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"Asset Pricing Anomalies and Factor Trading: an Empirical Analysis on the Swedish Market"

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Abstract

It is very important for investors to study the dynamics behind the movement of assets' prices, for this reason there is a wide literature covering the topic relative to Asset Pricing. In this research I study six-teen innovative pricing anomalies to verify whether they are statistically significant and then able to predict returns. The analysis is carried out on the Stockholm Stock Exchange between 1995 and 2016 and half of the treated predictors appear to work efficiently, i.e. they are statistically significant at 5% level. Then, I used those findings to develop different Factor trading strategies; the outcomes lead to the conclusion that the significant return predictors, when applied to parametric portfolios, manage to beat the market even for high levels of transaction costs.

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1. INTRODUCTION

Since the financial markets have been created, it has been fundamental for investors to develop models able to explain the behaviour of assets' prices. These models aim to explain the relationship between the expected return of a financial asset and the risks associated with this asset. Ever since its introduction by Sharpe (1964), the Capital Asset Pricing Model (CAPM) has been the most commonly used model to describe the risk-return trade-off of assets. The CAPM models the expected return of an asset as a linear function of its systematic risk, which can be measured as the sensitivity of the asset's return to the market return. The model is a single-factor model, i.e., it only includes the market return as a pricing factor.

However, since the introduction of the CAPM, a large number of studies have suggested additional factors that may provide additional information about the risk-return trade-off of financial assets. For example, Fama and French (1996) have shown that a firm's average stock return is related to its size and book-to-market ratio. Because these patterns in average stock returns are not explained by the CAPM, they are typically referred to as *pricing anomalies*. In their recent replication study, Hou, Xue, and Zhang (2017) collected 447 anomaly variables and analyzed whether these pricing anomalies are still relevant in explaining asset returns using the sample of US stock returns. They found that a significant portion of these anomalies is still relevant today.

The first aim of this thesis is to study whether a selection of these anomalies is also relevant for understanding return patterns of stocks listed on the Stockholm Stock Exchange (SSE) over the period from 1995 to 2016. In particular, Chapter 1 gives a detailed description of the selected asset pricing anomalies and provides an empirical analysis, using portfolio sorting techniques, to understand whether these anomalies are relevant on the chosen sample. Altogether, I consider 16 anomalies grouped into 6 bigger categories (momentum, reversal, maximum return, beta, volatility, and skewness anomalies). The results of the empirical analysis demonstrate that not all the anomalies work well on the Swedish market; some characteristics are found to be significant and able to help investors in their choices, while others do not provide any useful information.

It is also important to consider whether the anomalies can lead to implementable trading strategies. Therefore, Chapter 2 of the thesis presents a practical implication of the well performing anomalies studied in Chapter 1. Using the parametric portfolio policy framework of Brandt, Santa-Clara, and Valkanov (2009), I show that trading strategies based on the pricing anomalies are able to provide significant risk-adjusted returns (in terms of Sharpe Ratio) compared to commonly used benchmarks.

2. CHAPTER 1: ASSET PRICING ANOMALIES

2.1 Introduction to Chapter 1

In this chapter, the attention of the study will be focused on several pricing anomalies well known in the literature. The asset pricing theory has been central in the financial studies since the financial markets has existed. This is due to the fact that it is crucial for an investor to understand the dynamic behind the assets' returns in order to make the right decision in portfolio allocation. This is one of the reasons why researchers have developed several different models claiming that their findings succeed in explaining the behaviour of asset returns.

The first section provides the theoretical background of the considered anomalies, where the functioning and motivations behind the theory is explained. In addition, 2.3 provides the description for the actual implementation of the anomalies. The aim of this section is to let to the reader understand how it is possible to practically implement the considered pricing anomalies in order to obtain trading factors. In section 2.4 there is a description of the data used in order to carry out the analysis. Moreover, in 2.5, the results relative to the applications of the trading factors on all the stocks listed on the SSE have been highlighted since it is crucial to verify which, between the considered anomalies, appear to work successfully before to apply these findings to investment strategies.

Finally, the last section summarizes the conclusions and the most relevant findings presented in Chapter 1.

2.2 Previous Literature on Pricing Anomalies

In this section I present the pricing anomalies that will be studied in the thesis by reviewing the academic literature that brought these anomalies into attention. Altogether, I consider 16 anomalies grouped into 6 bigger categories (momentum, reversal, maximum return, beta, volatility, and skewness anomalies).

- Momentum Anomalies

The Momentum anomaly refers to an empirically observed trend for assets increasing in price to rise further in the next periods. This finding has been used in asset pricing in order to both explain assets' pricing behaviour and to develop trading strategies able to overperform the market. A first input on this topic has been given by Jegadeesh and Titman (1993) who discovered this interesting pattern. In particular, they proved that a trading strategy which buys stocks that have shown a positive trend during the previous months and sells the stocks that performed poorly produces positive returns. Their strategy is called *Prior 6-month Returns* and in the following pages it will be referred to as R_1^6.

Furthermore, Fama and French (1996) have also studied this phenomenon using a different approach. Starting from the same assumption that assets that have performed well in the past are more likely to overperform assets that have provided bad returns, they structed their portfolios according to different criteria: they used the stocks' return over the previous eleven months. The resulting trading strategy is called *Prior 11-month Returns* and is referred to as R_1^{11}.

More recently, Blitz, Huij, and Martens (2011) have used another method to investigate the previous findings. They argue that the residual momentum is more consistent over time and less concentrated to the extreme portfolios. The overall idea is still the same, but instead of using past returns to measure the performance of a stock, they suggest using residuals from a Fama-French three-factor model (Fama and French, 1996). From their paper it is possible to obtain two important return predictors called *11-month Residual Momentum* and *6-month Residual Momentum* that will be abbreviated as ϵ_1^{11} and ϵ_1^6, respectively.

- Reversal Momentum Anomalies

It has been argued that investors usually overreact to unexpected and bad events and prior loser portfolios tend to outperform the prior winners in the long run. As shown by De Bondt and Thaler (1985), thirty-six months after the portfolio allocation, the loser portfolios have gained on average 25% more than the winner portfolios. The resulting asset pricing anomaly is called *Long-term Reversal*, or *Rev*.

This finding has been furtherly developed by de Groot, Huij and Zhou (2011) who have exploited the possibility that abnormal returns are associated to prior loser portfolios taking into account a shorter time-period than the one originally proposed by the momentum literature. In particular, they claim that a *Short-term Reversal* strategy, or *Srev*, generates 30 to 50 basis points per week net of trading costs

- Maximum Daily Return Anomaly

Bali, Cakici, and Whitelaw (2011) have demonstrated the empirically observed tendency of preference for assets with lottery behaviours among investors. They find that there is a negative correlation between the maximum daily return, computed over a one-month time-period, and expected stock returns. Their research results in a trading strategy called *Maximum Daily Return*, or *Mdr1*.

- Beta Anomalies

According to Sharpe (1964), Lintner (1965), and Mossin (1966) the expected excess return on an asset is proportional to the asset's systematic risk, which can be measured by its Market Beta. The Market Beta is obtained by regressing the stock's excess return on the market excess return, and it is given by the slope coefficient of the regression.

In mathematical terms, the Beta is given by:

$$(1)\ \beta_i = \frac{\sigma_{i,m}}{\sigma_m^2}$$

where $\sigma_{i,m}$ is the covariance between the returns of asset *i* and the market while σ_m^2 is the market variance. Assets with a higher value related to this measure should provide higher expected return. The resulting trading strategy is named *Market Beta*, or $\beta 1$.

Given the significant importance of this result, many researchers have focused their effort on developing different models using the original work as foundation. Ang, Chen, and Xing (2006) have proposed a different approach based on the intuition that "investors care differently about losses versus upside gains". This implies that an investor who considers downside risk more important, would ask for a greater compensation for holding stocks that have shown to be more sensitive to downside movements. As a matter of fact, they have demonstrated that stocks that have a significant covariance with the market when the market performs badly have higher average returns, by about 6% per year. The resulting return predictor will be referred to as *Downside Beta*, or $\beta^{-}1$.

- Volatility Anomalies

Volatility has been always considered an important measure of risk in the stock market. For this reason, a wide number of studies have been carried out about how volatility is related to expected returns. Ang, Hodrick, Xing, and Zhang (2006) have investigated the possibility of using volatility as a cross-sectional return predictor. As a result of their research, they have found that stocks with high volatility are more likely to perform worse than their counterparts with low volatility. It is possible to build a trading strategy according to this finding which will be referred to as *Total Volatility*, or *Tv1*.

Ang, Hodrick, Xing, and Zhang (2006) have also investigated the same pattern using as measure the residual volatility. In particular, they have shown that stocks with high idiosyncratic volatility relative to the CAPM and Fama-French Models tend to have low returns. The relative trading strategies are called respectively *Idiosyncratic Volatility per the CAPM* and *Idiosyncratic Volatility per the FF 3-factor Model.*

- Skewness Anomalies

Skewness has been deeply studied in finance and investment theory since it has been shown that investors tend to prefer stocks that have right-skewed returns. This is due to the fact that if asset returns are right-skewed it means that extremely positive returns are more likely than big losses as stated by Arditti (1967) and Scott and Horvath (1980). This relationship has been used in asset pricing theory and resulted in a trading factor called *Total Skewness*, or *Ts1*.

Furthermore, given the relevance of the result stated above, the topic has been furtherly developed by Boyer, Mitton, and Vorkink (2008) who claimed that expected idiosyncratic skewness can be used in asset pricing. In particular, their research showed that stocks with high expected idiosyncratic skewness are more likely to present low expected returns. Accordingly, two different trading factors have been constructed, called *Idiosyncratic Skewness per the CAPM* and *Idiosyncratic Skewness per the FF 3-factors Model*, respectively.

