- Portfolio Strategies in Bad Times -

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Abstract

Institutional and private investors are being overwhelmed by information and theory. The difficulty lies in identifying what truly improves returns and reduces risk. In the midst of all this noise, the worry of an upcoming downturn following the recent years of strong market returns is brewing for the risk averse investors. This thesis attempts to address this by studying the cross-section of stock returns during historical bad times in Sweden. Attention is given to the performance of certain characteristics in the attempt of finding patterns for stocks that perform well in bad times and retain respectable returns in good times. Two portfolios are built on underlying factors of these characteristics, and thoroughly tested. The first is based on overall alpha performance while the second is based on alpha in bad times. Although the portfolios in fact perform well in bad times when tested in sample, they still underperform relative to the market portfolio. In addition to this, the results do not hold up when considering an out of sample robustness test conducted to evaluate the future predictability of the portfolio strategies. In fact, it does not seem possible to create portfolio strategies on the Swedish market that with confidence can perform well in bad times and in the long-term.

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1. Introduction

One of the things that scares people the most is losing money, at least when it comes to long term investments of personal savings. According to the prospect theory, and the pseudocertainty effect in particular (Kahneman and Tversky, 1979), people tend to be more risk averse when it involves the chance of losing money. Investing in financial instruments involves risk, and the idea for this thesis came about when considering the simple fact that risk averse investors look for strategies to minimise investment risk. Given the recent year's strong development of both the stock market and real estate prices, people are once again worried of an economic downturn or recession. Still, few investors are prepared to fully divest their equity portfolio and reinvest in safe assets. Consequently, one wonders if it is possible to construct a portfolio in such way that losses are limited in a potential downturn while maintaining a reasonable return in the current market. Research has been conducted on the subject, but there does not seem to be any conclusive results as to how one can invest in the long-term while avoiding sharp downturns. While this study has in part been inspired by the working paper Rainy Day Stocks by Gormsen and Greenwood (2017), the methodology and analysis is inspired by various studies as is evident throughout the thesis. The topic of this thesis can best be described by the following two fundamental questions:

1. Is it possible to outperform the market portfolio by investing in stocks that perform relatively well in bad times?

2. How can the risk-averse investor who is expecting bad times restructure their financial portfolio?

This thesis aims to answer these questions, and will hopefully offer guidance to both private and institutional investors towards optimal portfolio allocation. The primary focus is oriented towards looking at the Swedish market for financial instruments to identify characteristics that perform well in bad times, and build bad times portfolios based on these characteristics that exhibit positive returns in both bad and good times. These characteristics are measured by numerous key measures referred to as factors, and the suggested bad times portfolios are constructed from the most favourable and statistically significant factors. Based on the findings, this paper hopes to create guidelines and a trading strategy for investors who are looking to invest long-term and want to reduce risk in bad times. Since this study is intended to identify stocks and potential trading strategies based on characteristics that outperform the market portfolio on the Swedish market, the geographical scope is naturally set to only include stocks from Sweden. More precisely, the sample only includes stocks traded on the Nasdaq OMX Stockholm Stock Exchange, excluding Aktietorget and OMX Stockholm First North.

The presentation of this thesis is constructed in a way that first of all brings the reader up to speed with existing theory and how this paper relates to the theoretical framework. The results and contributions from previous research are established in the aforementioned section, laying the foundation for this thesis to contribute to today's financial research. Thereafter, a hypothesis and closer description of the data used for finding the empirical results are presented. This is followed by the description of applied methods and the approach taken when conducting the research. The paper will present empirical results followed by an analysis. This thesis is intended to guide the reader in a consecutive manner and since the research was conducted in many different steps the empirical results and analysis will be presented step by step. Important to note is that each step was analysed and interpreted before conducting the next, as the individual findings are subsequently crucial. Finally, the results of this thesis are established and a discussion is held around the study as a whole connecting it to existing theory while contributing to presently existing research. It is rationally reasoned whether one can draw any reliable conclusions and what one can learn from the thesis.

2. Literature Review and Theoretical Framework

2.1 CAPM and its Extensions

The Capital Asset Pricing Model (CAPM) is one of the most fundamental and widely recognised models in finance for pricing risky securities and perhaps stocks in particular. The traditional model simply describes the relationship between systematic risk and the expected return of stocks but has since its introduction been further developed and expanded. Two of the most prominent extensions to the CAPM have been made by Fama & French (1992) who first identified 3 new factors and extended to 5 factors (Fama and French, 2014) as well as Jensen (1968) who defined Jensen's alpha which is a risk-adjusted performance measure that represents the average return on a portfolio or investment above or below that predicted by the CAPM. Gaining an understanding for the research and literature surrounding the CAPM and its many extensions is fundamental to the modern day financial research and in particular to this thesis, which is precisely what this sections seeks to achieve. The literature outlined below lays the foundation for the decision making process in finding stocks, characteristics and portfolio strategies that perform well in bad times.

2.1.1 Developing the CAPM by Putting Focus on Characteristics

Many economists have researched possible extensions to the CAPM and found that different characteristics can explain the average returns more closely than what Sharpe (1964), Lintner (1965), and Black (1972) initially found based on the works of Markowitz (1952). The assumption that expected returns on financial instruments are a positive linear function of their market betas and that the market betas suffice to describe the cross-section of expected returns has since been developed. Banz (1981) looked at size effects and proved that small stocks have higher average returns and large stocks have inferior average returns to what the traditional CAPM beta predicts. Bhandari (1988) found a positive relation between leverage and average returns while Stattman (1980), Rosenberg, Reid and Lanstein (1985) and Chan, Hamao and Lakonishok (1991) found that the stocks are positively related to the book-to-market equity ratio both for the US and the Japanese stock markets. Additionally, it has been found that the P/E-ratio, also referred to as the inverted earnings-price ratio by Ball (1978) and Basu (1983), helps explain the cross-section of average returns. It was found that prices are higher relative to earnings (high P/E) for stocks with lower risks and expected returns. Finally, Fama & French (1992) found "that for the 1963-1990 period, size and book-to-market equity capture the cross-sectional variation in average stock returns associated with size, E/P, book-to-market equity, and leverage" (p. 450). As will become evident in this thesis, the use of characteristics and factors to shed light on stock performance is fundamental to the analysis from section 6.2 and onwards.

2.1.2 Jensen's Alpha

Jensen's alpha, sometimes also simply known as the alpha α, is a risk-adjusted performance measure that gives the return of a security or portfolio in relation to the return predicted by the CAPM by looking at two key variables: the return of a benchmark portfolio and the beta (Jensen, 1968). In other words, it extends the notion of simply looking at returns and takes the amount of risk exposure into account by providing a better measurement of performance. While two funds are able to produce the same return, one should ask which has the lower risk which will be indicated by a higher alpha. The formula for calculating Jensen's alpha in its simplest form is shown below:

$$\alpha_i = R_i - (r_f + \beta(R_m - r_f) \qquad (1)$$

One should however keep in mind that it is an absolute measure and as a result should generally be used in a homogeneous class of assets. It could be easier for a risky fund to generate a high alpha in comparison to a less risky one. The measure of alpha is widely used throughout this thesis and is extended to provide both good and bad times alphas.

2.1.3 Risk Adjusted Performance

Further research regarding the alpha and its relation to beta have been conducted in order to gain an increased understanding of the concept of risk adjusted performance. In fact, Frazzini and Pedersen (2013) found in their study called Betting Against Beta that low betas are associated with high alphas and vice versa. They created a betting-against-beta factor which is long low beta assets and short in high beta assets and proved that this factor produces significant risk-adjusted positive returns.

