the sample data will grow as we simulate forward. To be able to get results less dependent on the choice of sample data we use a rolling window consisting of the latest twelve years of data. As we step forward the oldest data point is removed from the sample. Identical simulations are done for both types of historical sample data.

5.2 Implemented Views

As mentioned earlier the SBAM eliminates the requirement for the investor to specify a level of confidence in the subjective views about the future. Instead the model requires a set-up of systematic views that produce a signal at every trading point. One could think of
it as a set up trading signals. It is up to the investor to create a universe of trading input signals that is suitable for the specific market.

In this section we will present the views created to fit the hedge fund data. All signals are applied on all four strategies giving us a total input of twelve trading signals (views) at every trading date.
5.2. IMPLEMENTED VIEWS

View 1

Our first signal is based on the theory of active share. Active share is a measure of how much a specific portfolio differs in its allocations compared to the benchmark index. Examining 2,650 funds from 1980 to 2003, Cremers and Petajisto (2004) found that the funds, with an Active Share of 80% or higher, beat their benchmark indexes by $2 - 2.71\%$ before fees and by $1.49 - 1.59\%$ after fees.

Active share is calculated as the sum of the absolute difference between asset weights divided by two

$$Active \ Share = \frac{1}{2} \sum_{i=1}^{N} |w_{fund,i} - w_{index,i}|.$$ \hspace{1cm} (5.1)

As mentioned in the previous chapter the strategy data consists of alpha weights for every asset included in the benchmark index i.e. how much the allocation in an asset differ from the benchmark market cap weight for that asset. The rationale behind View 1 is that higher active share will mean that the strategy is more likely to beat the benchmark and lower active share that the strategy will perform more in line with the benchmark index.

$$View 1 = \frac{1}{2} \sum_{i=1}^{N} |\alpha_i|.$$ \hspace{1cm} (5.2)

where

$$\alpha_i = w_{fund,i} - w_{index,i}.$$ \hspace{1cm} (5.3)

Figure 5.1. View 1 View 1 for all for strategies during the time period January 1975 until December 2010.
CHAPTER 5. IMPLEMENTATION

View 2

View 1 consider all assets equally and do not make any difference between large companies compared to small. Equities with small market cap are treated in the same way as equities with large market cap. View 2 individually consider each equities alpha weight in proportion to the market cap weight hence, the value depends on by how much the alpha weight differ from the market cap weight. A company with small influence in the index (small market cap) could influence the signal largely if the alpha weight is largely different.

\[ \text{View 2} = \sum_{i=1}^{N} \frac{|\alpha_i|}{w_{\text{Index},i}}. \]  

(5.4)

Figure 5.2. View 2 for all strategies during the time period January 1975 until December 2010.
5.2. IMPLEMENTED VIEWS

View 3

View 3 focus on the opposite compared to View 2. In View 3 small changes in the allocation in equities with large market cap will have much bigger impact than large changes in small companies since the alpha weight is multiplied with the market cap weight. Large equities influence on the signal will be scaled up while equities with small market cap will be scaled down.

\[ View^3 = \sum_{i=1}^{N} |\alpha_i| w_{\text{index},i}. \]  

Figure 5.3. View 3 for all for strategies during the time period January 1975 until December 2010.

5.2.1 Prior Views

The SBAM, as described in Chapter 3, calculates the entropy by focusing on the views rather than the historical return data. If View 1, View 2 and View 3 are applied on all four strategies at the same time the Prior Views distribution would by 3.17 look as follow

\[ F_v \text{ is specified by } \{(g_j, p_j)\}_{j=1,...,J} \]

where \( g = (g_1, g_2, g_3) \) and

\[ g_1 = (G_1, \text{strategy1}; G_1, \text{strategy2}; G_1, \text{strategy3}; G_1, \text{strategy4}) \]

\[ g_2 = (G_2, \text{strategy1}; G_2, \text{strategy2}; G_2, \text{strategy3}; G_2, \text{strategy4}) \]

\[ g_3 = (G_3, \text{strategy1}; G_3, \text{strategy2}; G_3, \text{strategy3}; G_3, \text{strategy4}) \]

where J is the number of observations and \( g_1, g_2, g_3 \) is View 1, View 2 and View 3 applied on strategy 1 – 4. Furthermore, in this test prior views \( p \) are uniformly distributed.
5.2.2 Portfolio Construction

In Chapter 3 we presented the theoretical methodology behind the three portfolio construction methods compared in this study. The first portfolio is the equally weighted portfolio (EQ). The methodology is quite clear cut. It is a portfolio that rebalances its weights every trading date to fulfill the condition to be equally weighted and fully invested.

