



UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Department of Economics

A Performance Evaluation of Black Swan Investments

Bachelor Thesis, 15 ECTS

Spring 2013

Tutor:

Charles Nadeau

Authors:

Fabian Brunåker & Andreas Nordqvist

Department of Economics
School of Business, Economics and Law at University of Gothenburg
Vasagatan 1, PO Box 640, SE 405 30, Göteborg, Sweden
+46 37 786 0000, +46 31 786 1326 (fax)
www.handels.gu.se infohandels.gu.se

Abstract: This thesis evaluates an investment strategy that involves investing in ten out of the 30 most traded stocks listed on the Stockholm Stock Exchange, exploiting the market's reaction to unpredicted events, so called Black Swans. By investing in ten of the stocks with the largest price change after days with extreme negative returns and ten of the stocks with the least change in price after extreme positive returns, the strategy outperforms the market. The authors also evaluate standard deviation (SD) as a risk measurement, finding that it captures the relationship between risk and return during volatile market periods.

Acknowledgement: We wish to thank Dr. Charles Nadeau for his support and constant availability.

Keywords: Black Swans, fat tails, standard deviation, mean reversion, investment strategy, downside deviation, extreme market movements

Contact:

Fabian Brunåker: gusbrunfa@student.gu.se

Andreas Nordqvist: gusdnomdan@student.gu.se

Table of Contents

1. Introduction.....	1
1.1 Background.....	1
1.2 Purpose.....	2
1.3 Research Questions.....	3
2. Theory.....	4
2.1 The Definition of a Black Swan	4
2.2 Mean Reversion	5
2.3 Literature Review	5
3. Data & Methodology	9
3.1 Data	9
3.2 Methodology	9
3.2.1 Investment Strategy	10
3.2.2 Standard Deviation as a Measure of Risk.....	11
3.3 Limitations.....	11
3.4 Normal distribution	12
3.4.1 Kurtosis.....	12
3.4.2 Skewness	12
3.4.3 Jarque-Bera Test for Normality.....	13
3.5 Performance evaluation.....	13
3.5.1 Arithmetic Mean.....	13
3.5.2 Geometric Mean	14
3.5.3 Standard Deviation	14
3.5.4 Downside Deviation.....	14
3.5.5 Risk-Adjusted Returns.....	15
4. Results & analysis	16
4.1 Hypothesis I.....	16
4.1.1 Results	17
4.1.2 Analysis.....	18
4.2. Hypothesis II	21
4.2.1 Results	22
4.2.2 Analysis	22
5. Conclusion.....	25

6. Suggestions for Further Research.....	26
7. References.....	27
7.1 Articles.....	27
7.2 Books.....	28
7.3 Internet.....	29
7.4 Databases.....	29
8. Appendix.....	30
8.1 Detailed Summary about the Distributions.....	30
8.2 Jarque-Bera Significance Points.....	30
8.3 Test for Skewness and Kurtosis.....	31
8.4 <i>t</i> -test for Hypothesis I	31
8.5 Graph 3: β -assets, Strategy, and OMXS30; Compounded	32

1. Introduction

Unpredicted events, or “Black Swans”, have caused stock markets all over the world to decrease, or increase, by several percent in a single day over the years. Based on Estrada and Vargas’ article (2012), we will investigate whether we can make use of unpredicted events in the Swedish Stock Exchange (SSE) (OMXS30) in order to achieve a higher return than the market index by relying on the mean reversion assumption. The methodology of Estrada and Vargas will be modified and instead of using beta, in this thesis we will be looking at price changes in order to select our stocks. We define a Black Swan as a monthly change in return for the OMXS30 of $\pm 5\%$ or more. Our investment strategy involves investing in stocks after a negative Black Swan and selling them after a positive Black Swan, at which time we purchase the stocks that had the minimum change in return. During the time frame of 21 years, from the 1st of January 1992 until the 31st of December 2012, the portfolio will be reallocated after each new Black Swan in opposite direction of the last one occurs. In this work we find that our strategy outperforms the market; the result is economically significant.

The second objective of this thesis is to examine the standard deviation as a risk measure. Estrada and Vargas test the merit of beta as a measure of risk during large market fluctuations, as do Chan and Lakonishok (1993) and Grundy and Malkiel (1996), due to previous scholars’ rejection of its usefulness (Chan and Lakonishok, 1993). Since standard deviation, like beta, does not adjust for downside risk we find it relevant to evaluate standard deviation as a measure of risk to appraise if it is an accurate tool for describing the relationship between risk and return during extreme market movements, we find that it does.

1.1 Background

Wall Street trader and subsequently philosopher, professor and author Nassim Nicholas Taleb coined the phrase “Black Swans” in his book *Foiled by randomness* (2001) as a metaphor for rare events. In his second book, *The black swan: the impact of the highly improbable* (2007a), he defines a Black Swan in greater detail. There are, according to Taleb (2007a), three criteria that need to be met for an event to be regarded as a Black Swan; unpredictability, extreme impact, and ex post explanation.

According to Taleb (2007a), we cannot predict Black Swans and should instead adjust for and profit from them. When looking at the OMXS30 index from January 1992 until December 2012, using the definition mentioned above, we find 99 Black Swan events. An investment in a passive index fund tracking the OMXS30 from 1992 until the end of 2012 would return 662%. Excluding the worst 5% of all months would return 3733%. If we instead were to exclude the best 5% of all months with the highest return, our investment would have increased only a mere 128%. These are striking evidences of the significance of Black Swans.

1.2 Purpose

Estrada and Vargas (2012) find that by investing in world scattered index funds and exchange-traded funds based on their beta, the market can be outperformed over time by exploiting large market movements. The main purpose of this thesis is to examine if said strategy will generate similar results when implemented on stocks listed on the Stockholm Stock Exchange, and if selecting stocks based on price changes rather than beta will be as successful.

Furthermore, using the same methods as Estrada and Vargas (2012) to evaluate beta as a measurement of risk, we will evaluate the standard deviation. The purpose of this is to analyze if standard deviation is a satisfying measurement of risk, and in particular its performance during extreme market movements. Knowing how much risk an investor faces before making an investment decision is crucial. Standard deviation answers the question “how much will the return of this investment fluctuate?”, but how well does it perform as a risk measurement?

1.3 Research Questions

We set out to explore two hypotheses in this bachelor thesis.

1.3.1 Hypothesis I

H_0 : It is not possible to construct a strategy based on past price changes that outperforms the market over time

H_1 : H_0 is not true

1.3.2 Hypothesis II

H_0 : Standard deviation is not a satisfying measure of risk for average stock returns in extreme market periods

H_1 : H_0 is not true

2. Theory

2.1 The Definition of a Black Swan

A Black Swan is an event which could not be predicted in advance by (all but a very few of) the observers. In econometrics and statistics an event such as a Black Swan would be considered to be an outlier, a value or number which deviates from the rest of the data (Newbold, 2013). Throughout his book, Taleb (2007a) considers all life changing moments in our lives as outcomes of randomness and uncertainty, our inability to predict these events, even by so-called “experts”, and our invariable reaction to these events (surprise). “The central idea of the Black Swan concerns the all-too-common logical confusion of absence of evidence with evidence of absence [...]”, (Taleb, 2007b). According to Taleb, a Black Swan is not only the occurrence of an unexpected event; it is also the absence of an expected event. Unpredictability is one of three criteria, the second being that the event carries with it a major impact. The event itself and its consequences can be either positive or negative. Technical innovations, natural disasters and wars are all rare events which change many people’s lives remarkably. The theory of Black Swans is not limited to major events happening to a large number of people, it also applies to an individual. The third and last criterion for an event to be considered a Black Swan is the ex post explanation, i.e. we are trying to find explanations for its occurrence after the event itself has taken place.