According to the traditional CAPM a stock's market beta is constant over time, both in good and bad times, and a stock's expected excess return is proportional to its beta. However, it is important to emphasise the fact that this may not be the best way to handle the market beta. As Bawa and Lindenberg (1977) suggest, a natural extension of the CAPM is to take the asymmetric treatment of risk into account by specifying asymmetric downside and upside betas. While this is important to keep in mind for future studies, it is out of the scope of this paper. This study does however uses rolling time varying betas instead of static ones which gives a more accurate measure than in the traditional CAPM, as the betas are calculated for each individual quarter. Important to keep in mind when conducting studies on time varying measures is that the accuracy of covariance estimation improves with the sample frequency (Merton, 1980).

2.1.4 Conditional CAPM

As mentioned previously the original CAPM is static and assumes constant betas. The most commonly recognised failure of the model is that is unable to explain the cross-section of average returns in a satisfactory manner. Later studies from the late 1900s and early 2000s have addressed these failures of the simple unconditional CAPM and some researchers have suggested that these failures can be explained by time varying beats and that the conditional CAPM might hold, period by period. The conditional alphas could in theory always be zero which means that the conditional CAPM could hold perfectly, with the exception that time-variation in beta might lead to unconditional pricing errors (Jensen, 1968; Dybvig and Ross, 1985; Jagannathan and Wang, 1996).

However, Lewellen and Nagel (2003) showed that when observing the conditional alphas, it was found that they were still significant which indicates that strong pricing errors still exist. In fact, the conditional CAPM does not outperform the unconditional CAPM by any substantial margin. Even though the conditional betas vary over time it is not sufficient to explain the unconditional alphas. This is important to have in consideration when conducting the analysis on both alpha and beta measures in this thesis.

2.1.5 Consumption CAPM

Yet another variation or extension of the CAPM is the Consumption CAPM (CCAPM). In essence the CCAPM says that 1% return in financial bad times is valued higher by investors than 1% return in good times and as such the investors utility function is not linear. The authors who are to be credited for the model are Douglas Breeden (1979) and Robert Lucas (1978) and the research has been further developed by Lettau and Ludvigson (2001). The reasoning behind this model is closely linked to some of the theories discussed later in section 2.3. The CCAPM relies on aggregate consumption to predict future asset prices rather than the market portfolio return. In contrary to the traditional CAPM, risky assets in the CCAPM create uncertainty in consumption rather than in the wealth of an investor. In other words, it is uncertain how much an individual is willing to spend when holding risky assets. The beta value of the CCAPM, referred to as consumption beta, is measured by the movements of risk premium in relation to consumption growth instead of the market.

Another distinct extension to the CCAPM is its ability to take several forms of wealth and multiple time periods into account, rather than looking at one period of asset returns at a time. The CCAPM helps one gain a more fundamental understanding for the relationship between risk aversion, consumption and of course wealth. This thesis has in part been inspired by the CCAPM, in particular to the definition of bad times described in section 5.1 and 6.1.

2.1.6 Flaws of the CAPM

Drawbacks of the CAPM are mainly directed toward the assumptions and inputs in the model. These include the uncertainty of which risk-free rate should be used, the short or long-term. In connection to this point, an apparent flaw is the assumption that an average investor can both borrow and lend money at the risk-free rate and without any associated trading costs. This thesis attempts to address the issue by considering a simple form of transaction costs in the final portfolios, found in section 6.4, and observing how they are affected. The most elementary and straight forward way of implementing transaction is to take the average annual transaction cost for a mutual fund in the U.S, which was 1.44%, according to a study by Edelen, Evans and Kadlec (2013). Furthermore, one should perhaps consider each investment decision separately from the core business of the company in which case a project proxy beta may be more accurate rather than using the company beta.

Other forms of the CAPM have also been criticised. Among others, the unconditional CAPM has been accused of not describing the cross section of average stock returns particularly well. Above all, not even the unconditional CAPM can account for the fact that small stocks outperform large stocks, that firms with high book-to-market ratios outperform those with low book-to-market ratios or that the momentum strategy is proven to be so successful over the life of the stock market. The bottom line when considering the original CAPM and the numerous extensions conducted on this theory is that no model in finance is perfect. As described above, the CAPM and its variations are however widely used and recognised and is both useful and applicable. Seeing as this paper is intended to further develop existing financial theory on long term investment it is natural to use the existing CAPM research as a starting point. Although it is criticized for its unrealistic assumptions it is perhaps the most widely accepted model in financial theory.

2.2 Bad Times and Recessions

During the past decades there have been several long booms in the economy which consistently are followed by sharp downturns (Konjunkturinstitutet, 2018). This is true for most markets globally including both the Swedish and US stock markets. In order to put this statement into context, one can look at data compiled by the National Bureau of Economic Research (2017). From April 1994 to the end of March 2000, the S&P 500 index grew by 221% only to decline by almost 40% in the following two years in the so called dot-com bubble or IT crash. Much like what was seen in the years leading up to 2000, the S&P 500 saw an increase of 75% from September 2002 until September 2007. The index then declined by 44% from the end of 2007 until March 2009.

An important set of questions when researching on bad times was asked by Campbell, Giglio and Polk (2013) in their paper called Hard Times. The authors ask how one should interpret these dramatic fluctuations and whether one should regard stock market booms as reflecting good news about the future returns or if the stock prices are driven up by declines in discount rates. Similarly, they consider if prices later fall because of pessimism or because future profits are discounted more heavily. Finding the most significant underlying factors gives information to the investor if they should expect a downturn to rebound or to be permanent. It has been found that individual downturns depend on different factors. The financial crisis was mainly caused by deteriorating prospects of cash flows while many of the previous recessions such as the IT crash was driven by increasing discount rates (Campbell et al., 2013). Naturally these underlying causes are not mutually exclusive and a large part of sharp downturns is due to psychology of the stock market, further described in section 2.3.

While bad times occur for different reasons and are sparked by various and dissimilar underlying factors, something that remains the same is that the average shareholder or investor incur significant losses. This paper utilises the knowledge from previous research conducted on historical bad times and aims to nuance these findings by looking at the outcome from several different periods of downturns. How these periods are defined is later described more precisely in section 5.1. The most apparent drawback of conducting the study in this way is that the knowledge, data and definitions are conducted on historical results while the future is of course more important. Although this is true, it is the way most financial studies are conducted since one only has access to historical. Predicting the future without building the foundations on historical results risks being subjective and unreliable.

2.3 How People React to Bad Times

Financial researchers and economists are in consensus that investors perceive risk differently. While it is common knowledge that people can be either risk averse, risk loving or somewhere in between it has also long been recognised that the perception of upside gains and downside losses vary. Ang, Chen & Xing (2006) have conducted a thorough study called Downside Risk based on their claim that previous empirical research has failed to find how the risk of losing money is priced in the cross section of stock returns. One might assume that investors will place greater weight on downside risk as losing money when wealth is declining or perceived as being low, as is often the case in bad times, they demand supplementary compensation for holding assets with high sensitivities to downside market movements.

Ang et al. (2006) have proven this assumption in four main steps by primarily considering what they call downside betas. Firstly, it is proven that stocks with larger downside betas have higher average returns. Secondly, the claim is made that as a result of this contemporaneous relationship the downside beta is a risk attribute. This is achieved in contradiction to the findings of previous researchers such as Fama and French (1992) by looking at short samples of daily data, rather than monthly data, in order to achieve a greater statistical power and to capture time-varying betas. Thirdly, the reward for holding stocks with downside betas is differentiated from that reward of holding stocks with coskewness found by papers such as Rubinstein (1973), Friend and Westerfield (1980), Kraus and Litzenberger (1976) and Harvey and Siddique (2000). As a final step the theory is tested by checking downside betas for the potential of future predictability and is found to hold for all stocks other than those of very high volatility. According to the authors "the cross-section of stock returns reflects a premium for bearing downside risk" (And et al., 2006, p. 1193).