The second portfolio is the Maximum Sharpe portfolio (MS) which is derived by maximizing \(3.23\) where the historical return data from the four strategies are used as input and with the constraints that the portfolio must be fully invested i.e. the weights must sum up to 1 and no short selling of the strategies is possible i.e. all weights must be larger or equal to 0.

The third portfolio is the SBAM portfolio. Like the MS portfolio the final weights are calculated by maximizing \(3.23\) but the input is the posterior market from equation \(3.20\). As with all portfolios, no short selling of the strategies is allowed and the weights must sum up to 1.

5.3 Trading Simulation

The quantitative testing can be broken up into two main parts. In part one the focus is on the SBAM. Different combinations of the three views are used to create and compare the different portfolios. In part two we compare the SBAM with the EQ and MS portfolio.

5.3.1 Test 1

In test 1, seven SBAM portfolios are studied. The difference between the portfolios is that they use different combinations of the views as input. The seven portfolio inputs are presented below.

- View 1 (V1)
- View 2 (V2)
- View 3 (V3)
- View 1 and View 2 (V1V2)
- View 1 and View 3 (V1V3)
- View 2 and View 3 (V2V3)
- View 1, View 2 and View 3 (V1V2V3)

All simulations start January 1987 and runs, rebalancing the portfolios on a monthly basis, until December 2010. Twelve years of data (January 1975 until December 1986) are used as starting sample data. The simulation is executed two times. In the first simulation the sample data grow by one month every time we step forward. The second time a rolling window consisting of the latest 12 years of data prior to current trading date is used as the sample.
5.3. TRADING SIMULATION

5.3.2 Test 2

Test 2 compare the SBAM to an equally weighted portfolio and the maximum Sharpe portfolio optimized purely on historical data. First the portfolios are simulated from January 1987 until December 2010 using data from January 1975 until December 1986 as starting sample data. Traditional fund performance measures are used to evaluate the portfolios.

An identical simulation is then executed with the difference that the annual standard deviation (ex ante) for the portfolios is fixed at 15%. This is done by first calculating the annual standard deviation in the portfolios and then linearly adjusts the portfolios exposure to reach the target volatility.

\[
\text{Target Portfolio Volatility} = x \{\text{Annual Portfolio Volatility}\}. \tag{5.7}
\]

In the equation above we show how to find the linear exposure adjustor \(x\). We will then use \(x\) to adjust the portfolio weights.

\[
\text{Volatility Adjusted Portfolio} = x \{\text{Portfolio}\}. \tag{5.8}
\]
6 Results

This chapter presents the results from the two tests described in Chapter 5. The chapter is organized as follows. First, the performance measures used for evaluation are described. This is followed by an analysis of the performance from the back test of the SBAM portfolios presented in Test 1 in the previous chapter. Next, we will compare the results for Test 2 in which we evaluate the equally weighted portfolio, the maximum sharpe portfolio and the SBAM portfolio. Finally we will summarize our findings.

6.1 Performance Measures

The two most known performance measures for evaluating trading performance are return and volatility. Other measures are also of interest when evaluating an investment strategy. Below is a list of all the measures used in this study.

- Total Return (The cumulative return for the entire period).
- Average Annual Return
- Average Monthly Return (Monthly traded portfolios hence the measure is a measure of average trade performance)
- Annual Volatility (Monthly standard deviation multiplied with the square root of 12)
- Information Ratio (Average Annual Return / Annual Volatility)
- Information Sortino Ratio (Annual Return / Annual Volatility from trading dates with negative performance)
- Largest Monthly Gain
- Largest Monthly Loss
- Average Monthly Gain
- Average Monthly Loss
- Positive Trades
- Maximum Drawdown
6.2 Results from Test 1

Test 1 - Part 1 Seven SBAM Portfolios

To begin the analysis, seven different SBAM portfolios are compared. The difference is that they use different combinations of the views as input. As can be seen in Figure 6.1 and Table 6.1 it is clear that if we only use one single view, it is View 3 that gives the highest information ratio and cumulative return. It is interesting to note that when combining View 1 and View 3 the performance increase compared to the two individually, but the opposite plays out when combining View 2 and View 3. The portfolio that gives the highest cumulative return over the entire time period is the portfolio using View 1 and View 3 as input (V1V3). This portfolio also has the highest information ratio. It is interesting to note how the seven portfolios perform differently depending on which views are used as input - this pointing out the importance to form views that fit an investors market.