Determining if an event qualifies as a Black Swan is theoretically up to the individual to subjectively consider. However, previous academics mostly use a technical requirement, such as $\geq 5\%$ monthly decrease/increase (Estrada and Vargas, 2012), $\geq 1.5\%$ daily decrease/increase (Burnie and De Ridder, 2010), and $>$ three standard deviations from the mean (Estrada, 2009), to define extreme returns. In this thesis, we will use the same definition of a Black Swan as Estrada and Vargas (2012), i.e. a $\geq 5\%$ monthly increase or decrease in return.

2.2 Mean Reversion

One of the key assumptions in our thesis will be that of mean reversion of stock prices. This assumption briefly states that there is a long run average level, or a fundamental value, in stocks to which prices regress after extreme past returns (Bali et al. 2008). However, academics such as Fama and French (1988), Narayan (2007), Lo and MacKinlay (1988) have disagreed on the existence of mean reversion in stock markets. If the stocks are not mean reverting they are presumed to follow a random walk, meaning that the stock prices move freely within the realms of possibilities and do not regress back to any fundamental value (Narayan, 2007).

The mean reversion debate continues partly because of the many ways to test for the existence of mean reversion. Some of the trialed tests include the Augmented Dickey and Fuller, Phillips and Perron, unit root tests, panel data test, and non-linear tests (Cunado et al. 2010). The results differ somewhat depending on testing method and also on the use of structural breaks, e.g. bull and bear markets, the January effect due to tax-loss selling (DeBondt and Thaler, 1985), and testing for linear- or nonlinear mean reversion. For studies that find evidence of reversion in stocks, different methodologies produce different estimates of the speed of the reversion. The estimates of reversion range from an average 18.5 years to absorb half a shock (Spierdijk et al. 2012), three to five years (Mukherji, 2010), three to three and one-half years to absorb half a shock (Balvers et al. 2000), two to three years (DeBondt and Thaler, 1985), four and one-half to eight years (Gropp, 2004), and one to eight months (Bali et al. 2008).

If the stocks in the OMXS30 are mean reverting, we expect our strategy as defined in the methodology section to be successful.

2.3 Literature Review

This thesis is based on the article by Estrada and Vargas (2012), in which the authors investigate whether beta is a useful tool for selecting portfolio assets. Estrada and Vargas conclude that by investing in high-beta funds after the market has decreased, and in low-beta funds after the market has increased, excess return is generated. However, as shown by Fama and French (1992) beta is not a flawless measurement of risk as they find little to no positive relation between market beta and average stock returns.

Estrada and Vargas find support in both Chan and Lakonishok (1993) and Grundy and Malkiel (1996) who examine the usefulness of beta and find that one cannot yet reject the CAPM, they also investigate the accuracy of beta themselves and find that it is useful. Estrada (2009a) examines the impact Black Swans had on the return generated from the Dow Jones Industrial Average between 1900 and 2006, as well as from 1990 to 2006. The author finds that extreme trading days are more frequent than what is expected under the normality assumption, thereby concluding that daily return data deviates from the normality assumption, and that Black Swans do have an extreme impact on return. Estrada (2009b) does the same examination in emerging markets and international markets (Estrada, 2008) and arrives at the same conclusion. Estrada (2009a) also stresses the virtually non-existent possibility of predicting the outcome of these days, confirming Taleb's (2007a) theory of adjustment and profit from the ensuing reversion.

Bali et al. (2008), who use daily data, find strong negative relation between market returns and past extreme lowest daily returns predicting the speed of reversion to be one to eight months, this being the shortest reversion time we find.

This is thought to be explained by a positive correlation between aggregate risk aversion, and minimum daily returns using the following regression model;

$$R_{m,d+1} = a_m + \gamma_m E_d(\sigma_{m,d+1}) + \varepsilon_{m,d+1}$$

Where $R_{m,d+1}$ is the excess return on day $d+1$ in month m for the aggregate market portfolio, $E_d(\sigma_{m,d+1})$ is the expected volatility on day d for day $d+1$ in month m , γ_m is the aggregate relative risk aversion parameter in month m , and $\varepsilon_{m,d+1}$ is a disturbance term. Testing the equation using three different measures of daily volatility they find when aggregate risk aversion increases, the market prices increase as well.

Bali et al. (2008), along with Spierdijk et al. (2012) and DeBondt and Thaler (1985), find the speed of reversion to be significantly higher for larger falls in the market. DeBondt and Thaler (1985) constructs a regression model that estimates portfolio returns given the assumption of semi-strong market efficiency. Using past data on excess returns they

construct a winner (W) and a loser (L) portfolio consisting of the top and bottom 35 stocks (or 50 stocks, or decile) respectively. If the efficient market hypothesis is true, the residuals from the regression are estimated to equal or not deviate significantly from zero.

$$E(\tilde{R}_{jt} - E_m(\tilde{R}_{jt}|F_{t-1}^m)|F_{t-1}) = E(\tilde{u}_{jt}|F_{t-1}) = 0$$

Where \tilde{u}_{jt} is the residuals at time t for security j , \tilde{R}_{jt} is the return at time t for security j , F_{t-1} represents the information set for semi-strong market efficiency at time $t-1$, and $E_m(\tilde{R}_{jt}|F_{t-1}^m)$ is the expected \tilde{R}_{jt} assessed by the market m on the basis of F_{t-1} .

For the overreaction theory they present to be true, the residuals for the winner portfolio are estimated to be $E(\tilde{u}_{Wt}|F_{t-1}) < 0$ and the residuals for the loser portfolio are estimated to be $E(\tilde{u}_{Lt}|F_{t-1}) > 0$, meaning past winners returns will decline and past losers returns will increase. DeBondt and Thaler (1985) conclude that the residuals for both portfolios are significantly different from zero over a 36 month period with the loser portfolio outperforming the market, on average, by 19.6% and the winner portfolio earning an average of 5.0% less than the market, resulting in a cumulative average of 24.6% with a t -statistic of 2.20. In a subsequent article DeBondt and Thaler (1987) re-evaluate their findings and strengthen them in an effort to cope with critique from Vermaelen and Verstringe (1986) who claim the proposed overreaction effect of the W and L portfolios to be attributed to market responses in risk changes.

Balvers et al. (2000) takes the regression model one step further. Instead of only estimating if the residuals statistically deviate from zero, they construct a regression model that measures mean reversion as a discrete parameter, $0 < \lambda < 1$. Using data from 18 countries market indices they construct a regression model with cross-country comparisons. Assuming it is difficult to estimate each individual country's fundamental process, they estimate the relation between two countries fundamental stock index values to be stationary in order to address this issue and get more observations.