2.3.1 Prospect Theory

Kahneman and Tversky (1979) won a Nobel Memorial Prize in Economics for developing the prospect theory which examines how people react differently to gains and losses. The theory was initially formulated in 1979 and later developed in 1986 (Tversky and Kahneman, 1986). This behavioural economic theory states that people make their decisions based on how they value gains and losses rather than objectively looking at the direct financial outcome. An example of this is that a person values the probability of success $p = 1\%$ disproportionately higher than $p = 0\%$ while conversely valuing the probability of success $p = 99\%$ much lower than $p = 100\%$ (Baron, 2006). Putting it in other words, investors value the avoidance of losses disproportionately higher than the upside of gains. Kahneman and Tversky (1979) came to the conclusion that people in general are risk-averse which in turn motivates the idea behind this paper as it is intended to find portfolio strategies based on performing relatively well in bad times.

2.3.2 Investor Psychology

If one dives deeper into the literature around investor psychology one will find that Daniel, Hirshleifer and Subrahmanyam (1998) proposed a theory of under- and overreactions. The foundation of their theory is that "stock prices overreact to private information signals and underreact to public signals" (p. 3). It is further clarified by looking at their modelled findings seen below in figure 2.1. It clearly shows that even though the markets expected price goes towards the rational expected value in the long term the expected price is more volatile in reality due to investor psychology.

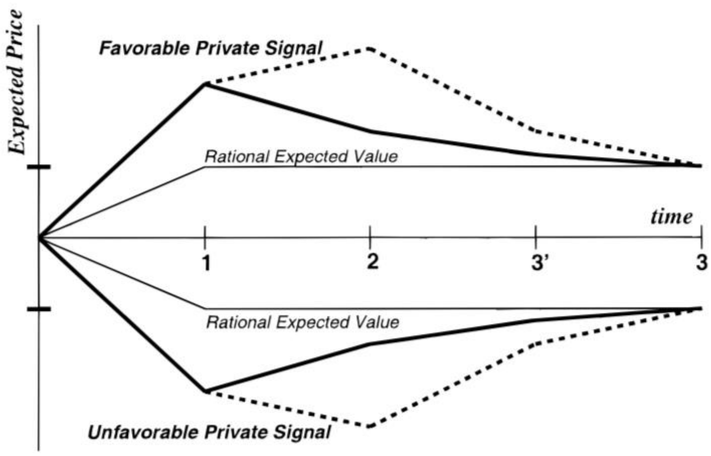

Figure 2.1 Investor Psychology and Market Reactions. The figure shows a model developed by Hirshleifer and Subrahmanyam (1998). It displays how investor psychology affects investment behaviour by highlighting under- and over reactions to information.

Given the fact that investor overconfidence and biased self-attribution exists implies market imperfections since it challenges the traditionally accepted fact that securities are rationally priced to reflect all public information. If this is true, then certain stocks with certain characteristics may be perceived as worse or better than others even though they rationally are not. If so, then this may be reflected in the stock price and returns. As a result, if this thesis is able to identify such stocks then one could perhaps create a portfolio which avoids (buys) those stocks in bad times (good times) and in turn outperform the market portfolio. The importance of human behavioural economics and the previous research conducted cannot be understated for this paper. In fact, it was the perception that people fear bad times that initially brought the topic for this thesis forth.

2.4 Creating Portfolios Based on Certain Characteristics

The mission of any professional investor is to yield satisfying or extraordinary returns given a certain set of guidelines and risk. A considerable amount of the asset management industry is dedicated towards outperforming a certain benchmark, such as the market portfolio. If the same benchmark is used for a portfolio, the risk of the benchmark return known as beta cannot be diversified. However, the performance differential in form of alpha is obtained by actively deviating from the benchmark can be obtained through superior skill, knowledge or strategy Gerdes (2009). Most financial and economic research is based on the proposition that securities markets are efficient. There are however researchers who disagree and claim that perhaps some asset prices are not rationally connected to economic realities. Summer (1986) stated that the economic consequences of market efficiency ultimately depend on prices. Nevertheless, most literature in finance considers the drivers of returns, not prices. This can lead one to ask if prices are consistently based on market efficiency.

2.4.1 Characteristics and Factors for Portfolios

A concept fundamental to portfolio theory is that investors look for assets or financial instruments with superior characteristics, sometimes referred to as qualities. Asness, Frazzini, and Pedersen (2013) define "a *quality* security as one that has characteristics that, all else equal, an investor should be willing to pay a higher price for: stocks that are safe, profitable, growing and well managed". They further emphasise that high quality securities are underpriced relative to their elevated attractiveness. Even though this underpricing fluctuates over time, giving exceptionally large underpricing during bad times, it is proven that one can generate substantial returns based on this information. It has been found that high quality firms in fact do exhibit a higher price which is consistent with market efficiency, but not a high enough price to motivate their higher returns. Asness et al. (2013) define a factor called quality-minus-junk (QMJ) that is long the top 30% high quality securities and short the bottom 30% low quality securities and prove that this factor indeed has significant positive risk adjusted returns both in the US and globally across 24 countries. The first interesting takeaways for this thesis from the QMJ factor is that it exhibits high returns during bad times. The authors found that QMJ has a mild positive convexity during crises and thus benefits from what they call flight to quality. Secondly, the way of constructing the QMJ factor by going long-short in high and low quality respectively strongly inspired the methodology for measuring performance characteristics described closely in section 5.3 and 6.3.

Gerdes (2009) wrote an article exploring the possibilities of earning positive return with risk that is little or not at all correlated with other known risks. This is of course something very attractive to all kinds of investors whether they are looking to diversify an existing portfolio professionally for their clients or if they are managing their private savings. The study was conducted by focusing on generating positive alpha for a portfolio by looking at a quality oriented management approach. Gerdes (2009) states that he "works on the basis that, although the 3-factor-model of Fama and French is powerful in explaining a lot of equity performance, there are plenty of other performance drivers in global equity markets that are not captured". In the article he concludes that the FF3F-model only has a small correlation to quality and that quality offers robust diversification benefits both historically and for the future. Finally, Gerdes (2009) states that quality passes his tests and therefore should qualify as an independent stock selection style.

Asness, Ilmanen, Israel and Moskowitz (2015) have conducted research in the field of investment strategies and wrote a paper called Investing with Style. They managed to find what they call four intuitive strategies with little correlation to each other. The four strategies are value, momentum, carry and defensive and have together both been efficient in many different classes of financial assets and delivered positive long-term returns. However, the most prominent takeaway from Investing with Style for the authors is outlined in the table on page 40. The way the different trading strategies are presented inspired and was the groundwork in comparing both the portfolios and developing table 6.4.

2.4.2 Momentum Crashes

The classic notion of a momentum strategy in financial theory is one where the investor believes that past returns predict future returns in the cross-section of assets. In essence one buys the winners and sells or shorts the losers and this is adapted quite widely by both quantitative investors and fund managers Jegadeesh and Titman (1993). Daniel and Moskowitz (2013) have conducted a study on momentum crashes during bad times. Even though momentum strategies historically have generated exceptionally high Sharpe ratios and substantially positive alphas they have been found to be negatively skewed. That is, the so called momentum crashes occur following market declines and what in this thesis is called bad times. In fact, the market prices of past losers exhibit a substantial premium and when poor market conditions ameliorate and the market starts to move upward again, the losers consequently experience strong gains which in turn are bad for momentum strategists seeing as they are short these assets (Daniel and

Moskowitz, 2013). These facts are important to keep in mind when considering characteristics of stocks such as momentum throughout the analysis if this thesis.

The conclusion that one can draw from the above listed portfolio theory is that characteristics of stocks could be considered as an indicator of future risk adjusted returns. The question lies in how one should identify these characteristics, and how to select in which periods to look at in order to achieve the most reliable results.