Additionally, Harvey and Siddique (2000) have demonstrated that if the asset returns present systematic skewness, this should be included as risk premium. They show that conditional skewness helps in explaining the expected returns pattern across different assets and that portfolios which presents low expected returns are related to higher conditional skewness if compared to the portfolios with high expected returns. This asset return predictor will be referred to as *Coskewness*, or *Cs1*.

2.3 Anomalies' implementation

In this section I provide the details about the practical implementation of the discussed anomalies. In particular, I will follow the strategies' construction proposed by Hou, Xue and Zhang (2017) for all the considered asset pricing anomalies. Hou, Xue and Zhang replicate a large number of anomalies presented in literature, exactly 447 anomalies. They use portfolio sorting techniques in order model the assets return and thus to verify whether the average excess return, resulting from the treated factors, is statistically significant at the 5% level.

The portfolio sorting technique consists in allocating stocks into a fixed number of portfolios at the beginning of each considered period, i.e. one month. In my study I consider 10 different portfolios, then stocks are sorted into deciles according to the relevance of the treated anomaly shown by each asset in each period. In particular, the first decile, i.e. P1, is composed by stocks which present the lowest values related to the considered anomaly while the last decile, P10, is composed by assets with the highest latter values. Then, at the beginning of each next period, which in the following analysis is equal to one month, the deciles are rebalanced according to the performance shown by the examined assets in terms of the studied anomaly. Namely, on the first day of each month the composition of the ten portfolio changes according to the procedure relative to the anomaly's construction. Taking the *Prior 6-month Returns* as an example, P1 is composed by assets which have shown the worst performance during the last $t-7$ to $t-2$ months while P10 includes stocks with the highest return in the considered period; thus, this methodology is followed every month. The anomaly-based trading factor is constructed assuming a long position on the winner portfolio and selling the loser portfolio, or viceversa depending on the structure of the anomaly. The result is a zero-cost strategy which, for each anomaly, claims to provide consistent and positive returns over time.

At the end of the analysis, it is collected a time-series of returns coming from the implementation of each anomaly over a fixed time period, which in the following analysis goes from 1995 to 2016. Then, in order to verify whether the anomaly successfully provided positive returns, and thus is able to explain asset returns, it is performed a t-test on difference between the average return of the two extreme portfolio, i.e. P1 and P10. The null hypothesis of the t-test is that the difference between the average returns provided by the two portfolios is equal to zero, then if the null is found to be rejected this implies that the anomaly provides consistent and positive returns, i.e. it can be used to predict returns.

- Prior 11-month Returns

At the beginning of each month t I split all the stocks in portfolios built according to their previous 11-month returns computed from month $t-12$ to $t-2$. The portfolios are rebalanced each month using the procedure explained above and the resulting anomaly is constructed by taking a long position on the winner portfolio and a short one on the loser, namely the investor chooses to buy the portfolio with the highest prior return and to sell the one with the lowest one.

- Prior 6-month Returns

At the beginning of each month t, all the stocks are split into ten different portfolios according to their prior six-month returns computed from $t-7$ to $t-2$. Following the same procedure explained above, the portfolios are rebalanced at the beginning of each month and the asset pricing factor is built by taking a long position on the portfolio with highest prior return and selling the one with lowest prior return.

- 11-month Residual Momentum

At the beginning of each month t, I split all the stocks in ten different portfolios according to their prior eleven-month average residual returns, scaled by their standard deviation, computed from $t-12$ to $t-2$. The residual returns are obtained by regressing each month the stock excess returns on the factors from the Fama-French three factor model over a time-period going from $t-36$ to $t-1$. The actual time-series regression to be estimated is:

$$(2)\ \ r_{it}^{e} = \alpha_i + \beta_{i,m} r_{mt}^{e} + \beta_{i,HML} HML_t + \beta_{i,SMB} SMB_t + \epsilon_{it}\ ,$$

where r_{it}^{e} is the excess return of stock i, $\beta_{i,m}$ is the slope coefficient related to the market excess return, r_{mt}^{e}, $\beta_{i,HML}$ is the regression coefficient related to the value factor, HML_t, and $\beta_{i,SMB}$ is the coefficient related to the size factor, SMB_t. The prior eleven-month average residual return for stock *i* is calculated by average the ϵ_{it} residuals from the above regression over the appropriate period.

The portfolios are then rebalanced at the beginning of each month following the procedure explained above and the resulting factor is given by a long position on the winner portfolio (stocks with the highest average residuals) and a short position on the loser portfolio.

- Six-month Residual Momentum

On the first day of each month t, all the stocks are divided into ten different portfolios according to their past six-month residual returns, scaled by their relative standard deviation, over a period going from $t-7$ to $t-2$. The residual returns are obtained in the same way as in the previous case, by regressing for each stock the excess return on the factors from the Fama-French three factor model for the previous $t - 36$ to $t - 1$ months. Then, at the beginning of each next month all the portfolios are rebalanced according to the procedure just explained.

- Long-term Reversal

In order to replicate this anomaly, on the first day of each month *t*, all the stocks are split into ten different portfolios according to their prior returns computed over a time period going from $t - 60$ to $t - 13$. Then, for any next month the portfolios are rebalanced following the reasoning explained above and the resulting trading factor is given by taking a long position on the loser portfolio and a short one on the winner portfolio.

- Short-term Reversal

In order to replicate the *Short-term Reversal* anomaly, at the beginning of each month t all the stocks are divided into ten portfolios according to the returns in month $t - 1$. The portfolios are rebalanced monthly following the procedure described above and the factor is made by buying the loser portfolio and selling the winner.

- Maximum Daily Return

At the beginning of each month *t*, all the stocks are organized in ten portfolios according to their maximal daily returns during the previous month (month $t - 1$). In order to consider the stock, at least 15 daily return observations are required and on the first day of each following month the portfolios are rebalanced. The resulting strategy is given by taking a long position on the portfolio with the lowest maximal daily returns and selling the one with the highest daily returns.

- Market Beta

In order to construct the trading factor, the stocks are organized in ten portfolios according to their Market Beta, which is estimated with monthly returns from month $t-60$ to $t-1$, on the first day of each month t using the formula in equation (1). Then, for any next month the portfolios are rebalanced and the strategy is obtained by buying the portfolio which includes stocks linked to higher betas and selling the portfolio related to low betas.

- Downside Beta

At the beginning of each month t, stocks are stored into ten portfolios according to their Downside Beta which is estimated taking into account daily returns from the prior $t-12$ to $t-1$ months. The Downside Beta is calculated according to the following formula:

$$(3)\ \ \beta_i^- = \frac{Cov(r_i, r_m | r_m < \mu_m)}{Var(r_m | r_m < \mu_m)}$$

where r_i represents the excess return on stock i, r_m is the market excess return, while μ_m is the average market excess return in the considered period. In order to obtain a consistent analysis, at least 50 daily observations are required over the prior year, and for each next month the portfolios are rebalanced according to the procedure stated above. The trading factor is then built with a long position on the portfolio which includes stocks with a high Downside Beta and a short position on the low Downside Beta portfolio

- Total Volatility

At the beginning of each month t all the stocks have been split in ten different portfolios according to their total volatility computed from daily returns over the month $t-1$. In order to have a consistent result, at least 15 daily observations for each stock are needed. For any next month, the portfolios are then rebalanced following the procedure discussed above. The resulting strategy is then the one that sells the portfolio with the highest volatilities and buys the one with low volatilities.

- Idiosyncratic Volatility per the CAPM

The idiosyncratic volatility per the CAPM has also been computed following the guide lines given by Hou, Xue and Zhang (2017). In particular, at the beginning of each month t all the stocks have been organized in deciles according to their residual volatility computed from month $t-1$. Residuals are obtained by regressing the daily stock excess returns on the value-weighted market excess return, where only stocks that have at least 15 daily observations during the previous month are considered. Residual volatility is simply obtained as the volatility of the residuals. Then, the portfolios are rebalanced on the first day of any next month following the mechanism described above. The trading factor is then given by selling the portfolio which includes the stocks with highest idiosyncratic volatility and buying the one with the lowest.

- Idiosyncratic volatility per the FF 3-factor Model

On the first day of each month t all the stocks are organized in ten portfolios based on the idiosyncratic volatility resulting from the Fama-French model computed from month $t-1$. The Idiosyncratic volatility is computed by regressing the stock's excess return on the factors from the Fama-French three factor model and it is given by the residuals (as in equation (2)). In order to obtain consistent results at least 15 daily returns are required. The portfolios are then rebalanced at the beginning of each month following the method described above. The trading factor is then given by selling the portfolio which includes the stocks with highest idiosyncratic volatility and buying the one with the lowest.

- Total Skewness

On the first day of each month t, all the stocks are split into ten portfolios according to the total skewness computed with daily returns over the previous one-month period. In order to obtain consistent results, at least 15 daily observations are required. Following the same procedure as before, the portfolios are rebalanced each month. The resulting trading factor is made by taking a long position on the portfolio which includes stocks with the lowest total skewness and a short position on the one with highly skewed stocks.

- Idiosyncratic Skewness per the CAPM

At the beginning of each month t all the stocks have been organized into deciles according to their idiosyncratic skewness computed from month $t-1$. The idiosyncratic skewness is computed by regressing the stock's excess return on the market excess return using daily data from month $t-1$ and it is given by the skewness of the regression's residuals. In order to obtain a consistent result, at least 15 daily returns are required and following the method described above the portfolios are rebalanced each month. The resulting trading factor is given by taking a long position on the portfolio which includes stocks with the lowest total skewness and a short position on the one with highly skewed stocks.