<table>
<thead>
<tr>
<th>Measure</th>
<th>V1</th>
<th>V2</th>
<th>V3</th>
<th>V2V3</th>
<th>V1V2</th>
<th>V1V3</th>
<th>V1V2V3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Ret.(%)</td>
<td>1307</td>
<td>1661</td>
<td>2069</td>
<td>1584</td>
<td>1467</td>
<td>2467</td>
<td>1548</td>
</tr>
<tr>
<td>Avg. Monthly Ret.(%)</td>
<td>1.01</td>
<td>1.10</td>
<td>1.14</td>
<td>1.09</td>
<td>1.07</td>
<td>1.21</td>
<td>1.08</td>
</tr>
<tr>
<td>Annual Vol.(%)</td>
<td>17.38</td>
<td>17.54</td>
<td>15.28</td>
<td>18.05</td>
<td>18.21</td>
<td>15.89</td>
<td>17.78</td>
</tr>
<tr>
<td>Inf. Ratio</td>
<td>0.70</td>
<td>0.75</td>
<td>0.90</td>
<td>0.73</td>
<td>0.70</td>
<td>0.92</td>
<td>0.73</td>
</tr>
<tr>
<td>Inf. Ratio (Sortino)</td>
<td>1.02</td>
<td>1.11</td>
<td>1.38</td>
<td>1.06</td>
<td>0.99</td>
<td>1.43</td>
<td>1.06</td>
</tr>
<tr>
<td>Largest Gain (%)</td>
<td>20.52</td>
<td>20.52</td>
<td>14.47</td>
<td>20.52</td>
<td>20.52</td>
<td>13.96</td>
<td>20.52</td>
</tr>
<tr>
<td>Largest Loss (%)</td>
<td>-25.02</td>
<td>-23.40</td>
<td>-22.03</td>
<td>-24.35</td>
<td>-32.36</td>
<td>-21.51</td>
<td>-24.36</td>
</tr>
<tr>
<td>Avg. Gain(%)</td>
<td>3.73</td>
<td>3.33</td>
<td>3.29</td>
<td>3.30</td>
<td>3.20</td>
<td>3.27</td>
<td>3.37</td>
</tr>
<tr>
<td>Positive Trades (%)</td>
<td>64.71</td>
<td>65.40</td>
<td>66.44</td>
<td>66.78</td>
<td>68.51</td>
<td>67.13</td>
<td>66.78</td>
</tr>
<tr>
<td>Max. Drawdown (%)</td>
<td>56.67</td>
<td>59.42</td>
<td>43.07</td>
<td>59.58</td>
<td>58.49</td>
<td>44.27</td>
<td>59.80</td>
</tr>
</tbody>
</table>

Table 6.1. Portfolio Performance Measures. Portfolio performance measures for all seven SBAM portfolios, all sample history used, calculated from January 1987 until December 2010.
6.2. RESULTS FROM TEST 1

Test 1 - Part 2: 12 Years Rolling Sample History

In part 1, twelve years of data is used as starting sample data, and for every month simulated forward all prior history is kept i.e. the sample data increase by one month. In part 2 the exact same simulation is replicated with the difference that a rolling window of the latest twelve years of data is used as the sample. For every month simulated forward the oldest data point in the sample data is removed.

We note that portfolio V1V2 is the highest performing portfolio with respect to total return and V1V3 is the third highest. As seen in Table 6.2 and Figure 6.2 the Information Ratio and Sortino Ratio for portfolio V1V3 is ranked second and first, only slightly below V1V2 and at the same time the V1V3 portfolio has the smallest maximum drawdown and the highest percentage of positive months together with portfolio V1V2. Overall all of the portfolios have a higher Information Ratio in Part 2 then in Part 1 except for the portfolio V1V2V3.