3. Expected Thesis Outcomes

A core belief of this study is that one can find certain common characteristics in stocks based on their bad time performance and that these characteristics can be used to construct portfolios that generate positive risk adjusted returns in bad times. While the intention is to find a strategy that outperforms the market in the long term, this is a hope with some reservation. Using bad times as a benchmark for performance, when organisations are under particularly high pressure and the financial environment is challenging, will shed light on which qualities are actually important for a stable and prosperous company in the long term.

The intention of analysing and testing different characteristics and factors is to suggest bad time portfolios that perform well in bad times and relatively well in good times. In accordance with previous literature, primarily described in section 2.4, the qualities of companies that perform relatively well in bad times are assumed to be the following: large in size, high book-to-market, low volatility, low P/E, low market beta, low momentum and finally low bid-ask-spread. Furthermore, it is believed that one can identify and separate alpha earned in good and bad times. Thereby being able to truly understand how the performance in different times helps explain the long term returns.

Finally, it is expected that reconducting the study in an out of sample robustness test will evaluate whether the findings and proposed strategies hold up. While positive results are expected for the in sample testing, it will be of utmost interest to see how they perform out of sample.

4. Data Description Overview

Gathering and using the best data available as well as setting a relevant scope is fundamental to the findings of this paper. While wanting to include as much historical data as possible to define bad times as accurately as possible, there are some constraints to how much data can reliably be included as described below.

4.1 Sample Construction

The study is conducted on the Swedish market and stock data. After evaluating several data sources and checking for the availability of data it is determined that Aktietorget and OMX Stockholm First north are excluded, partly due to the unavailability of data and partly due to the small and volatile nature of many of the firms on those exchanges. In order to find sufficient amounts of stock data from the Nasdaq OMX Stockholm Stock Exchange, several different databases are used. The main set of data is retrieved using the FinBas database, provided by the Swedish House of Finance Research Data Center. The FinBas Stock data is available from 1979 to 2016, and the Fama French factors are available from 1983 and forward. This amount of historical data is considered sufficient and is used to set the time scope of this paper.

The period includes most financial and economic crises in recent memory, such as the EU crisis, the financial crisis, the IT crisis along with the Swedish bank and real estate crisis. The delimitation generates a sample of 1003 individual companies, including all firms defaulting before 2016Q4 to avoid survivorship bias to the farthest extent possible and to provide the most accurate data possible when looking at the observations of any one quarter. Finally, the Thomson Reuter Datastream is used to complement with data on income measures and is matched to the FinBas data using ISIN-numbers. The Thomson Reuter Datastream was also used in order to acquire index return data for the MSCI World Index used in the paper to find world market betas for each individual stock in the sample.

4.2 Evaluation and Reliability of Data Sources and Sample Characteristics

With respect to the quantitative data in the study, a majority is retrieved from third-party information providers as described in the previous section. Due to the amount of data, stock prices and key figures collected for the defined time frame, it was beyond the scope of this paper to manually search and adjust possible errors in any third party data. While remaining aware and highlighting the potential risk of errors in these data sets, it is argued that potential errors in data will not significantly affect the results of the thesis since relatively large volumes of data are used. It was however found that the market portfolio returns of FinBas differ somewhat from that collected by Reuters, although being almost perfectly correlated. This created a question of which market portfolio to run the regressions and calculation on. In this particular case it was decided to use the market portfolio from FinBas as it was assumed that the two portfolios only differ because of several missing values in the Reuters data.

The above mentioned leads to another potential issue in the accuracy of data. There are several missing values and entries for certain companies. It is however deemed unnecessary to try and fill these missing values due to the limitations and time consuming nature of attempting to find many different sets of data for the Swedish stock market. The fact that missing values exist in the sample is acknowledged and dealt with throughout the paper. When comparing a study such as this one to a study on the US Stock Market, the importance of having complete data increases since the sample is much smaller. This is important to consider as the portfolios in section 6.4 and 6.5 are built on just a portion of the sampled data. It is also determined that both the A and B shares for a particular company would be included due to the fact that their returns should reflect the companies' underlying value and its characteristics, regardless of the voting power of any given share.

5. Methodology

The following chapter describes the methodology behind the research and goes into detail explaining how it was conducted. Even though it is not possible to display all of the calculations and formulas used on the data in both Excel and R the method is presented with the intent of enlightening the reader as much as possible. The chapter is divided into five progressing parts, beginning with the definition of bad times. The purpose of the first section is to determine which periods to include when looking at bad times. The second part identifies characteristics of stocks that have generated high returns in periods of bad times, as well as the spread in returns between these characteristics. The performance of these stocks are measured for both periods of good and bad times, to evaluate performance over time. In the third part it is explored whether any characteristics can generate positive alphas when going from good to bad times, a long-short portfolio for each factor is regressed against excess returns and a bad times dummy. Based on the results, the fourth part aims at developing recommended strategies for how to invest in bad times. This is done by constructing portfolios designed to outperform the market portfolio in periods of market shifts. The final and fifth part is an out of sample robustness test. The test is conducted by dividing the sample into two periods and consequently observing how well portfolios built on data from the first period perform in the second period. The idea is to test if the portfolios identified and constructed in step four have any ability to outperform the market in the future.

5.1 Defining Bad Times

For the purpose of identifying abnormal performance in times of financial distress, a period of bad times is first defined. To properly include all periods where investors can be assumed to experience distress, both a measure of *financial bad times* and *economic bad times* is included. The combined measure is used to define a period of *bad times*. These are assumed to be times in which investors experience distress and put an especially high value on investment returns in comparison to normal times.

5.1.1 Financial Bad Times

Financial bad times are defined as quarters in which the excess return on the Stockholm Stock Exchange is in the bottom quintile of the sample, which ranges from 1983Q1 to 2016Q4. Simply stated, these are the periods in which the stock market has performed the worst. The excess return is calculated as the value weighted return on the Stockholm Stock Exchange for each quarter subtracted by the return on the 1-month Swedish T-Bill, which is used as a proxy for the risk free rate. The continuous excess return on the Stockholm Stock Exchange is displayed on a monthly basis in figure 11.1 in the Appendix. It shows fluctuations in the market return which indicates periods of good and bad times. Figure 11.2 displays the excess return for quarters in the bottom quintiles. From the figure one can observe both which quarters are included and their relative size to each recession. Important to note is that these are quarterly excess returns, and not monthly.

In the cases where a quarter is not considered financial bad times but lies between two quarters that are financial bad times, the yearly return is considered. If the yearly return is in the lowest quintile the intermediary quarter is included as bad times. The reason is to include quarters that are not in the lowest quintile, but still considered financial bad times. For example, the entire period between 2000Q4 and 2003Q1 is included as a period of financial bad times, even though there are several quarters in this period that are not in the lowest quintile of the sample as seen in figure 11.2. The process extends the sample by nine observations and ensures that all periods of financial bad times are included, even in quarter where the market experience temporarily relief. Figure 11.3 in the Appendix graphically displays a times series of all periods included as financial bad times.

5.1.2 Economic Bad Times

Economic bad times is calculated using the same method as for financial bad times, and are defined as quarters in which the growth in the Swedish GDP is in the lowest quintile of the sample. The growth in GDP is used as an indicator of the general health of the economy, and as a proxy for economic bad times. The economic factor is included seeing as investors are assumed to put a higher value on investment return during periods of economic bad times, regardless of portfolio returns. Figure 11.4 displays quarterly growth in the Swedish GDP between 1983 to 2016. The graph indicates periods of economic bad times as well as the length and scale of each recession. Figure 11.5 further shows the Swedish GDP growth for quarters in the lowest quintile of the sample, used for defining periods of economic bad times. Finally, annual data is used to include periods where the economy is in partial recover the same way as is done for financial bad times. These are quarters between periods of economic bad times during years in which the Swedish GDP growth is in the lowest quintile of the sample. The procedure adds an additional nine quarters to the original definition and better reflects periods of economic bad times. Figure 11.6 in the Appendix graphically displays a time series with periods defined as economic bad times.