- Idiosyncratic Skewness per the FF 3-factor Model

At the beginning of each month t all the stocks have been organized into deciles according to their idiosyncratic skewness computed from month $t-1$. The idiosyncratic skewness is computed by regressing the stock's excess return on the Fama-French factors using daily data from month $t-1$ and it is given by the skewness of the regression's residuals (as in equation (2)). In order to obtain a consistent result, at least 15 daily returns are required and following the method described above the portfolios are rebalanced each month. The resulting trading factor is given by assuming a long position on the portfolio which includes stocks with the lowest total skewness and a short position on the one with highly skewed stocks.

- Coskewness

At the beginning of each month t all the stocks are sorted into ten different portfolios according to their Coskewness computed with daily returns from month $t-1$.

Coskewness is given by the following formula:

$$(4)\ \ Cs_i = \frac{E[\epsilon_i \epsilon_m^2]}{\sqrt{E[\epsilon_i^2]}E[\epsilon_m^2]}$$

Where ϵ_i stands for the residuals resulting from the regression of the excess return of stock i on the market excess return while ϵ_m^2 are the squared demeaned market excess returns.

According to the procedure described above, the portfolios are rebalanced at the beginning of each month and the resulting factor is given by assuming a long position on the portfolios with low conditional skewness and a short position on the portfolio composed by assets with the highest conditional skewness.

Table 1 below lists all the anomalies discussed above. The table also shows how the long-short portfolios are created for each anomaly: either by taking a long position on the highest decile portfolio and a short position on the lowest decile portfolio (P10 - P1), or the other way around, by taking a long position on the lowest decile portfolio and a short position on the highest decile portfolio (P1 - P10).

Name	Shortening	Long-Short structure
Prior 11-month Returns	R_1^{11}	P10 – P1
Prior 6-month Returns	R_1^{6}	P10 – P1
11-month Residual Momentum	ϵ_1^{11}	P10 – P1
6-month Residual Momentum	ϵ_1^{6}	P10 – P1
Long-term Reversal	*Rev*	P1 – P10
Short-term Reversal	*Srev*	P1 – P10
Maximum Daily Return	*Mdr1*	P1 – P10
Market Beta	$\beta 1$	P10 – P1
Downside Beta	$\beta^{-}1$	P10 – P1
Total Volatility	*Tv1*	P1 – P10
Idiosyncratic Volatility per the CAPM	*Ivc1*	P1 – P10
Idiosyncratic Volatility per the FF3	*Ivff1*	P1 – P10
Total Skewness	*Ts1*	P10 – P1
Idiosyncratic Skewness per the CAPM	*Isc1*	P1 – P10
Idiosyncratic Skewness per the FF3	*Isff1*	P1 – P10
Coskewness	*Cs1*	P1 – P10

Table 1, "Glossary Anomalies".

2.4 Data

The data used in the analysis have been obtained from the Research Data Center of the Swedish House of Finance which contains high quality data about the major financial markets in Scandinavia. The analysis is carried out using the companies quoted on the Stockholm Stock Exchange, SSE, during the period between 01-01-1995 and 31-12-2016.

I have obtained both monthly and daily return observations which have been computed using the following formula:

$$(5)\ r_t = \frac{P_t}{P_{t-1}} - 1 \ ,$$

where r_t stands for the asset return and P_t is the last traded price of the stock at the end of the day, or month, *t* while P_{t-1} refers to the same measure at the end of the previous period (day or month, respectively). For some stocks, observations for the last price is not available and these values have been replaced with the average of ASK and BID price to obtain a usable value. These manipulations have been performed for both monthly and daily observations. The dataset consists of 681 companies with at least one observation during the considered period. As expected, not all the companies have values during all the time period.

In order to give a visual representation of the number of companies considered in the following analysis, Figure 1 shows the amount of stocks that presents at least one return for each considered month.

In particular, it is possible to observe an increasing trend of companies listed on the Stockholm Stock Exchange. This implies that the Swedish market has faced a growth during the considered time period with a well-defined positive trend in number of stocks for which trading is feasible. Moreover, it is possible to notice that the maximum number of stocks listed on the market is reached on December 2016 when it equal to 337. Importantly, as it has already been stated above, the total number of stocks considered is equal to 681 even though this number is never reached in any month. This implies that there has been a significant turnover of companies listed on the SSE during the considered time-period.

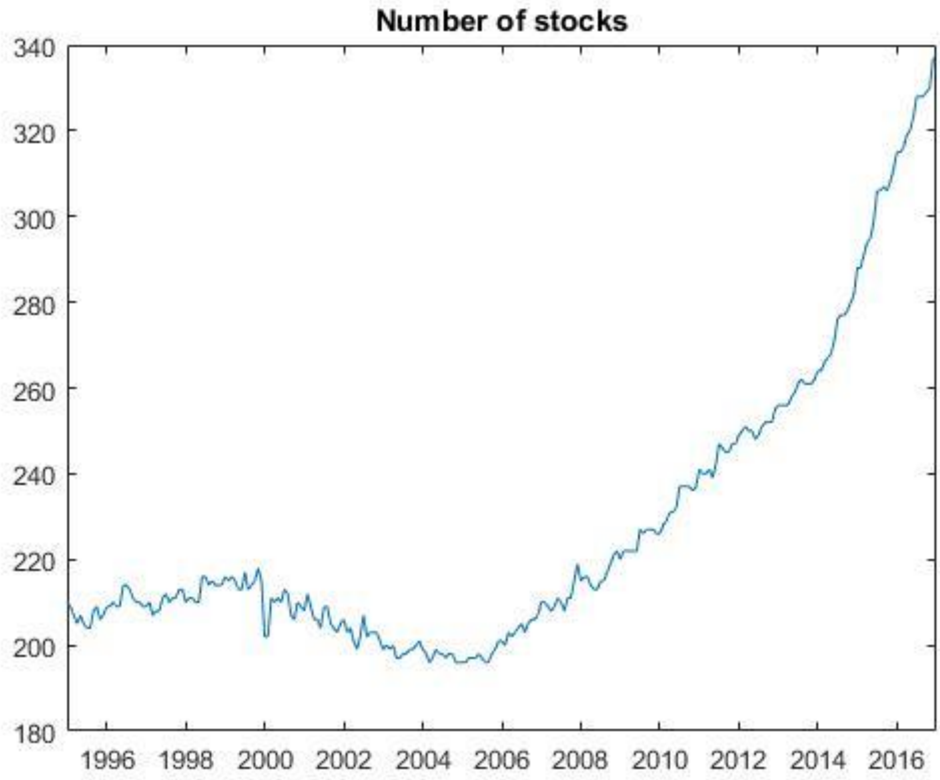


Figure 1, based on the author's own calculation, source: MATLAB

From the same data source, daily and monthly values of the Fama-French factors (Fama and French, 1996) have also been obtained. The Fama-French factors consist of the SMB (Small-minus-Big) and the HML(High-minus-low) factors that have been largely studied in literature. The HML factor is related to the value premium, in fact it represents the difference in terms of return between value and growth stocks. Fama and French (1996) have proved that companies with a higher book-to-market ratio (i.e., value stocks) outperform those with lower values (i.e. growth stocks). On the other hand, SMB is related to the small firm effect that refers to the empirically observed trend for stocks with a lower capitalization to offer higher returns than stocks that are highly capitalized (Banz 1981).

2.5 Results and Analysis

In this section, the results from the analysis on the Swedish stock market are reported. In particular, all the trading strategies described above are studied throughout the time period going from January 1995 to December 2016. The strategy returns reported in this section do not take into consideration transaction fees and costs generated by short-selling. Note, however, that the analysis will be later extended to consider the impact of transaction fees and short-selling costs. Table 2 provides the main results about the performance of the various trading strategies. Monthly average returns of all the decile portfolios and the average return of the trading strategy (long-short portfolio of deciles 1 and 10) has been reported together with the p-value resulting from the t-tests corresponding to the null hypothesis that the trading strategy has a zero average return.

	P1	***P2***	***P3***	***P4***	***P5***	***P6***	***P7***	***P8***	***P9***	***P10***	***Factor***	***Pvalue***
$\boldsymbol{R_1^{11}}$	0.44	0.99	0.91	1.42	1.43	1.42	1.35	1.49	1.67	2.13	1.68	0.0012
$\boldsymbol{R_1^{6}}$	0.41	1.08	1.25	1.24	1.40	1.33	1.37	1.49	1.49	2.14	1.73	0.0011
$\boldsymbol{\epsilon_1^{11}}$	0.73	0.89	0.98	1.13	1.21	1.45	1.14	1.39	1.63	1.55	0.82	0.0080
$\boldsymbol{\epsilon_1^{6}}$	0.85	1.16	1.02	1.18	1.06	1.21	1.39	1.47	1.11	1.67	0.82	0.0163
Rev	0.90	1.52	1.45	1.17	1.43	1.40	1.64	1.39	1.30	1.38	(0.48)	0.2507
Srev	1.09	1.60	1.44	1.56	1.42	1.71	1.37	1.30	1.23	0.84	0.24	0.5219
Mdr1	1.63	1.53	1.49	1.57	1.55	1.54	1.12	1.17	1.06	0.94	0.69	0.1166
$\boldsymbol{\beta 1}$	1.84	1.27	1.34	1.29	1.52	1.29	1.34	1.30	1.32	1.22	(0.63)	0.2732
$\boldsymbol{\beta^{-}1}$	1.46	1.57	1.55	1.64	1.23	1.49	1.20	1.35	1.06	0.96	(0.50)	0.2905
Tv1	1.71	1.65	1.42	1.56	1.60	1.37	1.31	1.40	0.84	0.76	0.96	0.0419
Ivc1	1.61	1.54	1.55	1.61	1.39	1.63	1.35	1.29	0.91	0.75	0.86	0.0601
Ivff1	1.68	1.47	1.49	1.53	1.57	1.62	1.35	1.18	1.06	0.70	0.98	0.0289
Ts1	1.28	1.52	1.23	1.25	1.34	1.58	1.24	1.23	1.38	1.60	0.32	0.2687
Isc1	1.03	1.41	1.32	1.46	1.57	1.21	1.28	1.53	1.23	1.59	(0.57)	0.0142
Isff1	1.13	1.38	1.30	1.39	1.43	1.41	1.23	1.46	1.27	1.63	(0.50)	0.0449
Cs1	1.26	1.47	1.45	1.35	1.43	1.60	1.61	1.02	1.11	1.33	(0.07)	0.7713

Table 2, "Anomalies' performance", based on the author's own calculation, source: MATLAB

It is important to notice that the returns presented in Table 2 are expressed in percentage, e.g., the average monthly return corresponding to the *Prior 11-month Returns* strategy (R_1^{11}) is 1.68% while the values between brackets correspond to negative values.