Combining the stationary relationship between two countries fundamental value with each individual country's estimated mean reversion regression model and assuming the

speed of reversion, λ , to be similar for every country, they construct what they call the *rolling regression* model:

$$R_{t+1}^i - R_{t+1}^r = \alpha^i - \lambda(P_t^i - P_t^r) + \sum_{j=1}^k \varphi_j^i (R_{t+1-j}^i - R_{t+1-j}^r) + \omega_{t+1}^i$$

Where $R_{t+1}^i - R_{t+1}^r$ is the difference between the instantaneously compounded returns for country i and reference index r , α^i is a constant, $(P_t^i - P_t^r)$ is the accumulated return differentials up to time t and serves as a correction parameter for subsequent periods, ω_{t+1}^i is a disturbance term with an unconditional mean of zero, and $\sum_{j=1}^k \varphi_j^i (R_{t+1-j}^i - R_{t+1-j}^r)$ is added lagged return differential to cope with possible serial correlation in the disturbance term. In short, the equation specifies the change of a price index relative to a reference index over time.

If $\lambda = 0$ then there is no correction to prices and hence no mean reversion, and for significant $\lambda > 0$ the prices are corrected according to $(P_t^i - P_t^r)$ and mean reversion is present in the data. The equation also has the property of signaling to the investor if he/she should reallocate his/her portfolio from a market that has performed well to a market that has underperformed over time, in other words reallocate from a market that is priced relatively high to one that is priced relatively low, and thus making a profit on the price reversion. Balvers et al. (2000) reject the no mean reversion hypothesis on the 5 or 1 percent significance level and find investing in a similar way as DeBondt and Thaler (1985) but using the estimates of the rolling regression yields a mean return of 20.7% for the single best market investment and a 19.8% mean return for the top three markets, compared to the buy-and-hold strategy that yields 13.7% for the World index and 14.2% for an equal weighted portfolio. They also find that their rolling regression investment beats that of DeBondt and Thaler and attributes this achievement to the fact that their regression model contains more information about the reversion to be exploited, than does DeBondt and Thalers. Gropp (2004) further cements the findings of both DeBondt and Thaler (1985) and Balvers et al. (2000) using the same rolling regression model as Balvers et al. but sorting stocks by industrial classifications instead of market capitalization in an attempt to minimize the likelihood of a bias against the detection of mean reversion.

3. Data & Methodology

3.1 Data

OMXS30 is a market value-weighted stock index consisting of the thirty most traded stocks on the Stockholm Stock Exchange. The financial and industrial sectors constitute almost two-thirds of the index, with 28.24% and 30.42% respectively. Other large sectors are consumer goods (6.51%), technology (8.43%) and telecommunication (8.36%), (NASDAQ OMX, 2013).

For this thesis, monthly return data from the 1st of January 1992 up until the 31st of December 2012 for the OMXS30, as well as the underlying stocks, will be examined. The OMXS30 did not consist of thirty stocks during the whole time period. Following corporations were listed later than the 1st of January 1992: Getinge (1993); ASSA ABLOY (1994); Nordea Bank, Swedbank (1995); Scania, Swedish Match, TELE2 (1996); MTG (1997); ABB, AstraZeneca, and Boliden (1999); TeliaSonera (2000); Lundin Petroleum (2001); Alfa Laval (2002) and Nokia (2007). The data was collected from Datastream and is in Swedish krona (SEK).

3.2 Methodology

Estrada and Vargas (2012) find that excess returns can be achieved by an investment strategy that exploits Black Swans. By constructing a portfolio of exchange-traded funds and index funds, that includes both country indices and industry indices, the strategy shifts between high- and low-beta portfolios. When a negative Black Swan occurs the strategy involves investing in the high-beta portfolio with the expectation of stock prices returning to their fundamental value, according to the mean reversion assumption, and thus making a profit. After a positive Black Swan the strategy is instead to invest in the low-beta portfolio, focusing on minimizing the losses. Although the work of Estrada and Vargas (2012) is based on whether beta is a good measure of risk and useful in the events of portfolio selection, they “tend to buy the countries whose prices have fallen the most or risen the least”. By adapting their strategy to the Stockholm Stock Exchange, we will invest in stocks, rather than indices, with the largest decreases in price (negative Black Swans), as well those with the least change in price (positive Black Swans). This modification of selecting stocks based on their change in returns on the month of a Black

Swan instead of their beta is the main change in methodology from Estrada and Vargas. With this strategy we aim to achieve a higher return than the OMXS30.

In order to construct our portfolio, we first need to look for Black Swan events in the market's value changes. Even though Black Swan events indicate that the returns are exhibiting fat-tail distribution, we will nevertheless use standard deviation as our measure of risk. As defined in the theory section, we will consider any monthly change equal to $\pm 5\%$ or more a Black Swan. As many as 99 months between 1992 and 2012 meet our requirements of Black Swans, out of these 99 we are investing in 36, of which 18 are negative and 18 are positive. Table 1 shows these dates.

Table 1: Black Swans from 1992-01-01 to 2012-12-31

Date	Return	Date	Return	Date	Return
1992-07-01	-9.50%	1997-11-01	-10,05%	2006-06-01	-7.19%
1992-12-01	27.70%	1997-12-01	5,33%	2006-09-01	7.03%
1993-12-01	-5.73%	1998-10-01	-11,87%	2007-12-01	-5.66%
1994-01-01	6.74%	1998-11-01	15,29%	2009-01-01	9.10%
1994-04-01	-7.76%	2000-04-01	-6,47%	2009-02-01	-9.10%
1994-05-01	7.05%	2001-05-01	15,11%	2009-04-01	9.73%
1994-07-01	-8.83%	2001-09-01	-9,20%	2010-06-01	-7.38%
1994-08-01	10.96%	2001-11-01	7,27%	2010-08-01	9.48%
1995-11-01	-7.64%	2002-10-01	-13,41%	2011-08-01	-7.07%
1996-03-01	7.29%	2002-11-01	10,87%	2012-02-01	6.59%
1996-08-01	-5.26%	2003-01-01	-13,59%	2012-06-01	-9.71%
1996-09-01	5.81%	2003-05-01	13,04%	2012-07-01	7.12%

Furthermore, we will examine if standard deviation is a satisfying measure of risk, using the same methods as Estrada and Vargas use to evaluate beta.

3.2.1 Investment Strategy

Based on the mean reversion assumption, our investment strategy involves investing in stocks which have had the largest (least) percentage decrease (change) after an extreme event. The month after a negative Black Swan has occurred, ten of the 30 stocks which have decreased the most in price are added to the portfolio (Strategy) with the expectation of high mean reversion. These are held until a positive Black Swan takes place, when they are sold off and equal weights of stocks that rose the least in that

month (bottom ten returns for the positive Black Swan) are purchased, since we expect those stocks to exhibit the least mean reversion. In the case of two or more consecutive negative or positive Black Swans, no new stocks are added to the original portfolio. This approach is repeated during the time period of investigation. Each stock added to the portfolio will be of equal weight, i.e. 10%.

3.2.2 Standard Deviation as a Measure of Risk

The second part of this thesis is to evaluate the standard deviation's performance as a measure of risk. To do this we will calculate the SD for each stock of up to 60 months prior to, but not including, each Black Swan month, depending on data availability. The SDs will then be grouped into three groups. The first group, G1, will contain a third of all SDs with the highest values. The third group, G3, will contain a third of all SDs with the lowest values, leaving the remaining SDs to the second group, G2. We also include the SD and return of the OMXS30. In each group we will then calculate the average portfolio returns on the month of the Black Swan.