5.1.3 Definition of Bad Times

Bad times are defined as periods in which the market experiences both financial and economic bad times in accordance with previous definitions. This is a narrow definition that excludes several periods in which the market has seen historically low returns, and that most investors would describe as bad times. However, the stricter definition reduces the risk of false positives and should provide more statistically robust results. Out of the total sample of 136 quarters, 18 quarters are defined as periods of bad times. This represents 13.2% of the total sample. The selection of bad times includes eight consecutive periods of bad times and covers five distinctive recessions. The results are graphically displayed in figure 6.1 and summarised in table 6.1 in section 6.1.

5.2 Characteristics of Stocks that Outperform in Bad Times

In order to later identify strategies for bad times, one must first identify characteristics of stocks that outperform in periods of historical bad times. This is done by sorting stocks into quintiles based on performance in periods of bad times and inspecting for trends amongst the stocks in the lowest and the highest quintiles. The results are presented in table 6.2.

5.2.1 Identifying Stocks that Outperform in Bad Times

The first step is to identify stocks that have outperformed in periods of bad time by calculating the excess return for each stock in each of the eight periods of bad times. For periods that include more than one quarter, the cumulative excess return of the entire period is calculated. As an example, for the period 1990Q1 to 1990Q4, it is the cumulative excess return of each stock that is compared. This generates a list with eight observations for each of the 1003 sampled companies. Stocks are then ranked based on their excess return from lowest to highest, and sorted into quintiles based on their performance. The first quintile being the lowest performing stocks and the fifth quintile including the highest performing stocks during each of the eight periods of bad times. In order to adjust for the correlation between excess returns and betas and to provide a risk-adjusted performance measures as described in section 2.1.2, performance is also estimated using alphas. This is achieved by repeating the previous procedure, but ranking stocks on alpha rather than excess return. In other words, the alpha is calculated for each stock and quarter, and all firms are sorted into quintiles based on their alpha rather than their excess return. The method for how alphas and betas are estimated is explained in detail below.

5.2.2 Estimating Beta and Alpha

In order to find and estimate the ex-post market beta and CAPM alpha for each stock, needed for finding and defining the characteristics in the next steps, each stock is regressed on the market portfolio. The method used is influenced by how Frazzini and Pedersen (2014) estimated betas but adapted and calculated through coding in order to maximise efficiency of the calculations. This is more precisely conducted in R. The market excess returns for each quarter in the sample constitute a vector representing the explanatory variable while the excess returns of each individual stock *i* constitute a vector representing the dependent variable for each individual regression *i*. While it might have been possible to use daily or monthly data rather than quarterly, as the accuracy of covariance estimation improves with the sample frequency (Merton, 1980), it was decided to continue using quarterly data for consistency and simplicity.

The code is designed to perform a rolling regression by creating a nested loop in R. The outer loop calculates beta and alpha for each given quarter *j* by creating a subset of data set to 20 consecutive observations, namely five consecutive years of four quarterly observations in each. As a result, the output generated by the first loop $j = 1$ in the model will calculate the beta and alpha for time period 20 (1987Q4) while the second loop $j = 2$ generates the output for time period 21 (1988Q1) rolling forward quarterly until 2016Q4. Since the calculation requires 20 consecutive observations, no values are estimated for the first five years of the sample.

The inner loop is designed to run the regression *i* times swapping out the dependent variable for each regression while maintaining the same explanatory variable and thus finding all of the outputs necessary in order to complete the calculation of stock characteristics. Since there are many NA and missing values in the sample, due to both data unavailability and the fact that many stocks in the sample either did not exist in the earlier years or are no longer listed in the later years, the regression was set to only calculate values if at least 5 observations in any subset of 20 are available. The regression itself was furthermore extended to use the na.exclude function meaning that residuals and predictions are padded to the correct length by inserting NAs for cases omitted by na.exclude in R. In other words, values of NA or missing values in the regression itself are excluded.

Since the regression is run for each individual stock *i* in each subset of data rolling forward one time period *j* at a time the results for the betas and alphas are stored in a vector of results for each stock between inner loops and for each period or row vector of stocks between outer loops using the package and library called "dplyr" in R. Finally, the results are stored as a dataframe and extracted to an excel file in order to prepare the outputs for the next steps.

To highlight some of the reasoning used when making choices in running the regressions it is important to note the betas were computed with respect to the market portfolio, in accordance with Fama and French (1992). One could have run the regressions on market portfolios specific to an asset class. However, seeing as Frazzini and Pedersen (2014) found that results hold both ways, focus was put on betas with respect to the overall market portfolio of all assets even though these betas run the risk of being slightly more noisy. Additionally, this method was used as a result of the availability of sample data in this paper. The above described methodology for calculating rolling betas is also used to calculate rolling world betas. These are calculated based on the MSCI World Index, which is supposed to reflect a world market portfolio, rather than a market portfolio for the Swedish market.

A second method is used to ensure that correct values have been estimated for alpha. A more direct approach is used by taking the excess return of each stock and subtracting the product of the excess market return and the stock's beta. The results are compared in order to ensure and validate accurate results.

5.2.3 Selecting and Estimating Characteristics

The second step is to identify differences in the characteristics by looking at deviating trends between the lowest and highest performing quintiles. The included characteristics are based on factors that have shown to have explanatory value on portfolio returns by previous research, as outlined in section 2.4. The selection of characteristics is based on a fundamental approach to investing and includes value (size, book-to-market, P/E, growth), low risk (beta, volatility, world beta), liquidity (turnover rate, bid-ask spread) and momentum. The size factor is measured as total market capitalisation, including all available stock classes. Book-to-market is measured as book value of equity divided by total market capitalisation. P/E is measured as total market capitalisation divided by net income. The growth factor is measured as the three-year growth in net income, similar to the method defined by Asness et al. (2014). Beta values are estimated using internal data rather than retrieved externally, as explained in 5.2.2. Volatility is calculated in accordance with the methods presented by Campbell and Cochrane (2000), using weekly data on stock returns to calculate the volatility on a quarterly basis. Turnover rate is measured as the number of stocks traded in the period divided by the total amount of stocks outstanding. The bid-ask spread is measured as the spread in percentage of the offer price.

Momentum is calculated as the simple 12-month growth in stock returns. Important to note here is that opening values are used rather than closing where possible and applicable. The reason is that this study intends to predict future outcomes based on historical data and as a result one must consider opening balances.

5.2.4 Identifying Characteristics Based on Performance

To evaluate how these characteristics are distributed between the different quintiles, the equal weighted factor of each portfolio is calculated. This is conducted by calculating the average value of the factor for each stock under every consecutive period of bad time. For example, when calculating the size factor in the period 1990Q1-1990Q4, the average market capitalisation of each firm in that time period is used. This generates a list with one observation per stock, which is the average market size of the firm in that specific period. All firms are then ranked based on their size from the smallest to the largest using percentile ranks, giving each observation a value between zero and one. For each quintile, the average percentile rank is then calculated. The result is five observations per period, one for each quintile. The percentile rank is an estimate of how the portfolio is weighted between small and large stocks. If the portfolio has a value below 0.5, it has an imbalanced distribution towards stocks with a low market capitalisation. Values above 0.5 means the portfolio is weighted towards stocks with a large market capitalisation. However, it should be noted that the percentile rank does not indicate how the proportion of individual stocks are distributed within the portfolio. It is possible for the portfolio with the lowest ranking to include the single largest stock, as the ranking only measures the average market size of stocks in the portfolio.