Now I am going to discuss the results from Table 2 in detail.

- Momentum Anomalies

The *Prior 11-month Returns* and the *Prior 6-month Returns*, or R_1^{11} and R_1^{6}, appear to perform very well on the considered sample. The portfolio that contains the stocks with highest prior 11-month returns provides a monthly average return equal to 2.13%, while the portfolio containing the stocks with the lowest prior 11-month returns, earns an average return of 0.44%. Therefore, the corresponding long-short strategy (labelled as "Factor" in Table 1) earns an average monthly return of 1.68%. The portfolios P10 and P1 behave in a similar manner for the 6-month strategy; the corresponding long-short trading strategy provides an average monthly return of 1.73%. In line with the previous literature, these trading strategies and pricing factors are meaningful and worth to be taken into consideration. This result is also supported by the t-tests, with p-values equal to 0.0012 and 0.0011, respectively. Thus, for a significance level of 5%, the trading and pricing factors are relevant.

The following figures show the cumulative returns of the two factors (the long-short portfolios obtained by taking a long position in P10 and a short position in P1):

Figure 2&3, based on the author's own calculation, source: MATLAB

As it is easy to see, one SEK invested at the beginning of the considered time-period would have resulted in a gain of approximately 3000% by December 2016 with the first strategy and of about 3300% with the latter one. This result does not take into consideration transaction fees and the costs relative to the short-selling required by the strategy but it emerges that it is significantly performing. It is also interesting to observe that the two momentum strategies do not provide comfortable results in crisis periods. In fact, as it appears from Figures 2&3, the cumulative return presents a big drop from 2008 to 2010 for both the strategies. Nonetheless, it clearly appears that the 11-month strategy presents a smaller downturn than the 6-month approach.

The *11-month* and *6-month Residual Momentum strategies* (ϵ_1^{11} and ϵ_1^{6}) have also been implemented on the stocks listed on the SSE. Table 1 shows that both factors perform in a significant manner; the winner portfolios beat the loser ones. Nonetheless, the difference in terms of average monthly return is smaller if compared to the previous two momentum strategies. The factors corresponding to ϵ_1^{11} and ϵ_1^{6} both provide a monthly average return of 0.82%. In addition, the p-values of the t-tests performed on the differences between P10 and P1 are respectively equal to 0.0080 and 0.0163 as it is possible to see from Table 2 thus, the difference is statistically significant.

- Reversal Momentum Anomalies

The *Long-term* and *Short-term Reversal* strategies (*Rev* and *Srev*), do not perform that well. As it can be seen from Table 1, the *Short-Term Reversal* strategy presents a monthly average return of 0.24% while the *Long-Term Reversal* strategy earns -0.48% per month. Since the two strategies do not show very high returns, it is important to verify whether they are statistically relevant or not. It arises that the return difference between portfolios P10 and P1 is not statistically significant for either of the approaches as it can be recognized from the p-values reported in Table 2.

- Maximum Daily Return Anomaly

The *Maximum Daily Return* strategy, or *Mdr1*, has been implemented for the considered time-period on the SSE and it displays a good performance. It is possible to inspect the performance provided by this approach by looking more closely to the returns given by the single portfolios built according the description of the strategy written in the previous section. The gains provided by the portfolios are consistent with the studies performed in literature. The portfolio composed by the highest maximum daily return stocks gives a return significantly lower than its counterpart and the resulting factor (a long-short portfolio buying P1 and selling P10) shows a monthly average return of 0.69%. The p-value of the corresponding t-test (p = 0.1165) shows that the factor return is not statistically different from zero. Nevertheless, the magnitude of the factor return is economically meaningful.

Furthermore, it is possible to see from the graph below that the cumulative return on the long-short strategy over the considered time period is 220%. One SEK invested with this strategy at the beginning of 1995 would have resulted in around 3.2 SEK at the end of 2016.

Figure 4, based on the author's own calculation, source: MATLAB

Additionally, it is observable from Figure 4 that differently to what has been observed with the momentum anomalies, the *Mdr1* seems to provide good results in terms of cumulative return during crisis periods as it is possible to notice from Figure 4 during the time-period going from 2008 to 2010.

- Beta Anomalies

The *Market Beta* and *Downside Beta* strategies ($\beta 1$ and $\beta^{-}1$) are built in a similar way but they differ in some features which, in fact, do not contribute to make them differ in performance. Taking into account a different time-frame in the estimation of the measure and the fact that the $\beta^{-}1$ is only computed when the market is below its average, it is possible to notice that both strategies perform badly.

The factors coming from the two Beta strategies provide similar results, in particular it is possible to observe from Table 2 that the portfolio including high beta stocks tends to perform badly in monthly average, then a strategy as the one suggested in theory is not profitable. As a matter of fact, it would be possible to use then a reverse approach in order to obtain a significant positive return. In fact, a strategy that sells the high beta stocks and buys their counterpart would gain an average monthly return, for both the approaches, of respectively 0.63% and 0.5%.

Nonetheless, these results are not supported by the p-values of the corresponding t-tests performed on the differences in portfolios returns since, as it appears from Table 1, they are respectively equal to 0.2732 and 0.2905. Clearly, it is not possible to reject the null hypothesis that the difference is zero.

- Volatility Anomalies

The *Total Volatility* anomaly, or *Tv1*, has been deeply studied in literature given its relevance as both an asset pricing anomaly and a trading strategy in addition to its general importance in financial markets. The *Tv1* seems to be an important factor which can be used to gain positive profits and explain the pattern of asset returns. As already explained in the previous section, the trading strategy is given by taking a long position on the portfolio including low volatility stocks and a short position on its counterpart. It is easy to notice from Table 2 that many of the ten portfolios follow a similar pattern on monthly average returns while the two portfolios containing the highest volatility stocks, P9 and P10, diverges sharply. This is the reason of the success of the strategy since the return difference of the P10 and P1 portfolios happens to be relevant. The long-short strategy that buys the P1 and sells the P10 portfolios provides an average monthly return of 0.96%. The t-test shows that the null of zero average return on the factor can be rejected at the confidence level of 5% (p = 0.0419).

Additionally, it is possible to observe from the graph below, that the cumulative return of this strategy is increasing over time even if it shows a large drop between 2003 and 2008. The trading factor seems to perform very well since if one SEK was invested at the beginning of the 1995, the profit would have been +500% by December 2016. Also, *Tv1* appears not to be influenced by the crisis, since it performs positively during the period 2008-2010.