Even though portfolio V1V3 offer an overall performance for the entire time period that is very close in both the case with a growing sample data and in the case with a 12 years rolling sample data the two portfolios behave differently. In Table 6.1, Table 6.2, Figure 6.1 and Figure 6.2 we can compare the measures and how the length of sample data affect the results. In Figure 6.4 we can more explicitly see how the different sample data affect the performance for the V1V3 portfolio.
CHAPTER 6. RESULTS

<table>
<thead>
<tr>
<th>Measure</th>
<th>V1</th>
<th>V2</th>
<th>V3</th>
<th>V2V3</th>
<th>V1V2</th>
<th>V1V3</th>
<th>V1V2V3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Ret.(%)</td>
<td>1745.85</td>
<td>1885.85</td>
<td>2584.79</td>
<td>2090.23</td>
<td>3081.93</td>
<td>2473.08</td>
<td>1372.13</td>
</tr>
<tr>
<td>Avg. Monthly Ret.(%)</td>
<td>1.11</td>
<td>1.14</td>
<td>1.22</td>
<td>1.18</td>
<td>1.32</td>
<td>1.21</td>
<td>1.03</td>
</tr>
<tr>
<td>Annual Vol.(%)</td>
<td>17.10</td>
<td>17.21</td>
<td>15.27</td>
<td>17.34</td>
<td>17.95</td>
<td>15.36</td>
<td>17.04</td>
</tr>
<tr>
<td>Inf. Ratio</td>
<td>0.78</td>
<td>0.80</td>
<td>0.96</td>
<td>0.81</td>
<td>0.89</td>
<td>0.94</td>
<td>0.72</td>
</tr>
<tr>
<td>Inf. Ratio (Sortino)</td>
<td>1.02</td>
<td>1.11</td>
<td>1.38</td>
<td>1.06</td>
<td>0.99</td>
<td>1.43</td>
<td>1.06</td>
</tr>
<tr>
<td>Largest Gain (%)</td>
<td>20.52</td>
<td>20.52</td>
<td>12.49</td>
<td>20.52</td>
<td>20.52</td>
<td>13.12</td>
<td>20.52</td>
</tr>
<tr>
<td>Avg. Gain(%)</td>
<td>3.66</td>
<td>3.38</td>
<td>3.24</td>
<td>3.27</td>
<td>3.27</td>
<td>3.33</td>
<td>3.29</td>
</tr>
<tr>
<td>Avg. Loss(%)</td>
<td>-4.10</td>
<td>-3.06</td>
<td>-2.98</td>
<td>-3.29</td>
<td>-3.43</td>
<td>-3.56</td>
<td>-3.41</td>
</tr>
<tr>
<td>Positive Trades (%)</td>
<td>67.13</td>
<td>64.71</td>
<td>65.74</td>
<td>67.13</td>
<td>67.82</td>
<td>67.82</td>
<td>67.47</td>
</tr>
<tr>
<td>Max. Drawdown (%)</td>
<td>52.89</td>
<td>59.27</td>
<td>35.12</td>
<td>53.37</td>
<td>44.64</td>
<td>38.80</td>
<td>57.46</td>
</tr>
</tbody>
</table>

Table 6.2. Portfolio Performance Measures. Portfolio performance measures for all seven SBAM portfolios, 12 years rolling sample history used, calculated from January 1987 until December 2010.

![Equity Curves](image)

Figure 6.2. Equity Curves. Equity curves for seven SBAM portfolios, 12 years rolling sample history used from January 1987 until December 2010.
6.2. RESULTS FROM TEST 1

Test 1 - Part 3 Entropy Behavior

In the first two parts we analyze how different lengths of sample history affect the portfolio. In this section we focus on the entropy values from the construction of the posterior market to show how it differs from using all sample history and 12 years rolling history. The entropy value show how similar the posterior probability vector is to the prior probability vector, where a lower entropy value means a smaller difference. A different way to interpret the entropy value is when you have more similar historical views compared the latest view (current trading day views), you will have a low entropy value, and when there is few similar views your entropy value will increase (compared to a uniformly distributed market prior).

The first four Figures, 6.3, show how the entropy changes over time for the different combination of View 1, View 2 and View 3. Figures over the views separately, A.1, are found in the Appendix A. Notice that the 12 years rolling sample period generally has lower entropy value, except during some short periods. During the end of the testing period a couple of the Views, for the 12 years rolling sample period, shows a consistently higher entropy value for a longer time period. This coincides with the financial crisis in 2008.