The last step is to calculate the weighted ranking for each of the five quintiles. In other words, the ranking from the first quintile in all eight periods of bad time needs to be combined to calculate the overall percentile rank of the lowest performing stocks. The time series weight for each period is calculated as the number of consecutive quarters in the period divided by the total number of quarters. As an example, the weight distributed to the period between 1990Q1-1990Q4 is equal to 4/18. This is the number of consecutive quarters in that specific period (4) divided by the total number of quarters (18) for the entire sample. The average percentile ranks in each quintile by the weight distributed to that period to obtain the weighted ranks. The final calculation is to sum the weighted ranks from all eight periods to determine the equally weighted percentile rank for each quintile. The result is a list of five percentile ranks, sorted from the lowest to the highest performing portfolio.

How the ranking changes between the low and high performing portfolio indicates if the characteristic outperform in bad times. The procedure is then repeated for each of the ten factors, and performed separately for excess return and CAPM alpha. As stated previously, the results are presented in table 6.2 in the following chapter.

5.3 Measuring Performance of Characteristics

To measure the performance of characteristics that outperform in periods of bad times, the value weighted excess return for the highest and lowest 30% of each factor is calculated. This methodology is inspired by Asness et al. (2013) who exercised a similar procedure when calculating the QMJ factor. The results are used to build long-short factor portfolios, similar to the method used by Fama and French (1992). The returns of the portfolios are used to indicate and analyse performance of the characteristics.

5.3.1 Calculating Excess Return of Factors

To calculate the difference in excess returns within a factor, two portfolios per factor are constructed. The first portfolio includes stocks that are ranked in the highest 30% within the factor, and the other includes stocks that are ranked in the lowest 30% within the factor. For example, the size portfolio for large stocks includes all firms that have a market capitalisation in the 70th percentile and above, while the low size portfolio includes firm with a market capitalisation below the 30th percentile. In other words, one portfolio goes long in large cap stocks and the other is long in small cap stocks. The percentile ranks are calculated on a quarterly basis and stocks are only ranked against other stocks in the same quarter. This means that the ranking is constantly updated, as the relative size of companies differ over time. Once the two portfolios have been constructed, the value weighted excess return of each portfolio is calculated. The value weighting is based on the market capitalisation of each stock in relation to the market capitalisation of all stocks in the portfolio for each quarter. If the market capitalisation of a stock is 10% of the total market capitalisation of all stocks in that quarter, the weight given to that stocks excess return is consequently 10%. If there is only one single observation in one of the quarter, that stock would receive 100% weight to the excess return in that quarter. Once the value weighted excess return has been calculated, results are separated between good and bad times using a bad time dummy. The procedure generates two lists, one with excess returns in good and bad times for portfolios with low factor values and one for portfolios with high factor values. The Sharpe ratio for each portfolio is also calculated for better comparison. The results are presented in table 6.3 in section 6.3.

5.3.2 Estimating Performance of Factors Over Time

To estimate the performance of investment strategies based on different characteristics over time, a long-short portfolio is built for each factor. The long-short factor portfolio invests in the portfolios previously constructed in 5.3.1 presented in table 6.3, which provides guidance to which side of each factor one should long and short respectively. The long-short portfolios are composed by going either long or short in stocks that are above the 70^{th} percentile within a factor., and takes an opposite position in stocks that are below the 30^{th} percentile within the factor. The long leg is determined by the side of the factor that is estimated to outperform in bad times based on alpha, using the results in table 6.3. The long-short factor portfolio for size is for example long stocks with a high market capitalisation and short stocks with a low market capitalisation. Once the portfolio is constructed, the average excess return is calculated and the result is presented in table 6.4. The table also includes results on tail returns, confidence intervals, Sharpe ratio, volatility, skewness and kurtosis. The tail return is the performance of each portfolio in quarters where the excess return of the market is in the worst 10% of the sample, representing the return of each portfolios during the absolute worst periods of financial bad times. The excess return is also separated between good and bad times and the results are presented in table 6.4. This is important, as the table shows a clear picture of how factors perform in bad times. Regression analysis is then used to calculate the alpha of each factor. The excess return of each long-short portfolio is regressed against the market return and a bad time dummy, in accordance with following equation:

$$R_p = \alpha_a + a_b D_b + \beta(R_m - \mathrm{r_f}) + e \tag{2}$$

R_p is the portfolio return of the factor, α_a is the alpha earned in good times, a_b the additional alpha earned in bad times, D is a dummy variable that takes the value 1 if the quarter is defined as bad times and 0 otherwise. The bad time alpha is calculated as $\alpha_a + a_b$, which is the alpha earned in bad times. $\mathrm{R_m} - \mathrm{r_f}$ is the excess return of the market, calculated as the market return minus the risk free rate and e represents the error term. As the results of the regression to some extent reflect each factors exposure to the market portfolio, the correlation between excess returns and the market has to be adjusted for. Instead of using a separate good and bad time market beta, a single beta is used to reflect a market where investors can hedge against market shifts ex ante. Including separate market betas for good and bad times would require the assumption that investors can predict changes in the market and adjust accordingly. The single market beta better reflects actual market conditions, even if the adjustment for beta is less accurate. The results from the regression is presented in table 6.5.

5.4 Building Bad Times Portfolios

To empirically test the performance of factors that have been found to perform well in periods of bad times, two portfolios are built based on the findings so far. The first portfolio is a zero cost portfolio equally invested in the factor-portfolios with the highest overall alpha. The second portfolio is a zero cost portfolio that is long in factors with the highest bad time alpha and short the market.

5.4.1 Portfolio 1, Long-term Portfolio

The first portfolio is based on the factors with the highest overall alpha. The two factors with the highest overall alpha are book-to-market and growth, which are also the two values with the highest statistical significance. The portfolio is build using the long-short factor portfolios constructed in 5.3, and is equally weighted between the two chosen factors. In other words, the portfolio is long in low book-to-market and high growth and short in high book-to-market and low growth. The reason for using overall alpha when selecting factors is to construct a portfolio that does not only perform well in bad times, but also in good times. Once the portfolio is constructed, the quarterly returns are then regressed against the market using equation 2. The results from the regression are presented in table 6.6. The table includes a separate column where a transaction cost for the short position of 1.44% per annum has been deducted from the excess return, in accordance with Edelen, Evans and Kadlec (2013). The performance of the portfolio over times is graphically displayed in figure 6.2.

5.4.2 Portfolio 2, Bad Times Portfolio

The second portfolio is built on the factors with the highest bad time alpha, as calculated in section 5.3. The bad times alpha for each factor is displayed on the bottom row of Panel B in table 6.5. The two factors with the highest bad time alphas are P/E and growth, these are also the only two factors that show statistical significance. The portfolio is constructed by going long in stocks that are in the highest 50% of both P/E and growth, and short in the market. The portfolio is value-weighted and is refreshed and rebalanced every quarter. The quarterly excess returns are then regressed against the market return, in accordance with equation 2. Summary statistics for the portfolio is presented in table 6.6 in Chapter 6. The performance is also displayed graphically in figure 6.3.

5.5 Out of Sample Robustness Test

In the final step of the paper a robustness test is conducted. The robustness check consists of an out of sample test, where the ability to predict future outcomes is tested. The time series is split in two periods, before and after 2004, and tested for how well portfolios constructed based on data up until 2004 would have performed between 2004 and 2016.