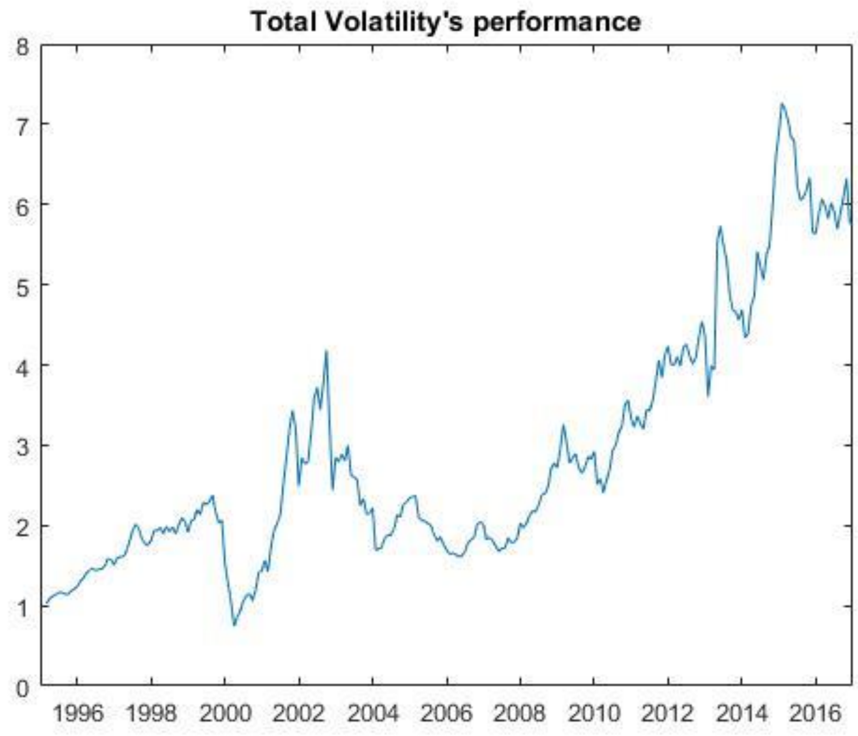
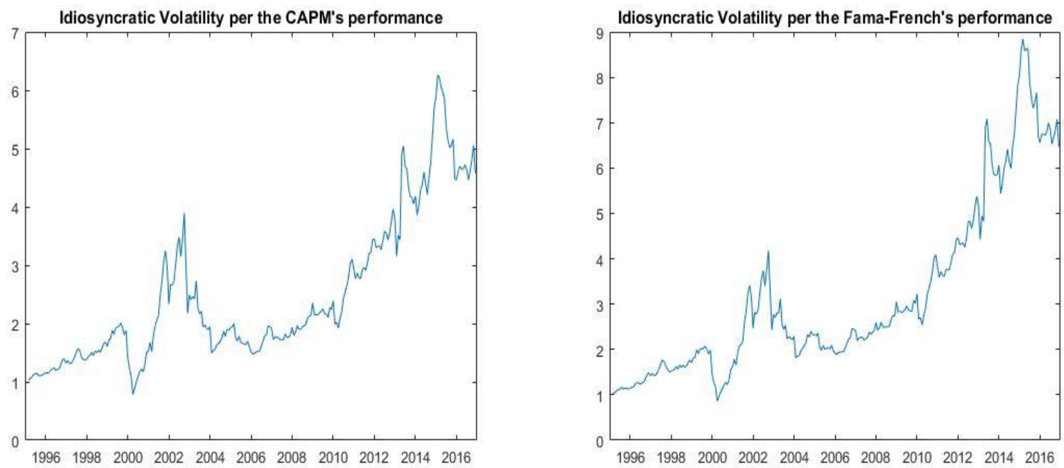


Figure 5, based on the author's own calculation, source: MATLAB

I have also implemented the two residuals approaches on the stocks listed on the Swedish market. The anomalies display several similarities since their close nature being the two considered models, the CAPM and Fama-French, highly correlated. They present related results but still with some differences that lead to choose one of the two factors as the better performing. It is possible to observe from Table 2 that the *Ivff1* presents an average monthly return of 0.98% while the one implemented using the CAPM realizes an average return of 0.86%. These results are further supported by the t-tests. The Idiosyncratic volatility per the Fama-French Model performs better than the one referring to the CAPM since, for a significance level of 5% the null hypothesis is rejected for *Ivff1* while it cannot be rejected for *Ivc1*. Nevertheless, the performance provided by the *Ivc1* is still important, since for significance level of 10% the factor return is significant.

It is possible to observe from the graphs below that the cumulative returns of both trading strategies are positive. Over the time-period going from the beginning of 1995 to the end of 2016, it is respectively equal to 400% and 600%.



Figures 6&7, based on the author's own calculation source: MATLAB

Nonetheless, it is noticeable that even if they follow a very similar pattern, the return given by the CAPM strategy appears to be a bit more volatile and this could be the reason why it results to have a lower statistical significance.

- Skewness Anomalies

The trading strategy based on *Total Skewness* (*Ts1*) seems to perform in a decent manner since it provides a positive factor return over the considered period. It can be seen from Table

2 that the low skewness portfolio, P1, present an average monthly return which is lower than the one presented by P10, and the corresponding long-short strategy provides a monthly average return equal to 0.32%.

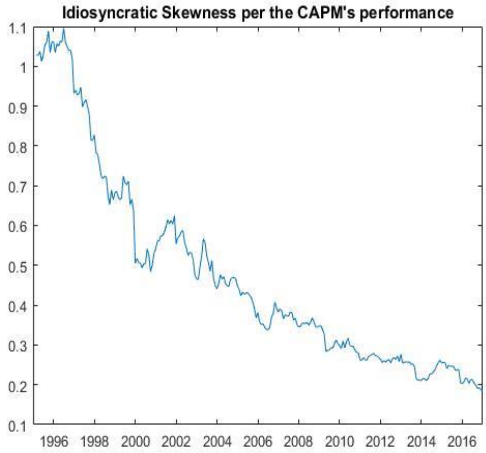
Furthermore, it is interesting to check if this difference in the portfolios' behaviour is important from a statistical viewpoint. The corresponding t-test gives a p-value of 0.2687. Consequently, even considering its relatively good performance as a trading strategy, it is not possible to claim that the difference between the returns of the two extreme portfolios is statistically significant and hence the pricing anomaly cannot be considered statistically relevant.

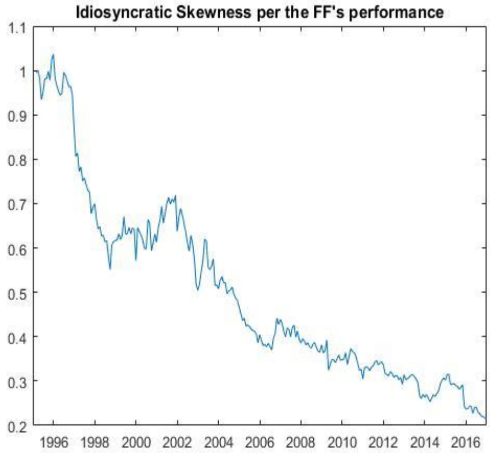
The trading strategies based on *Isc1* and *Isff1* present similarities both between themselves and with the *Ts1* presented above. In fact, as for the *Total Skewness* anomaly, also the latter does not perform as expected and studied in literature. On the other hand, the results are very interesting since a different behaviour from the one already well known has been found; in fact, it appears that the trading strategy implemented as proposed by Hou, Xue and Zhang (2017) is not profitable and instead it produces a significant loss. This leads to the necessity to evaluate the possibility that an implementation of a reverse strategy could lead to a positive return and to a significance in assets' return explanation.

Again, it is possible to notice the average monthly returns of the ten different portfolios for each strategy and it clearly appears from Table 2 that even if the pattern is similar for all the built portfolios, the one related to low-skewed asset, P1, presents a monthly return significantly lower than its counterpart, P10.

Given this anomalous result, a t-test has been performed on the difference between the two extreme portfolios in order to verify if their difference in returns is statistically significant. The fallout is as interesting as the results already shown above since it appears that the difference is statistically important with a significance level of 5%. This implies that a reverse approach would contribute significantly in explaining the behaviour of assets' returns.

Furthermore, it is noticeable from the graphs attached below that the cumulative returns related to *Isc1* and *Isff1* behave in analogous ways presenting a downtrend which result in a loss of respectively 80% and 75%. Naturally, a reverse approach would lead to the opposite outcome with a considerable profit over the considered period.





Figures 8&9, based on the author's own calculation, source: MATLAB

As it has been described in the previous section, some studies have shown that the conditional skewness (*Cs1*) is an important anomaly which could help in explaining returns' behaviour and thus be used as a trading strategy. However, its application on the SSE does not lead to such a conclusion since the corresponding factor return is virtually zero. The analysis is supported by the t-test that gives a p-value of 0.7713, which implies that null hypothesis cannot be rejected.

2.6 Conclusions from Chapter 1

In Chapter 1 I have carried out an extensive replication of some of the most important asset pricing findings available in literature, for the Swedish stock market. In particular, the ultimate aim of Chapter 1 has been to statistically demonstrate that it is possible to predict returns using different portfolio sorting variables. The return predictors result in different trading factors that have been presented in the empirical analysis.

As a matter of fact, it has been proved that, on the SSE, not every anomaly is performing in significant tone during the time-period going from beginning 1995 to the end of 2016.

Nonetheless, many characteristics, such as the ones referring to the Momentum, Volatility and a reverse approach to the *Total Skewness*, are found to be statistically significant. In particular, eight out of the sixteen anomalies are relevant for a significance level of 5%.

Then it is possible to make a further analysis of the results stated in the current chapter in order to implement trading strategies able to provide a better performance than the one offered on the market.

3. CHAPTER 2: TRADING STRATEGIES

3.1 Introduction to Chapter 2

In the previous chapter I have shown that a significant number of anomalies appear to perform in a profitable manner when implemented on the SSE. In particular, several pricing anomalies are found to be statistically relevant and able to describe the behaviour of stock returns. Thus, one could think to use the well-performing anomalies in order to create trading strategies based on these findings. In this chapter, several approaches relative to factor trading will be studied in order to underline the practical application of the pricing anomalies found above.

The trading strategies are implemented on the 30 biggest stocks listed on the SSE since liquidity issues are much less relevant for these stocks, compared to smaller ones listed on the exchange. I only included 29 stocks in my analysis since one stock, i.e. Essity B, has been only recently listed on the stock exchange and it is not included in my initial data. The detailed list of considered companies, together with their market capitalization can be found in the Appendix.

As already stated above, the factor investing strategies have been implemented only for the pricing anomalies that have shown a good performance during the test carried out in the previous chapter. In particular, it has been shown that the momentum factors perform very well when tested on the SSE. The four momentum factors share similarities since the *Prior 11-month Returns* and *Prior 6-month Returns* are identical except for the time-period considered for calculating prior performance, while the Residual Momentum strategies are very correlated both between each other and with the latter ones. For this reason, I chose to use only the *Prior 6-month Returns* given the fact that it has achieved the best level of profitability and statistical relevance from the four momentum factors.

The *Maximum Daily Return* factor has met importance in profitability while the statistical relevance has failed to meet the 5% significance level. Nevertheless, it has been included in the current chapter since it is interesting to observe the behaviour of a factor which seems to perform efficiently from a return point of view but does not provide comfortable results in statistical terms.