We then compare the group SD with the average return for each group to see if they rank the same, i.e., if a higher SD yields higher change in returns and a lower SD yields lower change in returns. We do this for both positive and negative Black Swans.

3.3 Limitations

Even though suggested as a criterion for Black Swans, we will not try to look back at historical ex ante announcements to evaluate if the events were unimaginable. This task would pose too great of a historic analysis for the scope of this thesis and we would also run the risk of excluding determining factors and/or including irrelevant factors. Instead we use a simplified, technical, definition of Black Swans as explained in the theory section.

Neither the return of the OMXS30 nor the individual stocks includes dividends as the inclusion of dividends from thirty corporations would be a laborious task. It may be worthwhile to note that between the 30th of December 1999 (at which time SIX30 Return Index was introduced) and the 7th of April 2006 the OMXS30 decreased by

11.95%, while at the same time SIX30RX, which includes reinvested dividends, increased by 2.02% (SIX, 2013).

Moreover, we will not be taking transaction costs into consideration in this thesis. The reason for this being that during the time frame of 21 years, the transactions we are involved in are too few to have a significant impact on the result.

3.4 Normal distribution

The observations in a population are normally distributed when both sides of the mean are symmetric. Extreme values have less frequency than do average values (Newbold, 2013). Both skewness and kurtosis will cause the distribution to adopt a shape other than that of the bell-shaped curve. To test if our sample suffers from non-normality we use the Jarque-Bera test. It tests for both kurtosis and skewness.

3.4.1 Kurtosis

Assuming normal distribution when the data contains a greater number of extreme values causes us to underestimate the occurrences of these values. The distribution curve will be narrower around the mean and have fat tails. Kurtosis is the measure of weight in the fat-tails of a distribution curve. It is calculated as follows:

$$kurtosis = \frac{\sum_{i=1}^n (x_i - \bar{x})^4}{ns^4}$$

where the sum of the deviation from the mean is raised to the power of four, divided by the product of the sample size (n) and the standard deviation raised to the power of four (s^4). A sample with a normal distribution has a kurtosis of 3.

3.4.2 Skewness

A distribution of observations which is not symmetric is skewed to either side of the mean. A skewed-right distribution has a longer tail to the right, while a skewed-left distribution has a longer tail to the left. Skewed distributions are caused by outliers, such as the distribution of income (skewed-right), where a small amount of the

observations account for the highest values, (Newbold, 2013). In a situation where the distribution is skewed either to the right or to the left, the standard deviation will respectively overestimate and underestimate risk (Bodie et al. 2013). Skewness is calculated with the following formula:

$$skewness = \frac{\sum_{i=1}^n (x_i - \bar{x})^3}{n s^3}$$

3.4.3 Jarque-Bera Test for Normality

The Jarque-Bera test for normality is an adaption of the chi-square test (Newbold, 2013) and is used to test if a sample of observations is normally distributed. It is calculated as follows:

$$JB = n \left[\frac{(skewness)^2}{6} + \frac{(kurtosis - 3)^2}{24} \right]$$

The Jarque-Bera test uses both skewness and kurtosis to test for normality. Skewness is raised to the power of 2 and divided by 6. A normally distributed population has a kurtosis of 3, and the JB statistic should be zero for a normal distribution, hence 3 is first subtracted from the kurtosis. The kurtosis is then raised to the power of 2 and divided by 24. The sum of the squared skewness and the squared kurtosis is then multiplied by the number of observations.

The null hypothesis, that the sample is normally distributed, is rejected if the JB statistic is larger than the significance points (see Appendix 8.2).

3.5 Performance evaluation

3.5.1 Arithmetic Mean

The arithmetic mean will give us the average monthly returns for the portfolio strategy as well as for the passive index for comparison.

$$AM = \frac{\sum_{i=1}^N x_i}{N}$$

3.5.2 Geometric Mean

The geometric mean is used to calculate monthly average returns. It is a better measurement of returns than the arithmetic mean since it considers the compounding effect (Newbold, 2013).

$$GM = \left[\prod_{i=1}^n (1 + r)_i \right]^{1/n} - 1$$

where the product of the data values is raised to the power of one divided by the number of observations, the sum is then subtracted by one.

3.5.3 Standard Deviation

As mentioned at the beginning of the thesis, our main measure of risk will be the standard deviation.

$$SD = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N}}$$

Instead of using a risk measuring instrument like the arbitrage pricing theory that bases the volatility of an asset on a benchmark portfolio (Bodie et al. 2013), such as the market portfolio, we use standard deviation and base the risk of the security on its historical returns.

3.5.4 Downside Deviation

Since we explore the possibility of profiting on abnormal returns, or statistical outliers, we expect the return distribution to have fat tails and, perhaps, to be skewed. To properly estimate downside risk we calculate Downside Deviation (DD).

$$DD = \sqrt{\frac{\sum_{i=1}^N (R_i - MAR)^2}{N}}$$

where MAR (minimum acceptable return) < 0

3.5.5 Risk-Adjusted Returns

We will be calculating risk-adjusted returns using both SD and DD. We do this in order to get a better estimate and compare the risk-return tradeoff in case of a non-normal distribution of returns.