Figure 6.4 shows how the performance and entropy differs during the test period for V1V3. With a longer sample period strategy V1V3 tends to take more risk than for the shorter sample period, with a slightly higher standard deviation and a higher maximum drawdown, which are shown in Table 6.1 and 6.2. The entropy values follow the same trend, but the 12 years rolling sample period has generally a slightly lower entropy value.
CHAPTER 6. RESULTS

Figure 6.3. **Entropy Comparison.** Entropy displayed in top figure for V1V3, top-middle figure for V1V2, bottom-middle figure V1V3 and bottom figure V2V3. All sample history and 12 years rolling sample history is compared, from January 1975 until December 2010.
6.2. RESULTS FROM TEST 1

![Figure 6.4. Entropy and Performance Comparison.](image)

Figure 6.4. **Entropy and Performance Comparison.** Entropy displayed in top figure and performance in bottom for V1V3, all sample history and 12 years rolling sample history, Displayed from January 1987 until December 2010.
6.3 Results Test 2

Test 2 - Part 1 Portfolio Comparison

This paper’s main attempt is to introduce a method that uses the mixed estimation model’s ability to include subjective views about the future but in such a way that there is no need to set a level of confidence. Part two is the main scope of this analysis since it compares the SBAM with other, commonly used, allocating models. From Test 1 we have chosen the V1V3 portfolio that includes two types of views to represent the SBAM in the comparison.

Looking in Table 6.3 it is clear that the SBAM portfolio is the one with the highest volatility. It gives the highest return and has the highest information ratio. The Equally Weighted portfolio and the Maximum Sharpe portfolio performance measures are very similar.

Figure 6.6 shows how the three portfolios allocation weights have changed during the simulation. The SBAM approach produces a higher allocation turnover and invests in all four strategies. Whereas the Maximum Sharpe portfolio changes more slowly and it does not invest in strategy 2.

<table>
<thead>
<tr>
<th>Measure</th>
<th>SBAM (V1V3)</th>
<th>Equally Weighted</th>
<th>Maximum Sharpe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Ret. (%)</td>
<td>2467</td>
<td>1894</td>
<td>1814</td>
</tr>
<tr>
<td>Avg. Annual Ret. (%)</td>
<td>14.55</td>
<td>13.34</td>
<td>13.15</td>
</tr>
<tr>
<td>Avg. Monthly Ret. (%)</td>
<td>1.21</td>
<td>1.11</td>
<td>1.10</td>
</tr>
<tr>
<td>Annual Vol. (%)</td>
<td>15.89</td>
<td>15.05</td>
<td>14.99</td>
</tr>
<tr>
<td>Inf. Ratio</td>
<td>0.92</td>
<td>0.89</td>
<td>0.88</td>
</tr>
<tr>
<td>Inf. Ratio (Sortino)</td>
<td>1.43</td>
<td>1.33</td>
<td>1.32</td>
</tr>
<tr>
<td>Largest Gain (%)</td>
<td>13.96</td>
<td>13.61</td>
<td>13.02</td>
</tr>
<tr>
<td>Largest Loss (%)</td>
<td>-21.51</td>
<td>-25.21</td>
<td>-24.04</td>
</tr>
<tr>
<td>Avg. Gain(%)</td>
<td>3.27</td>
<td>3.24</td>
<td>3.31</td>
</tr>
<tr>
<td>Avg. Loss(%)</td>
<td>-3.60</td>
<td>-3.26</td>
<td>-3.39</td>
</tr>
<tr>
<td>Positive Trades (%)</td>
<td>67.13</td>
<td>65.74</td>
<td>65.74</td>
</tr>
<tr>
<td>Max. Drawdown (%)</td>
<td>44.27</td>
<td>42.68</td>
<td>41.69</td>
</tr>
</tbody>
</table>

Table 6.3. Portfolio Performance Measure. Portfolio performance measures for V1V3, Equally Weighted and Max Sharpe, all sample history used, calculated from January 1987 until December 2010.
6.3. RESULTS TEST 2

**Figure 6.5. Equity Curves.** Equity curves calculated for V1V3, Equally Weighted and Max Sharpe, all sample history used and displayed from January 1975 until December 2010.
Figure 6.6. Portfolio Weights. Portfolio weights between strategies 1, 2, 3 and 4. V1V3 displayed in top figure, Equally Weighted in middle and Max Sharpe in bottom figure, all sample history used and displayed from January 1975 until December 2010.
6.3. RESULTS TEST 2

Test 2 - Part 2 Equal Volatility

As we could see in 6.3 it is obvious that the SBAM portfolio has higher volatility. Even though information ratio is a measure that should make the portfolios comparable, the other measures might be harder to evaluate against each other.