The volatility strategies have presented interesting outcomes. Both the *Total Volatility* and *Idiosyncratic Volatility per the Fama-French* factors operate profitably both from and economic and from a statistical point of view. Again, I chose to implement only one of the two strategies given their close nature and since the *Tv1* is the original version of the volatility factors it has been selected as a trading strategy.

One of the main accusations to the empirical research in trading strategies is that generally most of the analysis does not take into consideration the transaction costs. One of the first drawbacks is that one could claim that if they were taken into account an important part of the profit would be taken away. In order to avoid this criticism, the considered strategies are implemented both with and without transaction costs.

The performance of the presented factor investing strategies is measured by the Sharpe Ratio (Sharpe 1994) defined by the following formula:

$$(6)\ \frac{r_x - r_f}{\sigma_x}$$

Where r_x is the average monthly return relative to the portfolio *x*, r_f is the risk-free rate and σ_x is the standard deviation relative to the returns of *x*.

3.2 Theoretical Framework

In line with Brandt, Santa-Clara, and Valkanov (2009), the ultimate goal in this chapter is to show that portfolios with a large number of stocks can be managed differently from the traditional approach given by a mean-variance optimization largely proposed in literature (Markovwitz, 1952). The objective of the analysis is to demonstrate that a trading strategy is possible to be implemented following a quantitative approach related to assets' characteristics. For this reason, the portfolio rules proposed below allow to parametrize the portfolio weights as a function of specific factors that have been studied in the previous chapter.

The portfolio weights follow the procedure explained successively: let us assume that there are a certain number of stocks in the market N_t where *t* refers to a given date and each stock k is associated with a definite characteristic (e.g. Momentum) and presents a return from date t to $t+1$ defined as $r_{k,t+1}$. As already stated above, each asset will be associated with a certain weight which is function of the pricing factor.

Brandt, Santa-Clara, and Valkanov (2009) propose a linear formula for the portfolio weights construction that is reported below:

$$(7)\ \ w_{k,t} = \frac{1}{N_t}\left(1 + \sum_{i=1}^{I} \theta_i Z_{k,t}^{i}\right)$$

where $\frac{1}{N_t}$ is the weight related to the stock k in a benchmark portfolio, that in our case is the Equally Weighted portfolio and θ_i is the coefficient related to the pricing factor $Z_{k,t}^{i}$ which is standardized in order to obtain a zero mean and standard deviation equal to 1.

It is important to notice that the term $\theta_i Z_{k,t}^{i}$ gives the intensity of the deviation of the considered portfolio from the Equally Weighted portfolio. Furthermore, the pricing factors have to be standardized for technical reason; in fact, thanks to this procedure the cross-sectional distribution of the characteristics is stationary and the sum of the weights related to each asset is equal to unity.

The coefficient θ, that represents the relevance of the pricing factor associated, is constant for all the considered assets; this implies that whether two stocks show similar pricing factors they will have close weights even if they differ with respect to returns. It follows that our approach assumes that the characteristics are able to fully evaluate the joint distribution of the assets' returns making the task extremely simple.

In general, the analysis implemented in this chapter is carried out taking into consideration the following general formula:

$$(8)\ \ w_{k,t} = \frac{1}{N_t}\left(1 + \theta_{MOM} Z_{k,t}^{MOM} + \theta_{Tv} Z_{k,t}^{Tv} + \theta_{Mdr} Z_{k,t}^{Mdr}\right)$$

For example, in January 1995 only 16 out of the 29 considered stocks were listed on the market, then the value assumed by N_t is the same. As already explained above $Z_{k,t}^{MOM}$ is the standardized momentum characteristic related to asset k. Let us now consider the stock AstraZeneca that in January 1995 presents a prior 6-month return equal to 0.4146 while the average cross-sectional return as -1.7412 and the standard deviation equal to 7.9524, which leads to $Z_{k,t}^{MOM} = 0.2711$. Then assuming that the momentum coefficient is equal to 1 ($\theta_{MOM} = 1$) and all the others have not relevance (i.e. $\theta_{Tv} = \theta_{Mdr} = 0$), it follows that the portfolio weight related to AstraZeneca in January 1995 is equal to 0.0794 according to equation (8).

In the procedure explained above short-selling is allowed. However, in the analysis it is interesting to impose some restrictions to the portfolio weights; for example, one could claim that it is important to observe the behaviour of the different strategies when short-selling is not allowed. In fact, a very common remark is that when short-selling is allowed transaction costs can reach very high levels and the profitability of the investment tends to disappear (Diamond, Douglas, and Verrecchia, 1987).

For this reason, the following analysis also takes into account this issue and, for each proposed strategy, a no short-selling counterpart has been implemented. In the proposed approach, the constraint has to be imposed through the parametrization and it is done using the following formula:

$$(9)\ \ w_{k,t}^{+} = \frac{max[0, w_{k,t}]}{\sum_{k=1}^{N} max[0, w_{k,t}]}$$

Once the weights are computed, it is possible to evaluate the different factor investing strategies considering the return provided by the resulting portfolios that it is computed as it follows:

$$(10)\ \ r_{p,t+1} = \sum_{k=1}^{K} w_{k,t} r_{k,t+1}$$

where $w_{k,t}$ is the weight related to asset k at time t (at the beginning of the month), while $r_{k,t+1}$ is the return given by the same asset at from date t to $t+1$ (i.e., over the following month).

It is also important to consider transaction costs. Transaction costs can be seen as a fee paid to the bank for its important service necessary in order to complete the trade between two agents and it is an important topic in financial investment, and especially in trading, since it can affect even largely the profit resulting from trading (Stavins 1995).

Brandt, Santa-Clara, and Valkanov (2009) propose the following procedure to take into account the effect of transaction costs. In order to compute the transaction costs, it is crucial to investigate the turnover of the strategies. First let us introduce the, so called, “hold portfolio”, which is defined as follows:

$$(11)\ \ w_{k,t}^{h} = w_{k,t-1}\frac{1+r_{k,t}}{1+r_{p,t}}$$

If a certain portfolio is held for an entire month, the portfolio weights will change according to changes in the values of the constituents. This is reflected in the above formula. On the first day of month t, the portfolio is the same as the portfolio at beginning of month $t-1$, but with the weights that have been changed by the returns from $t-1$ to t.

The turnover for month t is then defined as the sum of all the absolute changes in portfolio weights that has to be made on the first day of month t in order to achieve the new weights desired by the specific trading strategy:

$$(12)\ \ T_t = \sum_{k=1}^{N_t}\left|w_{k,t} - w_{k,t}^{h}\right|$$

Then, given a fixed amount corresponding to the transaction cost expressed as c, it is possible to write a formula for the return of the portfolio when transaction costs are taken into account:

$$(13)\ \ r_{p,t+1} = \sum_{k=1}^{N_t} w_{k,t}r_{k,t+1} - c\left|w_{k,t} - w_{k,t}^{h}\right|$$

3.3 Implemented Strategies and Results

3.3.1 Unrestricted case in absence of transaction costs

In the next pages, the results relative to the trading strategies considered in the analysis will be presented. In particular, as it has been already claimed in the previous paragraph, trading strategies which take into account the pricing anomalies that have been shown to be more significant will be considered.

The analysis is composed by ten different trading strategies which consider both single anomalies, with different level of intensities, and also multiple anomalies at the same time. Namely, for each strategy it has been applied the full intensity and half of the original relevance (i.e. θ coefficient equal to 1 and 0.5) and then the most performant approach, for each single characteristic, has been applied for the mixed strategies. It is possible to achieve the stated goal using the general formula (8) for the portfolio's weights stated above. In addition, in order to test whether the short-selling has an impact on profitability, it has been chosen to realize a long-only approach for all the investment applications.

The main features of the trading strategies are explored in Table 3, which reports the average monthly return, standard deviation, Sharpe Ratio and average turnover for each strategy when transaction costs are not considered. It is important to notice that all the values reported in Table 3 refer to monthly measures. Moreover, each strategy is identified thanks to the values assumed by θ for each considered anomaly.

Equally important to the measures themselves is to compare them to the ones presented on the market, for this reason the same analysis has been developed taking into account the OMXS30. The OMXS30 is the index that includes the thirty biggest stocks listed on the SSE. The same companies, except for one, have been used in our analysis then it is interesting to investigate the difference in performance given by the proposed approaches and the one resulting from the official index. In particular, I have computed the Sharpe Ratio and the average monthly return for the OMXS30 in the same time-period and they are respectively equal to 0.1380 and 0.78%. Both values are lower than all the corresponding values presented in Table 3. This implies that the parametric portfolios, and thus the factor investing strategies, have managed to achieve better levels of risk-return than what it is offered on the market.

Furthermore, the benchmark portfolio of the considered analysis is the Equally Weighted (EW) portfolio which attributes in fact the same weight to each of the stocks taken into account. The Equally Weighted portfolio is the benchmark of our analysis since it is the simplest portfolio that can be taken into consideration and it has been shown in literature that even being a very basic strategy, it performs pretty well (Rouwenhorst, 1998).

As it appears from Table 3, the EW strategy is very profitable in terms or return. In fact, this approach provides am average monthly return of 1.61% if transaction costs are not taken into account. Additionally, the EW portfolio does not require a large assets' turnover since its value is the lowest one among all the considered strategies. The good performance of the strategy is supported by the value assumed by the Sharpe Ratio which is equal to 0.2868 which is significantly larger than the one offered by the OMXS30 index.