$$RAR1 = \frac{AM}{SD}$$

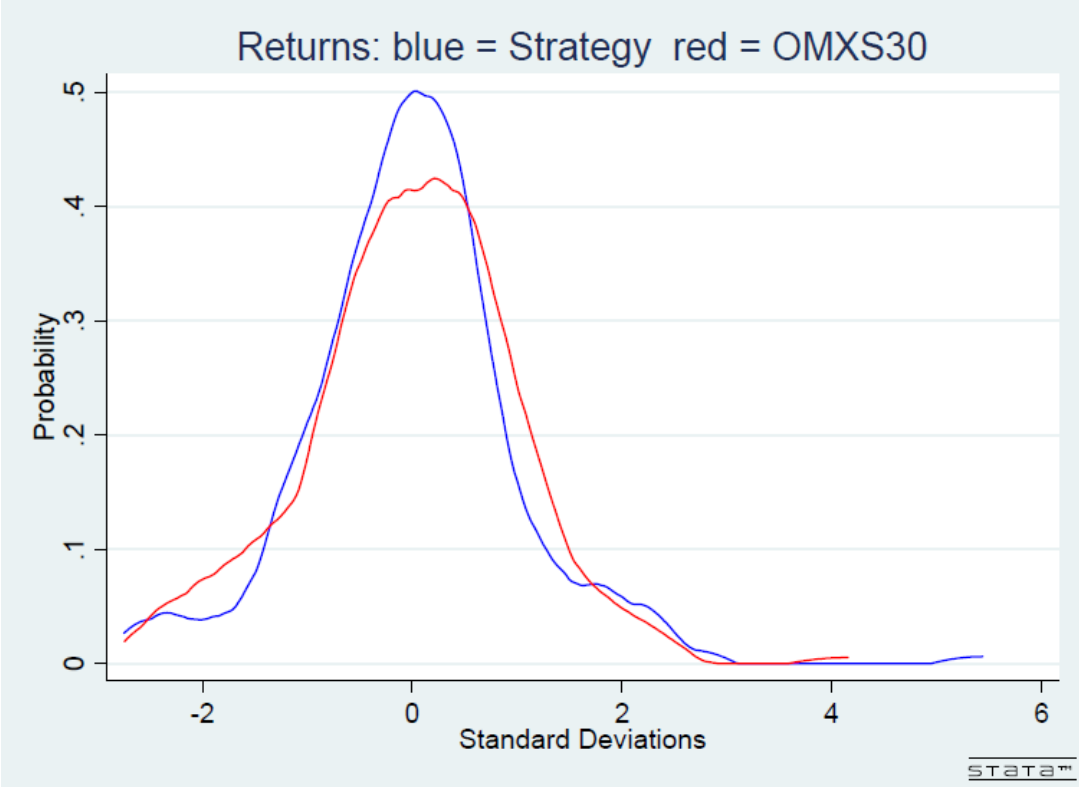
$$RAR2 = \frac{AM}{DD}$$

4. Results & analysis

4.1 Hypothesis I

Our data consists of monthly returns for the OMXS30 as well as for the stocks which constitute the OMXS30. The first Black Swan occurs in July 1992; from the ensuing month we are holding a portfolio until the end of December 2012. This holding period is 246 months, while the whole period for which the passive investment in the OMXS30 is held is 252 months. A normal distribution curve should have zero kurtosis, which is not the case in our study. Table 2 (see next page) shows that the kurtosis is 6.50 for our portfolio and 3.95 for the market (after subtracting 3 to get 0 equal to normal distribution). This implies that the distribution of returns of the portfolio as well as the returns of the market have fat tails. We also find that the distribution is skewed to the right in our sample, being the result of few extreme values. The STATA results show that the skewness is significant for the strategy (p -value of 0.0006) but not for the OMXS30 (p -value of 0.9533). The STATA results also show that kurtosis are significant in both samples, with p -values of <0.05 . Graph 1 shows the distribution curves of both investments.

Graph 1: Distribution of Returns



4.1.1 Results

The first objective of this thesis was to look at the same strategy that Estrada and Vargas (2012) use, but implementing their strategy on the OMXS30 and modifying it. Our approach has been to choose stocks by their change in price, rather than their beta. In table 2 below, the results for the investment strategy and the passive market index, the OMXS30, are shown.

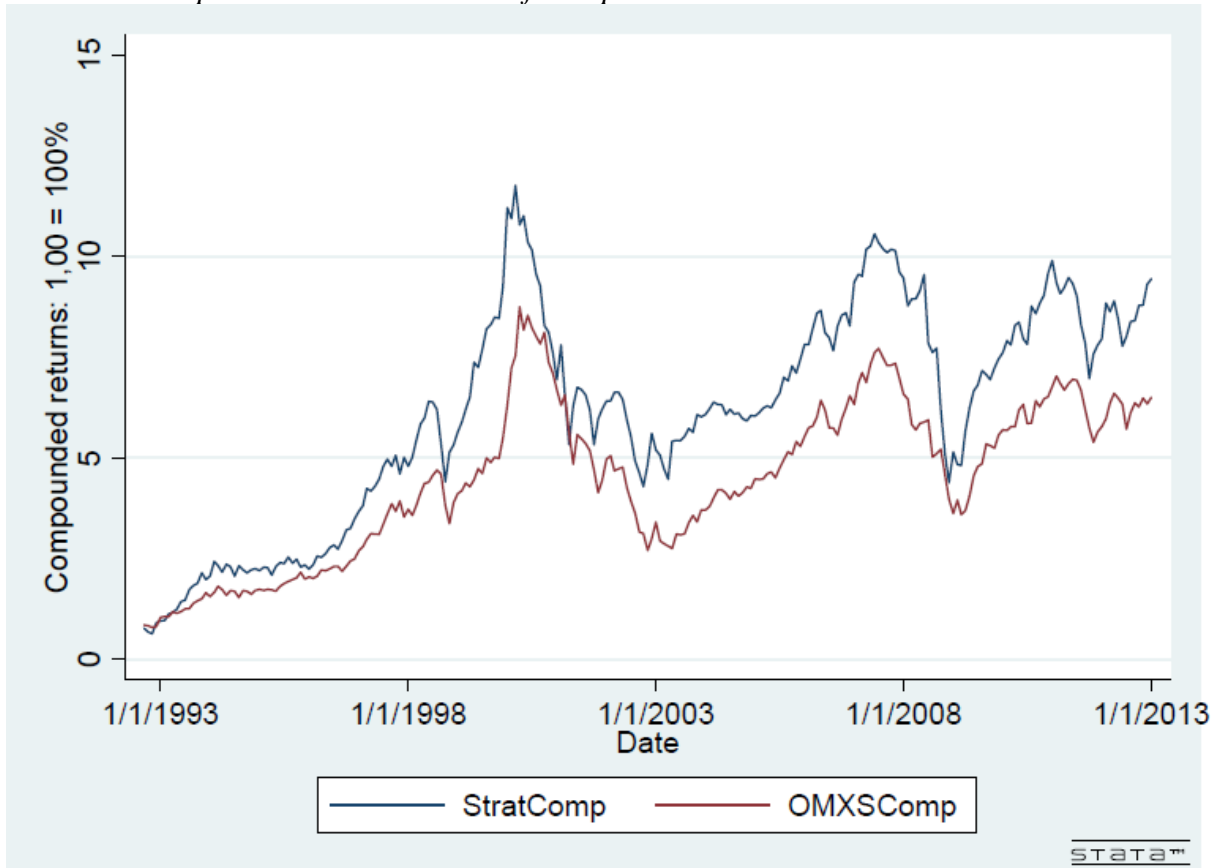
Table 2: Performance Evaluation

	AM	GM	SD	DD	Min	Max	Skw	Krt
Strategy	1.199%	0.906%	7.62%	4.69%	-19.7%	42.6%	0.551	6.50
OMXS30	0.976%	0.761%	6.44%	4.11%	-16.6%	27.7%	-0.009	3.95

	ASD	AGM	TV	TV5	TV10	TV15	RAR1	RAR2
Strategy	26.4%	11.3%	9 440 kr	1 707 kr	2 913 kr	4 971 kr	0.158	0.193
OMXS30	22.3%	9.3%	6 502 kr	1 561 kr	2 439 kr	3 809 kr	0.152	0.185

During the time frame of investigation our portfolio yields an average monthly return of 1.1990%, outperforming the market with an average monthly return of 0.9758%. An initial investment of 1000 SEK in our portfolio would at the end of the period be worth 9440 SEK, while placing 1000 SEK in a fund tracking the OMXS30 would return 6502 SEK. TV5, TV10 and TV15 show the return for both investments for a period of five, ten, and fifteen years, respectively. The strategy yields a higher return than the market in all periods. Furthermore, our portfolio has an annualized return of 11.3% and a total return of 944%. For the market, the annualized return and the total return amounts to 9.3% and 650%, respectively. The investment yields are shown in graph 2 (see next page).

Graph 2: Time Distribution of Compounded Returns on Base Investment



Our results show that by choosing the investment strategy we achieve a higher maximum monthly return (42.6%) than that of the market (27.7%), at the expense of a lower minimum monthly return (-19.7%) than the market (-16.6%). The portfolio has a slightly higher volatility than the market, with a monthly SD of 7.61%, versus the market SD of 6.43%. The null hypothesis of Hypothesis 1.3.1 is rejected, it is possible to construct a strategy based on past price changes to outperform the market over time. We find that the strategy is economically significant because our investment constantly yields a higher return, but never less, than the market, as well as averaging higher AM, GM, and RAR. However, it is not statistically significant with a p -value of 0.167.