5.5.1 Out of Sample Test

The time series is first divided into two samples. The split is set to 2004, where the first part of the sample ranges from 1987Q4-2003Q4 and the second part between 2004Q1-2016Q4. The reason the time series starts in 1987 rather than in 1983, is because the alpha and beta values are generated starting from 1987Q4 as explained in section 5.2. The split is set to 2004 to properly include the effects from all periods of bad times prior to the 2008 financial crisis. The test is then conducted by repeating all procedures previously explained in section 5.1 through 5.4, but in accordance with the new time series. In the first step, new periods of bad times are defined using the same methodology as explained in section 5.1. All stocks are then sorted into quintiles based on performance, and portfolios are constructed for each of the ten factors. Percentile ranking is used to identify how each factor is distributed going from the lowest to highest performing portfolio, as was done in section 5.2. Based on the portfolios sorted on alpha values, long-short factor portfolios are constructed. The long side includes the 30th percentile of stocks that display high alphas, and the short side includes the 30th percentile of stocks that display low alphas. The excess return for each long-short factor portfolio is then calculated, and the results are used to construct the first portfolio. The return of each long-short factor portfolio is then separated between good and bad times, and a regression is used to estimate the bad time alpha. This procedure was explained in detail in section 5.3. The second portfolio is then constructed based on the bad time alphas. The two portfolios are constructed in the same manner as explained in section 5.4. The first portfolio includes the size and growth factor, compared to the original portfolio consisting of book-to-market and growth. The second portfolio interestingly also consists of the size and growth factor, compared to the original portfolio which included P/E and growth. These results are analysed and further explained in section 6.5. It should be noted that the t-statistic for the bad time alpha for the size factor used in the second out of sample portfolio is 1.94, which in fact is not significant at the 5% level. The factor is still included as it is the second most significant bad time alpha value, and the only one significant at the 10% level.

Once the two portfolios have been constructed, the performance of each portfolio is tested going forward. In other words, how well would an investor following the methodology presented in this thesis have done if implementing the strategy in 2004. The start date is set to the first of January 2004, and the portfolios are value-weighted, refreshed and rebalanced every quarter. The quarterly returns are then regressed against the market return and a bad time dummy, in accordance with equation 2. The results for both portfolios are presented in table 6.6 in Chapter 6. Finally, an aspect of market timing is included by implementing the strategies in 2006 rather than in 2004. This only affects the performance of the portfolios marginally, however including an aspect of when the strategy is implemented affects the relative performance to the market portfolio. The results are graphically displayed for each of the two portfolios in figure 6.4 and figure 6.5 in Chapter 6.

6 Empirical Results and Analysis

In the following chapter the empirical results from the quantitative testing outlined in Chapter 5 are presented and analysed. The chapter is presented in a descriptive manner, and divided into five progressive parts. The first part describes what periods are defined as bad times. The second part demonstrates the characteristics of stocks that perform well in bad times by looking at individual factors. The third part presents how each factor performs in both periods of bad and good times. In the fourth part the two portfolios are built based on the results from the previous analysis. The final part includes an out of sample robustness test which is conducted to assess if the results found in part four are expected to hold in a future crisis.

6.1 Defining Bad Times

Following a consumption based model and the idea behind a non-linear utility function, bad times are defined as quarters in which the market experiences both financial and economic bad times. This definition intends to capture both when income is low and when investor returns are low. Consequently, the definition of bad times highlights truly bad times when people are especially sensitive to returns. This differs from the more common approach of only considering financial bad times, and absolute return in the stock market. Financial bad times are defined as quarters in which the excess return on the Stockholm Stock Exchange is in the bottom quintile of the sample, while economic bad times are defined as quarters in which the growth in the Swedish GDP is in the lowest quintile of the sample. For the period between 1983 and 2016 this generates a sample with 18 quarters of bad times, which covers 13% of the total sample period. The result is graphically displayed in figure 6.1, together with the excess return of the market which is used as a reference line.

As a result, bad times are defined as periods in which investors experience distress and put a higher value on investment returns than what they do in other times. This definition indicates that the utility function of the average investor is not linear, but affected by the relative value of their returns depending on consumption (Lucas, 1978; Breeden, 1979). For example, this holds true if an investor would put a higher value on a 1% return on their portfolio in a recession, such as in 2008, than what they would during an economic boom. This opposes the view of the Sharpe-Lintner CAPM model, which only considers absolute returns. There are many intuitive reason for why this could be, an investor might be more risk averse because risk of unemployment is higher, income is down or simply due to market uncertainty.

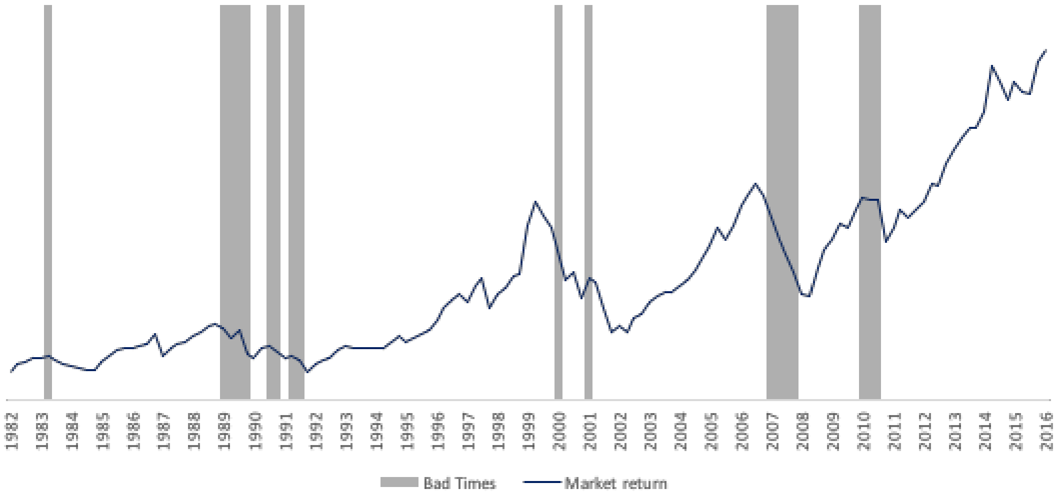

Figure 6.1: Periods of bad times. The figure shows a time series from 1983 to 2016 including periods defined as bad times and the excess return of the Stockholm Stock Exchange, referred to as the excess return of the market. The blue line is an index of the excess return of the market, and the grey bars indicate periods defined as bad times. Bad times are defined as periods of both financial and economic bad times, where financial bad times are defined as quarters in which the excess return on the Stockholm Stock Exchange is in the bottom quintile of the sample and economic bad times are defined as quarters in which the growth in the Swedish GDP is in the lowest quintile of the sample. The reason for including both a financial and an economic aspect to the definition of bad times is to asses all periods where the economy is troubled on a broader scale and investors are assumed to put higher relative value on returns than what they would in normal times.

The selection of bad times includes eight consecutive periods of bad times and covers five distinctive recessions; the early eighties recession, the real estate crisis of 1990-1994, the IT-crash of 2001, the financial crisis of 2008 and the EU-crisis of 2011. The eight periods defined as bad times are 1984Q2, 1990Q1-1990Q4, 1991Q3-1991Q4, 1992Q2-1992Q3, 2001Q1, 2002Q1, 2008Q1 -2008Q4 and 2011Q1-2011Q3. From looking at figure 6.1 it is clear that all financial bad times have not been highlighted, as several quarters of market downturn are not marked in grey. The stricter definition in this thesis ensures that periods defined as bad times corresponds to periods in which investor experience distress. For instance, only parts of the IT-crash of 2001 are highlighted as bad times. This is because the recession was concentrated to a smaller sector of the market. Because of this, the IT-crash did not have the same nationwide economic effects as the financial crisis of 2008. More households were affected in 2008 than in 2001 which is reflected in the GDP and reflected in the definition of bad times.