We try to make the three portfolios equally volatile by using 5.8. The annual volatility (ex ante) is attempted to be fixed at 15% for all portfolios. As can be seen in 6.4 the volatility is now at a more equal level for all portfolios. We note that the performance measures have greatly increased for all portfolios. This is due to the fact that historically, volatility has increased in periods of economic turmoil. With fixed volatility the portfolios exposure is adjusted down as volatility increase hence the portfolios have suffered smaller losses in periods of economic retraction. A look at the largest loss and maximum drawdown in tabular 6.3 and 6.4 point out this fact. In Figure A.2 and Figure A.3 in Appendix A one can see how the annual volatility has changed for the portfolios.

The V1V3 portfolio gives an information ratio slightly higher than the other two portfolios. It still has a larger maximum drawdown then the Maximum Sharpe portfolio, but with target volatility it is only slightly higher. The V1V3 portfolio gives a higher performance over the entire time period. It also has the highest percentage of positive months.

We should again highlight the fact that we do not take transaction costs into consideration. In Figure 6.6 we can see how the three portfolios have changed their weights between the strategies over time. The equally weighted portfolio is of course always equally weighted. The maximum Sharpe portfolio is more flexible but we see that it follows trends in its changes. The SBAM portfolio is the most extreme when it comes to allocation weights. Transaction cost could be assumed to be higher in this portfolio compared to the others assuming the four strategies are approximately equally frequent in their trading.

<table>
<thead>
<tr>
<th>Measure</th>
<th>SBAM (V1V3)</th>
<th>Equally Weighted</th>
<th>Maximum Sharpe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Ret.(%)</td>
<td>2571</td>
<td>2366</td>
<td>2389</td>
</tr>
<tr>
<td>Avg. Monthly Ret.(%)</td>
<td>1.23</td>
<td>1.20</td>
<td>1.20</td>
</tr>
<tr>
<td>Annual Vol.(%)</td>
<td>15.65</td>
<td>15.60</td>
<td>15.53</td>
</tr>
<tr>
<td>Inf. Ratio</td>
<td>0.94</td>
<td>0.92</td>
<td>0.93</td>
</tr>
<tr>
<td>Inf. Ratio (Sortino)</td>
<td>1.48</td>
<td>1.41</td>
<td>1.44</td>
</tr>
<tr>
<td>Largest Gain (%)</td>
<td>17.84</td>
<td>16.60</td>
<td>15.84</td>
</tr>
<tr>
<td>Largest Loss (%)</td>
<td>-30.21</td>
<td>-28.79</td>
<td>-29.50</td>
</tr>
<tr>
<td>Avg. Gain(%)</td>
<td>3.52</td>
<td>3.50</td>
<td>3.54</td>
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<tr>
<td>Avg. Loss(%)</td>
<td>-3.47</td>
<td>-3.13</td>
<td>-3.22</td>
</tr>
<tr>
<td>Positive Trades (%)</td>
<td>67.13</td>
<td>65.74</td>
<td>65.74</td>
</tr>
<tr>
<td>Max. Drawdown (%)</td>
<td>32.69</td>
<td>32.95</td>
<td>30.73</td>
</tr>
</tbody>
</table>

Table 6.4. Portfolio Performance Measures. Portfolio performance measures from Test 2 part 2, all sample history used with target volatility, calculated from January 1987 until December 2010.
Figure 6.7. Equity Curves for Fixed Target Volatility. Equity curves calculated for V1V3, Equally Weighted and Max Sharpe, all sample history used with target volatility displayed from January 1975 until December 2010.
7 Conclusions

This paper presents the SBAM, a hybrid between a scenario based allocation model and a mixed estimation model. The models main advantage is that it can blend subjective views about the future with historical data but without the need to quantify a level of confidence. This is done by calculating, and minimizing, the entropy on the distribution of the views rather than the historical return data. During the testing at the systematic hedge fund company IPM in Stockholm, Sweden, the model proved much more profitable compared to an equally weighted portfolio or classical portfolio optimization.