4.1.2 Analysis

Vargas and Estrada (2012) state that for the investment strategy to outperform the market, mean reversion must be present. Thus their results imply that the indices do not follow a random walk but are mean reverting. We followed this assumption in our thesis when formulating our investment strategy. However, reading through articles on the subject of mean reversion, we cannot definitely conclude the presence of mean

reversion simply on our findings. First there is the debate over the speed of the reversion. Mukherji (2010) finds weak-to-moderate evidence of mean reversion for large company stocks over five year periods and moderate-to-strong evidence of mean reversion for small company stocks over three to four years. Spierdijk et al. (2012) find evidence of mean reversion of stock prices absorbing half of a shock for a minimum time period of two years and an average of 18.5 years. DeBondt and Thaler (1985) find mean reversion to occur in the second and third year of the test period, with only little mean reversion within the first 12 months. Gropp (2004) finds evidence of mean reversion absorbing half of a shock after four and one-half to eight years. There is also evidence of the level of impact of past returns. The greater the drop the market suffers, the faster the speed of reversion (Bali et al. 2008, Spierdijk et al. 2012, DeBondt and Thaler 1985). Spierdijk et al.'s results suggest that the speed of reversion back to the fundamental value of the stock increases in times of high economic uncertainty, especially after the Oil crises of 1973 and 1979, and after Black Monday in October of 1987. Looking at the frequency of Black Swans during our observed time period of January 1992 to December 2012, the longest absence of abnormal returns is between May 2003 and June 2006 and the average and median for the entire period is 2.5 months and 2 months, respectively, between two abnormal events. Many Black Swans are only one month apart, at which mean reversion would have little to no effect on the outcome, given the estimated speed of the reversion.

Since most research assume mean reversion to be a slow process over multiple years, and sometimes even use yearly observations instead of monthly in their data, the findings of Mukherji (2010), Spierdijk et al. (2012), DeBondt and Thaler (1985), and Balvers et al. (2000) do not seem to help in explaining why our strategy is successful, we find little support in these articles.

One of the cornerstones of the efficient market hypothesis is the statement that current information based on past and expected future events is reflected in present stock prices (Fama, 1995). In combination with the random walk theory, which states that stock prices exhibits no pattern from which investors can profit, the conclusion is that a strategy which consistently over time outperforms the market is not achievable. This leads us to consider behavioral finance. The main statements of behavioral finance theory are 1) that traders are not rational, theorists find that "irrationality can have

substantial and long-lived impact on prices”, and 2) that the possibility of arbitrage is limited, (Barberis and Thaler, 2002). Hence, contrary to what the efficient market theory states, rational investors will not cause the price of a stock to return to its fundamental value after being mispriced. These mispricings may be caused by overreactions to negative information or by risk aversion.

Bali et al. (2008) find that lowest daily returns increase aggregate risk aversion, which in turn causes the market prices to increase as well.

The aggregate risk aversion is in turn explained by liquidity constraints, short-sale constraints, and other types of constraints that kick in for downside returns. These constraints have the effect of increasing returns in the next period.

DeBondt and Thaler (1985) also investigates the behavioral causes for mispricing. They claim that investors tend to overreact on large price fluctuations, that they put too much weight on recent information and underweight base data or prior information. This makes investors overly pessimistic after a period of bad events which results in company stocks being undervalued. When the company starts doing well again, the overly pessimistic estimates are proven to be wrong and prices adjust. This is also the case in the opposite direction after a series of positive events.

Other possible explanations state that after firms in a country suffer large losses, they tend to be more highly leveraged. This results in higher betas and higher expected returns. A third explanation is that when the firms in a country suffer substantial losses, the country index tends to end up with smaller firms. Since smaller firms tend to have a higher risk factor, the resulting lower-priced country index is expected to yield higher returns. Yet another explanation indicates that low-priced stocks are subject to serious microstructure biases which could generate abnormal returns (Balvers et al. 2000).

We do not know if any of these theories give legitimate explanatory power to our results and further tests are needed both to conclude if the OMXS30 as well as the stocks it contain are mean reverting and if we find any of the above explanations relevant to this study.

We are also reserved over the implications of our findings due to a number of reasons. The RAR1 and RAR2 results for the OMXS30 and our strategy, 0.152 (OMXS30) to 0.158

(Strategy) and 0.185 (OMXS30) to 0.193 (Strategy), indicates that there is little advantage in return-to-volatility for our strategy over the OMXS30 benchmark, meaning the higher returns our strategy yield come at a proportionately higher risk. As Estrada (2008) states, broad diversification reduces the downfall caused by Black Swans. Graph 2 shows this relation as the investment is more volatile than the market index with larger fluctuations but they still follow similar trends. We also observe that our investment strategy yields returns similar to a high-beta asset compared to the OMXS30 passive investment, Graph 3 in the appendix shows this relation in greater detail. Although our investment moves within the span of a 1.2-1.4 beta asset, the calculated beta for the investment strategy is 1.04. The estimated risk of our investment is thus close to that of the market portfolio but the returns on the investment are well above the returns of the market. The low-beta value together with the p -value of 0.167 for the investment is an indication that although we manage to consistently beat the market portfolio during the time of observation, in the long run we expect to perform only marginally better than the passive investment.

The method by which we choose which stocks to invest in is also of questionable reliability. Estrada and Vargas (2012) use betas estimated on 60 months prior to Black Swan events, DeBondt and Thaler (1985) use a mean reversion regression model and choose stocks based on residuals statistically different from zero, and Balvers et al. (2000) as well as Gropp (2004) use a regression model with a discrete parameter to measure the strength of mean reversion in order to select which stocks to invest in. We simply rely on the assumption that the stocks that has had the largest change in returns in one specific month will have the strongest reversion in the future and that the stocks that has had the lowest change in returns will have the weakest reversion in the future. This is not a technical or sophisticated method for selecting stocks and we cannot exclude luck as a factor in our results, seeing that our compounded investment ends at a peak instead of at a period where it almost tangents the OMXS30 passive portfolio.

4.2. Hypothesis II

The second objective was to evaluate the performance of the standard deviation as a measure of risk. This is performed by using the very same approach as Estrada and Vargas (2012).

4.2.1 Results

By constructing three groups based on their underlying stocks SD, calculated from the previous 60 months (G1 being the portfolio with the highest SD), and measuring their average portfolio returns on the month of the Black Swan, we find that standard deviation describes the downside risk well during extreme decreasing markets (p -value <0.001), as well as in extreme increasing markets (p -value of 0.008). Portfolio G1 has the highest SD when the market experiences extreme market movements and also the highest average return. G2 has lower SD than does G1 as well as lower average returns, while G3 has the lowest SD during Black Swans, and the lowest average returns. Seeing that the amount of volatility (SD) is consistent with the amount of return leads us to reject the null hypothesis; standard deviation is a satisfying measure of risk for average stock returns in volatile market periods. Table 3 below shows the return and SD of each group as well as for the OMXS30.