Name	$\boldsymbol{\theta_{MOM}}$	$\boldsymbol{\theta_{Tv}}$	$\boldsymbol{\theta_{Mdr}}$	***Average Return***	***Standard Deviation***	***Sharpe Ratio***	***Average Turnover***
EW	0	0	0	1.61%	0.0561	0.2868	5.82%
S1	0.5	0	0	1.77%	0.0541	0.3275	22.12%
S2	1	0	0	1.93%	0.0573	0.3370	42.81%
S3	0	-0.5	0	1.39%	0.0512	0.2708	32.02%
S4	0	-1	0	1.17%	0.0545	0.2137	63.42%
S5	0	0	-0.5	1.39%	0.0522	0.2659	40.56%
S6	0	0	-1	1.17%	0.0524	0.2122	78.63%
S7	1	-0.5	0	1.71%	0.0522	0.3263	55.31%
S8	1	0	-0.5	1.70%	0.0531	0.3204	65.37%
S9	0	-0.5	-0.5	1.16%	0.0545	0.2126	65.85%
S10	1	-0.5	-0.5	1.47%	0.0551	0.2667	84.52%

Table 3, "Factor trading: unrestricted scenario", based on the author's own calculation, source: MATLAB

Table 3 shows the results relative to the implementation of the factor trading approach on the thirty biggest stocks listed in Sweden using a parametric portfolio strategy. The first evidence that clearly appears is that all the considered strategies perform better than the OMXS30. In particular, it is possible to notice that all the values presented in Table 3 relative to average return and Sharpe Ratio provide better results than the ones shown by the Swedish index.

In Chapter 1 it has been shown that the momentum anomalies are the most performing in terms of statistical relevance and average monthly return. Not surprisingly, when the momentum anomaly, *Prior 6-month Returns*, is applied to the parametric portfolio it performs very well. In fact, S1 and S2 are the strategies that consider this asset pricing characteristic and as it appears from the results reported in Table 3, they provide the best performance (in terms of average return and Sharpe ratio) among all the considered strategies. It is then observable that for the momentum strategy it is optimal to take fully into account the returns' predictor since S2 gives better outcomes than the S1 strategy. Moreover, S2 provides 0.32% in excess to the Equally Weighted portfolio per month with a Sharpe Ratio significantly higher than its benchmark, this implies the momentum predictor is highly significant even when applied to a parametric portfolio.

On the other hand, it is interesting to observe that the both Volatility approach and the Maximum Daily Return one provide the same results in term of average monthly return. In particular, when the characteristic is only partly considered the average return is equal to 1.39% while when it is fully observed the return decreases to 1.17%. This implies that contrarily to the behaviour shown by S1 and S2, those predictors perform better when they are not fully treated. The Sharpe Ratio follows the same pattern as the average monthly return since it tends to decrease when the relevance increases. Although the results are worse than the ones provided by the momentum application, it is important to observe that those strategies still give better outcomes than the ones presented by OMXS30 and when they are compared to the Equally Weighted strategy, the more successful examples (S3 and S5) appear to be pretty close in terms of Sharpe Ratio to the EW portfolio.

As a result, it has been noticed that the best strategy among the ones implemented using the momentum predictor is the one with θ equal to 1 while the others perform better when partly considered, i.e. when θ is equal to -0.5. Then, it has been tested a mixed approach taking into account the coefficient which gives the more satisfying outcomes. It follows that when the momentum characteristic is considered it is noticeable an improvement in terms of average return and Sharpe Ratio as in the case of S7 and S8 with respect to the single applications using *Tv1* and *Mdr1*. In fact, these strategies furnish results much better than the ones provided by the *Maximum Daily Return* and *Total Volatility* singularly studied. The data reported in Table 3 also demonstrate that both these strategies perform better than the OMXS30 and the Equally Weighted portfolio under both an average monthly return and Sharpe Ratio point of view. On the other hand, it has to be considered that when only the *Prior 6-month Returns* is treated the results achieved are better, then it is possible to conclude that *Mdr1* and *Tv1* tend to decrease the profitability of the latter when mixed together.

I have also implemented a strategy which considers all the anomalies at the same time, S10, and it appears that as it follows the pattern demonstrated by S8 and S9 since the return and Sharpe Ratio tend to be lower than the one presented by S2 (i.e., Momentum only).

3.3.2 Long-only portfolios

In this section all the parametric portfolios previously implemented have been restricted to the case in which short-selling is not allowed, i.e. all the portfolio weights have to be non-negative at all dates. This condition needs to be tested in order to verify whether short-selling has an impact on profitability, since excessive use of short-selling can lead to a decrease in profit due to high costs involved (Ali and Trombley, 2006).

In order to compare the two approaches, the values already computed in Table 3 have been recomputed for the restricted approach. Table 4 presents the main features of the strategies when all the portfolio weights are restricted to be non-negative. In order to give a visual representation of the improvement achieved through this restriction, the values, relative to average monthly return, standard deviation, Sharpe Ratio and average turnover, which represent an upgrade (compared to Table 3) have been highlighted in Table 4.

Name	$\boldsymbol{\theta_{MOM}}$	$\boldsymbol{\theta_{Tv}}$	$\boldsymbol{\theta_{Mdr}}$	***Average Return***	***Standard Deviation***	***Sharpe Ratio***	***Average Turnover***
EW	0	0	0	1.61%	0.0561	0.2868	5.82%
S1 long	0.5	0	0	**1.78%**	**0.0543**	**0.3282**	**21.64%**
S2 long	1	0	0	**1.96%**	**0.0577**	**0.3393**	**35.61%**
S3 long	0	-0.5	0	**1.40%**	**0.0511**	**0.2916**	**28.88%**
S4 long	0	-1	0	**1.50%**	0.0499	**0.3000**	**44.99%**
S5 long	0	0	-0.5	**1.48%**	**0.0521**	**0.2843**	**36.19%**
S6 long	0	0	-1	**1.47%**	**0.0511**	**0.2876**	**54.45%**
S7 long	1	-0.5	0	**1.81%**	0.0524	**0.3456**	**41.26%**
S8 long	1	0	-0.5	**1.77%**	0.0531	**0.3337**	**48.32%**
S9 long	0	-0.5	-0.5	**1.48%**	**0.0504**	**0.2933**	**47.41%**
S10 long	1	-0.5	-0.5	**1.70%**	**0.0506**	**0.3356**	**54.07%**

Table 4, "Factor trading: long-only scenario", based on the author's own calculation, source: MATLAB

The results in Table 4 provide convincing evidence that ruling out short-selling leads to a general increase in average returns and Sharpe Ratios. In fact, all the trading strategies achieve a higher Sharpe Ratio when the restriction is applied. It is important to notice that the EW is already a long-only strategy by construction, so it is not possible to observe any difference for this strategy between Table 3 and Table 4.

Despite the general improvement shown in terms of performance, there are some strategies which achieve a larger benefit from this restriction than others. In particular, comparing Table 3 with Table 4 it clearly appears that S4 and S6 produces results largely more performing than in the unrestricted scenario. In fact, it is observable that the average return for these strategies increases by 33 and 30 basis points, respectively, only by applying the no-short-selling restriction on the portfolio construction. This trend is also confirmed by the Sharpe Ratio which shows consistent benefits when short-selling is not allowed since it is now equal to 0.3 for S4. Another strategy that increases its performance is S9 since it passes from an average return of 1.16% per month to 1.48% with the Sharpe Ratio that improves from 0.2126 to 0.2933. Again, S10 shows a large improvement since, according to the considered measures, it becomes among the most performing implemented approaches.

Generally, on the basis of the evidence currently available it is possible to claim that the largest improvement has been experienced by the strategies based on the *Maximum Daily Return* and *Total Volatility* and then subsequently also by the ones following a mixed approach.

It is also interesting to notice that in all the cases the average return appears to increase as well as the Sharpe Ratio. On the other hand, there are few strategies that show a higher standard deviation than in the unrestricted scenario. Anyway, given that the Sharpe Ratio has improved for every strategy this implies that the benefits in terms of average return are more significant than the increase in standard deviation, as for example in the case of S4.

3.3.3 Positive transaction costs

The next aim is to investigate the impact of positive transaction costs on the performance of these trading strategies. In particular, it is commonly claimed that an active portfolio management leads to high transaction costs which reduce revenues significantly (Morton and Pliska, 1995). In order to test whether this statement is appropriate, the issue under scrutiny in the next few pages is the introduction of different levels of transaction costs applied to the long-only strategies since the latter have been proved to perform better than the unrestricted ones. Different levels of transaction costs are introduced using equation (13).

The results of this application can be found in Table 5, which presents Sharpe Ratios corresponding to the strategies when different transaction cost levels are considered. Three different levels of per trade transaction costs are taken into account: 10, 30, and 50 basis points (bp). For reference, Table 5 also reports the Sharpe Ratios of the strategies without transaction costs (in the column with $c = 0$); these Sharpe Ratio values are identical to the ones reported in Table 4. I chose to report only the Sharpe Ratio values since they provide a summary of the performance referring both to the standard deviation and average monthly return. In addition, the values that are able to beat the Equally Weighted portfolio have been highlighted to give a first visual idea about strategies' performance for each level of transaction costs.