Portfolios were simulated over a time period of 24 years. The portfolios were rebalanced on a monthly basis. First we simulated the portfolios over 24 years keeping all historical data in the sample. The sample data did grow by one month as we simulated one step forward. Second we simulated portfolio over the same time period of 24 years but instead we used a rolling window of historical sample data of 12 years. In both cases the SBAM with the views described in Chapter 5 provided more profitable solutions than an equally weighted portfolio or classical portfolio optimization based only on historical data.

When comparing the seven SBAM portfolios, with the difference that they used different combinations of views as input and using all sample history, the portfolio with the View 1 and View 3 provided the highest return. This is a case specific finding though and what views to use is up to the individual investor to decide. Fundamental knowledge about the investment strategies applied by the investor is of significant importance if the investor is to be able to construct views that can catch different behavior. To select views properly is of great importance as the results are sensitive to view input.

The results are of interest for several reasons but two points stand out. First, it is obvious from the numerical implementation that it is possible to find higher returns by more frequently changing the weights compared to an equally weighted portfolio or a portfolio optimized purely on historical data. To search for alternative methods for portfolio allocation could prove very profitable for a fund company.

Second, the SBAM could provide an alternative worth to consider. The views applied in this study are only examples of how to calculate systematic views and of course other options might be much more suitable. None the less the V1V3 portfolio provides higher return compared to the other portfolio allocation methods under investigation in this study. In the case without fixated volatility the V1V3 portfolio gave almost 1 – 1.5% higher annual performance and 3 – 4% higher information ratio than the other portfolios with all sample history. The elimination of the requirement to quantify a level of confidence could make the SBAM more appealing to fund companies. The study proves that the portfolios provided by the SBAM provide suitable portfolios even though the level of confidence was never needed to consider. One should note though that the four possible investments i.e. the four simulated strategies developed by IPM are in themselves constructed to behave in a specific manner hence, it would be hard for any type of model to produce extreme results.

Transaction costs would most likely be higher for the SBAM portfolios since the method
is much more volatile with respect to the changes in portfolio allocations. The reader should note though that we have not considered any transaction costs in this study and that this is just a well educated guess.

The drawbacks with the SBAM are that views cannot be expressed as expectations about future realizations. Furthermore the model might not be suitable to implement in all kinds of investment structures. For example in a fundamentally driven environment it might be hard to produce systematic view signals. In more algorithmic driven environments it is likely to be much easier.

To sum up the SBAM portfolio could offer an alternative to current allocation models. The elimination of the requirement to set a level of confidence in views about the future is likely to be a much wanted feature by the capital management community. It requires a set-up of systematic views and hence it might not be suitable for all type of investors. Mixed estimation models have been discussed in the finance industry over the past decades since their ability to include subjective views about the future is something professional practitioners are looking for but the need to quantify a level of confidence have been a big hurdle. The SBAM could offer one solution that possibly could lead to that they will become more widespread among professional investors.
8 References


Managing quantitative and traditional construction. *Journal of Asset Management* Vol 1, 2, pp. 138-150.

Appendices
## A Tables and Figures

<table>
<thead>
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**Table A.1. Yearly Information Ratio.** Information ratio calculated yearly for all SBAM portfolios, Equally Weighted and Max Sharpe with all sample history used and calculated from January 1975 until December 2010.
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Table A.2. Yearly Information Ratio. Information ratio calculated yearly for all SBAM portfolios, Equally Weighted and Max Sharpe with 12 years rolling sample history used and calculated from January 1975 until December 2010.
Figure A.1. Entropy Comparison. Entropy calculated for all sample period and 12 years rolling sample period. Top figure displays View 1, middle figure displays View 2 and bottom figure displays View 3. Calculated from January 1975 until December 2010.
Figure A.2. One Year Rolling Volatility for Fixed Target Volatility. One year rolling volatility is calculated for V1V3, Equally Weighted and Max Sharpe for underlying strategies with all sample history used and fixed target volatility. Volatility is calculated from January 1975 and displayed in figure from January 1976 until December 2010.

Figure A.3. One Year Rolling Volatility. One year rolling volatility is calculated for V1V3, Equally Weighted and Max Sharpe for underlying strategies with all sample history. Volatility is calculated from January 1975 and displayed in figure from January 1976 until December 2010.