Table 3: Negative Black Swans

	OMXS30	G1	G2	G3
Standard deviation	6,21%	13,18%	9,31%	6,97%
Return	-9,92%	-11,78%	-8,61%	-4,56%

Positive Black Swans

	OMXS30	G1	G2	G3
Standard deviation	6,41%	13,68%	9,38%	7,04%
Return	8,69%	13,72%	9,36%	6,45%

4.2.2 Analysis

Standard deviation describes the volatility of the market or a stock by measuring the returns. One of the drawbacks of the SD is that it includes both negative and positive returns in the calculations. For an investor with a long position, only negative returns

should be of concern when measuring risk. Likewise, an investor with a short position faces infinite risk in positive returns. Our results show that standard deviation matches risk with return during both negative Black Swans as well as positive Black Swans. Consequently, standard deviation captures the relationship between return and risk in extreme market movements.

Furthermore, by analyzing the data with the Jarque-Bera test for normality we arrive at the conclusion that our data is not normally distributed. For our strategy, a JB statistic of 446.05 is sufficient to reject the null hypothesis at the 5% significance point, 5.99. The returns of the OMXS30 have a JB statistic of 160.14, also a sign of non-normality. Sortino et al. (2002) suggest that returns are not normally distributed, because one cannot lose more than everything, the distribution of returns does not go to negative infinity and is therefore positively skewed. Due to the skewness, the standard deviation may under- or overestimate risk (Bodie et al. 2013). Since the skewness is 0.551 for the portfolio (p -value <0.0006), the standard deviation has overestimated downside risk on our investment. The skewness for the OMXS30 is -0.009, but insignificant (p -value <0.9533). For estimating the downside risk with better precision and ignoring positive returns, the downside deviation, DD, can be used. Downside deviation only considers returns below a minimum accepted return, MAR, and substituting standard deviation in the Sharpe Ratio with DD will give us the Sortino Ratio, a measurement which is preferable when a sample is asymmetric (Chaudry and Johnson, 2008). An investment that generates small negative returns is compensated by the Sortino Ratio when the sample is positively skewed (Chaudry and Johnson, 2008). A small DD produces a high Sortino Ratio, implying a high return-to-volatility ratio. Setting MAR to zero would allow for only negative returns to be considered.

But, as Sortino et al. (2001) recognizes, SD has yet more faults. First off, risk is relative and two investments with the same standard deviation but with different means are considered equally risky. An investment with a mean closer to zero ought to be considered riskier than an investment with a higher mean. In addition, it uses historical returns to forecast risk, but historical return is not an assertion of future return. Finally, standard deviation, like most other measures, does not include utility preferences, thereby ignoring the investor's level of willingness to risk exposure.

We do, however, agree with Sortino and Forsey (1996) that each measure of risk serves a different purpose but none of them captures every aspect of risk; beta measures the risk of being in the stock market, downside risk captures the risk of not achieving the minimal acceptable return, and standard deviation best captures the risk of not achieving the mean (Sortino and Forsey, 1996).

The kurtosis is 6.50 for the returns generated by the investment strategy and 3.95 for the OMXS30, indicating that both distributions have fat tails. This is expected since a fat-tailed distribution is the consequence of extreme values, and in this work we are exploiting extreme market movements. Kurtosis in the sample proves the existence of abnormal returns, i.e. Black Swans, and is not captured by the standard deviation.

5. Conclusion

The purpose of this thesis is to evaluate the performance of an investment strategy, with the aim of outperforming the market. In their article, Estrada and Vargas (2012) find that by using an investment strategy which focuses on investing in high-beta indices (both countries and industries) when the market has plummeted and low-beta indices when the market has risen, the strategy outperforms a passive benchmark index. Instead of using beta as a tool for selecting the stocks in our portfolio we are using prices. In this thesis we learn that implementing Estrada and Vargas (2012) strategy on the Stockholm Stock Exchange with our modification, is as successful. Our results show that by investing in a portfolio constituted of ten stocks from the OMXS30 which have decreased the most (changed the least) in price during a negative (positive) Black Swan, we can outperform the OMXS30, our benchmark index.

The 944% return of the portfolio is greater than the return of the OMXS30 during the same period, 650%. The difference in return between both investments is economically significant but not statistically significant, (p -value < 0.167). A result which leads us to conclude that the utilization of the investment strategy tested is successful to use when aiming to achieve a higher return than that of the market.

We also evaluate the standard deviation's performance as a measurement of risk, the same way Estrada and Vargas evaluate beta. Three groups are arranged by the underlying stocks SD calculated for a period of up to 60 months prior to every Black Swan event. We then calculate the returns for each group for all negative Black Swans and the returns for each group for all positive Black Swans. The results show that investments with a higher standard deviation has larger declines during negative Black Swans and yield higher returns during positive Black Swans, thus matching the ranking by SD with the expected ranking of returns. However, when ranking all individual stocks by SD and looking at the individual returns after Black Swan events, the results yield inconsistent rankings. We thereby conclude that the standard deviation is a satisfying measurement of risk in extreme market periods. In our analysis we point out that standard deviation, although the perhaps most widely used measure of risk, has its drawbacks.

6. Suggestions for Further Research

We do not draw any firm conclusion about the existence of mean reversion in the data or of any of the possible explanations mentioned in the analysis section. We therefore suggest further research in the OMXS30 using the *rolling regression* model of Balvers et al. (2000) in order to gain as much information as possible about the speed of reversion, if it is present, in the market, and implement this information in the investment strategy to see if one can beat the OMXS30 index with statistical significance. We also suggest further research in all of the possible explanations etc.

7. References

7.1 Articles

Barberis, N. Thaler, R. 2002. *A Survey of Behavioral Finance*. NBER Working Paper No. 9222

Brown, S.J. Warner, J.B. 1985. *Using Daily Stock Returns*. Journal of Financial Economics 14; p3-31

Burnie, D. De Ridder, A. 2010. *Far Tail or Extreme Day Returns, Mutual Fund Cash Flows and Investment Behavior*. Applied Financial Economics, Vol. 20, Issue. 16; p1241–1256

Balvers, R. Wu, Y. Gilliland, E. 2000. *Mean Reversion Across National Stock Markets and Parametric Contrarian Investment Strategies*. Journal of Finance; Vol. 55 No. 2, p745-772

Chaudhry, M. Johnson, H. 2008. *The Efficacy of the Sortino Ratio and Other Benchmarked Performance Measures Under Skewed Return Distributions*. Australian Journal of Management (University of New South Wales); Vol. 32 Issue 3, p485-502, 18p

Chen, S-L. Kim, H. 2011. *Nonlinear Mean Reversion across National Stock Markets: Evidence from Emerging Asian Markets*. International Economic Journal; Vol. 25, No. 2, p239-250

Cunado, J. Gil-Alana, L.A. Perez de Garcia, F. 2010. *Mean Reversion in Stock Market Prices: New Evidence Based on Bull and Bear Markets*. Research in International Business and Finance 24; p113-122

DeBontd, E. F. M. Thaler, R. 1985. *Does the Stock Market Overreact?* Journal of Finance; Vol. 40 No. 3, p793-805

Estrada, J. 2008. *Black Swans and Market Timing: How Not to Generate Alpha*. Journal of Investing; Vol. 17 Issue 3, p20-34, 15p