Name	$\boldsymbol{\theta_{MOM}}$	$\boldsymbol{\theta_{Tv}}$	$\boldsymbol{\theta_{Mdr}}$	***SR with c = 0***	***SR with c = 10bp***	***SR with c = 30bp***	***SR with c = 50bp***
EW	0	0	0	0.2868	0.2858	0.2837	0.2817
S1 long	0.5	0	0	**0.3282**	**0.3243**	**0.3164**	**0.3085**
S2 long	1	0	0	**0.3393**	**0.2910**	**0.3088**	**0.3332**
S3 long	0	-0.5	0	0.2859	**0.3287**	0.2747	0.2635
S4 long	0	-1	0	**0.3000**	**0.2910**	0.2731	0.2552
S5 long	0	0	-0.5	0.2843	0.2773	0.2635	0.2497
S6 long	0	0	-1	**0.2876**	0.2770	0.2558	0.2345
S7 long	1	-0.5	0	**0.3456**	**0.3379**	**0.3224**	**0.3069**
S8 long	1	0	-0.5	**0.3337**	**0.3247**	**0.3067**	**0.2887**
S9 long	0	-0.5	-0.5	**0.2933**	0.2840	0.2652	0.2465
S10 long	1	-0.5	-0.5	**0.3356**	**0.3251**	**0.3040**	**0.2829**

Table 5, "Effect of positive transaction costs", based on the author's own calculation, source: MATLAB

A closer look at the results presented in Table 5 indicates that there is a negative correlation between Sharpe Ratio and transaction costs. In fact, there is overwhelming evidence for the notion that for every strategy the value assumed by the Sharpe Ratio decreases when the transaction costs become greater. This is due to the fact that the returns are by construction influenced by the transaction costs. Thus, when the transaction cost increases, the returns tend naturally to decrease.

Furthermore, it is important to compare the change in Sharpe Ratio with the turnover required by the strategies. As a matter of fact, it clearly appears that the strategies which need a higher turnover are found to be more affected by transaction costs than the ones which require a lower level of change in the portfolio's structure. In fact, looking for example at the Equally Weighted portfolio which requires only about 5% of turnover per month it is evident that the change in Sharpe Ratio is very small, while for strategies with high turnover, such as S8 long, the change is much more important. Despite it has been proved that the introduction of positive transaction costs has an impact on the performance of active management strategies, it is important to notice that all the approaches are still found to overperform the OMXS30 index. In addition, in most of the cases the long-only portfolios also succeed to beat the performance shown by the Equally Weighted portfolio even for high levels of transaction costs such as 50bp per trade.

To illustrate the effect of transaction costs on the cumulative performance of these strategies, Figure 10 shows the cumulative return of the strategy S7 for the different levels of transaction costs:

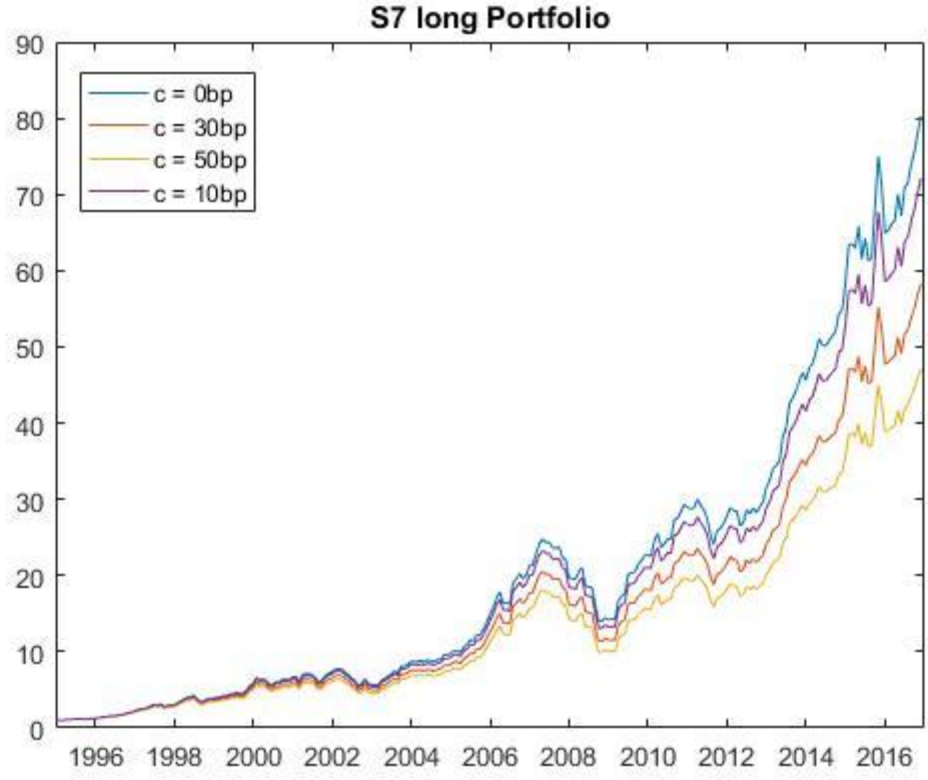


Figure 10, based on the author's own calculation, source: MATLAB

It clearly appears that large levels of transaction costs tend to cut the profit coming from the strategy, in fact the total cumulative return passes from almost 80 units when transaction costs are absent to less than 50 for c = 50bp. Moreover, it is important to notice that the pattern is totally similar for the different values assumed by *c*, then it is possible to conclude that positive levels of transaction costs have not an impact on the essence of the strategies but they only downscale the revenues.

In conclusion, taking into account a reasonably fair 30bp per trade level of transaction costs it appears that half of the implemented strategies beat the benchmark portfolio and all of them outperform the OMXS30 index, thus it is not possible to claim that an active portfolio management leads to a zero profit.

3.4 Conclusions from Chapter 2

In the current chapter I have analysed the possibility of implementing trading strategies on the basis of pricing anomalies. In particular, applying a parametric portfolio construction to the findings relative to Chapter 1, it has been shown that it is possible to achieve more profitable levels of average monthly return and risk-adjusted return (expressed in terms of Sharpe Ratio) than the one offered on the market.

Moreover, it has been demonstrated that short-selling generally leads to a decrease in average return per month and Sharpe Ratio, then a restriction relative to this procedure appears to be useful in order to gather more profitable levels of performance.

In conclusion, the analysis relative to the introduction of positive transaction costs leads us to claim that strategies with high turnover are more significantly affected by fees than the ones which do not require a great change in portfolio structure. Nonetheless, even considering the decrease in performance for positive levels of transaction costs, all the strategies appear to provide better conditions than the one offered by the OMXS30 index, and a handful of strategies provide a better performance than the equal-weighted portfolio. That is, a factor investing approach appears to be profitable and able to improve the performance of standard portfolios.

4. CONCLUSION

The thesis investigated whether pricing anomalies have a certain relevance on the Stockholm Stock Exchange. Further, the thesis used the results of this first analysis in order to develop trading strategies based on a factor investing approach.

In Chapter 1, it has been found that not all the presented anomalies perform in a satisficing manner when applied on the stocks listed on the Stockholm Stock Exchange. In fact, only eight anomalies, out of the six-teen studied, appear to be statistically relevant for a significance level of 5%. It is important to note that the time-period taken into account goes from January 1995 to December 2016, thus it is possible that observing another time-period would lead to different results.

Furthermore, the findings coming from Chapter 1 have been applied to a more practical approach. In fact, the successful anomalies, such as the Momentum, Volatility and Maximum Daily Return, were used to develop trading strategies able to overperform the Swedish Index OMXS30 and a benchmark portfolio, the Equally Weighted one.

In order to achieve this goal, the framework of parametric portfolios has been used, which claims that it is possible to build efficient investment solutions based on the factors that are related to patterns in average stock returns.

In Chapter 2 then, ten different strategies have been proposed and it has been shown that all of them are able to provide better conditions than the ones offered on the market; for this reason, it is possible to claim that the anomaly variables considered extremely useful for investors who desire to find profitable trading strategies.

Different common critiques, such as the impact of transaction costs and short-selling on profit, have been explored. It has been found that as commonly claimed short-selling tend to decrease the revenues coming from trading then a long-only restriction is useful to obtain better performances. On the other hand, positive transaction costs do not have an impact important enough to eliminate the benefits coming from an active management of portfolios.

5. APPENDIX

Company	Ticker	Capitalization
ABB Ltb	ABB	116,621,688,368
Alfa Laval	ALFA	97,523,593,238
Autovil SDB	ALIV SDB	82,160,982,257
ASSA ABLOY B	ASSA B	202,991,690,226
Atlas Copco A	ATCO A	306,378,845,040
Atlas Copco B	ATCO B	129,708,798,259
AstraZeneca	AZN	81,506,870,564
Boliden	BOL	87,988,543,067
Electrolux B	ELUX B	68,716,295,217
Ericsson B	ERIC B	207,878,296,580
Essity B	ESSITY B	151,522,847,082
Fingerprint Cards B	FING B	1,964,833,767
Getinge B	GETI B	21,592,785,610
Hennes & Mauritz B	HM B	211,242,384,640
Investor B	INVE B	173,949,410,633
Kinnevik B	KINV B	75,775,690,360
Nordea Bank	NDA SEK	358,744,740,985
Sandvik	SAND	204,339,466,857
SCA B	SCA B	64,987,199,650
SEB A	SEB A	181,847,616,837
Securitas B	SECU B	48,812,656,469
Sv. Handelsbanken A	SHB A	190,090,474,867
Skanska B	SKA B	67,885,842,615
SKF B	SKF B	79,540,878,901
SSAB A	SSAB A	15,373,422,466
Swedbank A	SWED A	219,326,108,638
Swedish Match	SWMA	73,547,100,000
Tele 2 B	TEL2 B	54,730,550,002
Telia Company	TELIA	188,272,086,278
Volvo B	VOLV B	265,564,623,052

N.B. The Market Capitalization is expressed in SEK and the highlighted company is the one which is not considered in the analysis

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