Estrada, J. 2009a. *Black Swans, Market Timing and The Dow*. Applied Economics Letters, 16, p1117–1121

Estrada, J. 2009b. *Black Swans in Emerging Markets*. Journal of Investing; Vol. 18 Issue 2, p50-56, 7p

Estrada, J. Vargas, M. 2012. *Black Swans, Beta, Risk, and Return*. Journal of Applied Finance; Vol. 22 Issue 2, p77-89

Fama, E.F. French, K.R. 1988. *Permanent and Transitory Components of Stock Prices*. Journal of Political Economy 96, p246–273

Fama, E.F. French, K.R. 1992. *The Cross-Section of Expected Stock Returns*. Journal of Finance; Vol. 47, p427-465

Gropp, J. 2004. *Mean Reversion of Industry Stock Returns in the U.S., 1926–1998*. Journal of Empirical Finance 11; p537–551

Kim, H. Stern, L.V. Stern, M.L. 2009. *Nonlinear Mean Reversion in the G7 Stock Markets*. Applied Financial Economics 19; p347-355

Lo, A.W. MacKinlay, A.C. 1988. *Stock Market Prices Do Not Follow a Random Walk: Evidence from a Simple Specification Test*. Review of Financial Studies; 1, p41–66.

Narayan, P.P. Narayan, S. 2007. *Mean Reversion in Stock Prices: New Evidence from Panel Unit Root Tests*. Studies in Economics and Finance; Vol. 24, No. 3, p233-244

Mukherji, S. 2011. *Are Stock Returns Still Mean-reverting?* Review of Financial Economics 20; p22-27

Sortino, Frank A. Forsey, Hal J. 1996. *On the Use and Misuse of Downside Risk*. Journal of Portfolio Management, Vol. 22, Issue 2; p35-42

Spierdijk, L. Bikker, J.A. van den Hoek, P. 2012. *Mean Reversion in International Stock Markets: An Empirical Analysis of the 20th Century*. Journal of International Money and Finance 31; p228–249

Taleb, Nassim N. (2007b). *Black Swans and the Domains of Statistics*. The American Statistician, Vol. 61, No. 3; pp. 198-200

Vermaelen, T. Verstringe, M. Unpublished Manuscript. *Do Belgians Overreact?* Catholic University of Lovain, Belgium

7.2 Books

Bodie, Zvi, Kane, Alex & Marcus, Alan J. 2011. *Investments and Portfolio Management*. Global ed., 9. ed. New York: McGraw-Hill/Irwin

Newbold, Paul, Carlson, William L. & Thorne, Betty. 2013. *Statistics for Business and Economics*. 8. global ed. Harlow: Pearson

Sortino, Frank A. & Satchell, Stephen E. (red.) 2001. *Managing Downside Risk in Financial Markets: Theory, Practice and Implementation*. Oxford: Butterworth-Heinemann

Taleb, Nassim Nicholas. 2001. *Fooled by Randomness: the Hidden Role of Chance in the Markets and in Life*. London: Texere

Taleb, Nassim Nicholas. 2007a. *The Black Swan: the Impact of the Highly Improbable*. 1. ed. New York: Random House

7.3 Internet

Browning, E.S. 2007. *Exorcising Ghosts of Octobers Past*. [Online] Wall Street Journal. Available at: http://online.wsj.com/article/SB119239926667758592.html?mod=mkts_main_news_hs_h#MARK
[Accessed 15 April 2013]

Flicking, D. Robinson, M. 2012. *McGraw-Hill Plummets After Australian Court Ruling*. [Online] Available at: <http://www.bloomberg.com/news/2012-11-04/s-p-found-liable-by-australian-court-for-misleading-ratings.html>
[Accessed 23 April 2013]

Valetkevitch, C. 2013. *S&P 500 Posts Worst Day Since November; McGraw-Hill Shares Sink*. [Online] Available at: <http://www.reuters.com/article/2013/02/04/us-markets-stocks-idUSBRE9130FX20130204.html>
[Accessed 22 Mars 2013]

NASDAQ, 2013. *Breakdown for OMXS30*. [Online] Available at: <https://indexes.nasdaqomx.com/Index/Breakdown/OMXS30.html>
[Accessed 5 Mars 2013]

SIX, 2013. *Nytt Index SIX30 Return Index*. [Online] Available at: <http://www.six-telekurs.se/sv/Nyhetslista/Nytt-index-SIX30-Return-Index/>
[Accessed on 21 May]

7.4 Databases

Thomson Reuters Datastream

8. Appendix

8.1 Detailed Summary about the Distributions

. sum OMXS30 Strategy, detail

OMXS30					
	Percentiles	Smallest			
1%	-.1410402	-.1663221			
5%	-.1055208	-.1552045			
10%	-.074885	-.1410402	Obs		246
25%	-.0249791	-.1396435	Sum of Wgt.		246
50%	.0148644		Mean		.0097579
		Largest	Std. Dev.		.0643884
75%	.0493265	.15119			
90%	.0825655	.1529776	Variance		.0041459
95%	.1087383	.160647	Skewness		-.0088915
99%	.1529776	.2770305	Kurtosis		3.952784
Strategy					
	Percentiles	Smallest			
1%	-.1787819	-.1968154			
5%	-.1094795	-.1882562			
10%	-.0737224	-.1787819	Obs		246
25%	-.028495	-.1775575	Sum of Wgt.		246
50%	.0130421		Mean		.0119898
		Largest	Std. Dev.		.0762228
75%	.0485688	.1797176			
90%	.094608	.2099703	Variance		.0058099
95%	.1358981	.2110584	Skewness		.5512783
99%	.2099703	.4261658	Kurtosis		6.503957

8.2 Jarque-Bera Significance Points

Significance Points (Bera and Jarque, 1981)

Sample size n	10% point	5% point	Sample size n	10% point	5% point
20	2.13	3.26	200	3.48	4.43
30	2.49	3.71	250	3.54	4.51
40	2.7	3.99	300	3.68	4.6
50	2.9	4.26	400	3.76	4.74
75	3.09	4.27	500	3.91	4.82
100	3.14	4.29	800	4.32	5.46
125	3.31	4.34	∞	4.61	5.99
150	3.43	4.39			

8.3 Test for Skewness and Kurtosis

```
. sktest OMXS30 Strategy
```

Skewness/Kurtosis tests for Normality					
Variable	Obs	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	joint Prob>chi2
OMXS30	246	0.9533	0.0138	5.95	0.0511
Strategy	246	0.0006	0.0000	29.58	0.0000

8.4 t-test for Hypothesis I

```
. ttest OMXS30= Strategy
```

Paired t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
OMXS30	246	.0097579	.0041053	.0643884	.0016718	.017844
Strategy	246	.0119898	.0048598	.0762228	.0024175	.0215621
diff	246	-.002232	.0023072	.0361866	-.0067764	.0023125

```

mean(diff) = mean( OMXS30 - Strategy)          t = -0.9674
Ho: mean(diff) = 0                             degrees of freedom = 245

Ha: mean(diff) < 0                             Ha: mean(diff) != 0           Ha: mean(diff) > 0
Pr(T < t) = 0.1671                             Pr(|T| > |t|) = 0.3343       Pr(T > t) = 0.8329

```

8.5 Graph 3: β -assets, Strategy, and OMXS30; Compounded