Table 6.1 reports summary statistics for different periods of financial and economic bad times. As can be seen in the table, periods defined as bad times capture times of high distress on the market. The average excess return is down from positive 2.6% to negative 11.1%, GDP growth is down from 2.3% to negative 1.8%, the inflations is up from 2.9% to 5.5% and the volatility of the market is up from 19% to 24%. Overall, the definition of bad times seems to capture periods which most investors would agree to define as hard times. The narrow definition also manages to capture some of the worst financial quarters, as the average return is lower in bad times than what it is in periods of only financial bad times. The sharp-sighted reader will notice that the return in periods of only economic bad times almost looks artificially high. This is because these quarters essentially succeed periods of recessions where the financial market is in recovery and experiences abnormal returns.

	All Quarters	Bad Times	Financial Bad Times	Economic Bad Times	Financial only	Economic only
Quarters	136	18	35	39	17	21
Market Returns (%)						
Average excess return, quarterly	2.6	-11.1	-9.9	-0.4	-9.3	9.4
Average excess return, annualized	10.9	-37.6	-34.1	-1.4	-32.2	43.1
Volatility of the market	19.0	24.0	24.8	22.1	24.8	19.4
Economic Indicators						
Average GDP growth	2.3	-1.8	1.1	-1.6	4.0	-1.4
Average Inflation	2.9	5.5	4.5	4.6	3.5	3.9

Table 6.1: The table displays the financial health of the Swedish economy under different definitions of bad times. Bad times are defined as periods in which the market experience both financial and economic bad times. Financial only is defined as periods in which the market experiences financial bad times, economic only is defined as periods of economic bad times. Volatility is measured by the weekly standard deviation of the excess return. The sample period is between 1983 and 2016. The definition of bad times seems to capture periods which most investors would agree to define as hard times.

6.2 Characteristics of Stocks that Perform Well in Bad Times

The second step is to identify characteristics of stocks that historically have performed well in periods of bad times. To achieve this, stocks are sorted into quintiles based on performance in bad times and ranked from low to high. The first quintile contains the bottom 20% performing stocks and the fifth quintile is the top 20%. In order to analyse the characteristics of stocks each characteristic is divided into underlying factors. For instance, the characteristic low risk is described by three underlying factors; beta, volatility and world beta. The columns in Table 6.2 describe how each factor performs in bad times. The numbers presented are percentile ranks for each factor, where a low value means that the quintile has an imbalanced distribution towards stocks with low exposure to the factor. In other words, the high value of 69.0 in the first quintile for volatility means that the worst performing stocks in bad times tend to have a high average volatility. The finding suggests that an investor who wants to hedge against bad times could short high volatility and go long in low volatility. However, the table does not give the investor any insight regarding how the portfolio will perform over time, that requires further analysis. An in-depth explanation to how the percentile ranks are calculated is available in section 5.2, but something to note is that opening balances are used when applicable since the aim is to find trends that predict future outcomes.

The results are presented in table 6.2, where the performance in Panel A is based on excess returns and Panel B on CAPM alphas. The first thing to notice is the small difference in the trends between performance in excess return and alpha. The low risk factors are affected the most, which is to be expected when adjusting for market exposure. The excess return of a stock is directly related to its beta value, where stocks with low beta are less exposed to the market and therefore suffers smaller losses in the event of a market crash. When adjusting for market exposure by sorting performance on alphas in Panel B, the strong trends in low risk disappears. This is one of the reason why risk adjusted returns are more relevant when measuring performance, and why the main focus of this paper is on identifying alpha rather than excess return.

Based on the findings in Panel B, stocks that perform well in bad times seem to share some distinct characteristics. The strongest trends are found for book-to-market, growth and momentum, which all show strong and clear trends in performance. However, the trends are not necessarily as one would expect. It is found that low book to market outperforms high book to market, which means that firms with a high valuation going in to the crisis does better than firms with a low valuation. Investors remain confidence in the companies that were considered good before the crisis, while companies considered bad are considerably worse off. This to some extent opposes the view of Fama and French (1993) that value companies would do better in bad times, due to the higher book value to back their market value. The second factor to outperform in bad times is growth, where companies with high growth outperform companies with low growth. This opposes the view that companies with a stable income would do better in bad times, and that growing firms are more sensitive to market changes due to cash flows constraints. The third factor is momentum, where stocks with a high momentum continues to outperform stocks with low momentum in bad times. This opposes the more general view of momentum crashes (Daniel and Moskowitz, 2013), previously discussed in the literature review section 2.4.2.

In addition to these findings, Panel B indicates slighter trends for size, P/E and bid-ask spread even though these are not as clear cut as the factors mentioned previously. The size trend shows that firms with high market capitalisation outperform smaller firms in bad times, which can be expected based on previous literature. Large companies are less likely to go into bankruptcy compared to small firms, and have lower liquidity risk. However, the trend is decreasing in the fifth quintile, which means the highest performing stocks in bad times are not the ones with the largest market capitalisation. This observation is interesting, as it means going long in stocks with the highest market capitalisation does not capture the highest performing stocks and as a result reduces the explanatory power of the factor size. High P/E outperforms low P/E, which is similar to the finding of book-to-market. Firms with high valuation tend to do better in bad times. The last observation is that stocks with low bid-ask spread outperform stocks with a high spread. This is in accordance with the literature, as investors value liquidity in periods of bad times.

If this study were solely based on the findings in table 6.2, the first suggested portfolio would consist of stocks that have low book-to-market, high growth and high momentum. This portfolio should achieve a positive alpha in periods of bad times, however the long-term performance is still unknown. The aim of the thesis is not only to identify characteristics that do well in bad times but also retain positive good times returns. The results in Panel B only indicate that these three factors generate positive alphas in bad times. Strong individual bad times alpha trends do not necessarily mean that the factors would generate a high overall alpha. In order to accurately choose which factors are best suited to build portfolios on, the performance of factors needs to be investigated further. In the next step long-short portfolios are constructed for each factor with the intention of shedding more light on the performance of characteristics in bad times.

Panel A: Percentile Ranks sorted on Excess Return in Bad Times

		Size and Value		Good Funadmentals		Low Risk			Momentum	Illiquidity	
	Quintile	Size	BM	P/E	Growth	Beta	Volatility	World Beta	Momentum	Turnover	Bid-Ask Spread
Low returns	*1*	44.4	58.3	48.8	42.0	60.1	69.0	58.5	31.3	54.6	51.9
	2	51.0	51.2	53.9	46.2	52.1	54.4	49.5	45.8	48.3	51.3
	3	53.9	50.3	45.4	52.6	47.3	43.8	47.7	54.7	49.5	47.6
	4	54.2	47.4	44.7	54.0	39.6	38.6	39.4	58.1	45.3	47.7
High returns	*5*	45.2	40.7	52.4	54.6	35.6	41.7	39.6	64.1	51.7	51.1
	5 - 1	**0.8**	**-17.6**	**3.6**	**12.6**	**-24.5**	**-27.4**	**-18.8**	**32.8**	**-3.0**	**-0.8**

Panel B: Percentile Ranks sorted on CAPM Alpha in Bad Times

		Size and Value		Good Funadmentals		Low Risk			Momentum	Illiquidity	
	Quintile	Size	BM	P/E	Growth	Beta	Volatility	World Beta	Momentum	Turnover	Bid-Ask Spread
Low returns	*1*	31.4	61.0	42.5	36.3	50.2	57.9	45.6	28.3	49.8	59.2
	2	46.7	54.7	46.8	41.9	45.2	46.8	45.5	44.5	46.1	48.0
	3	55.4	45.2	46.5	45.4	45.0	40.8	46.5	50.3	43.9	42.0
	4	55.0	40.2	43.8	54.5	48.6	39.7	49.1	54.5	46.9	41.2
High returns	*5*	46.6	31.8	58.5	57.5	47.0	50.6	49.1	62.1	49.8	44.6
	5 - 1	**15.2**	**-29.2**	**16.0**	**21.3**	**-3.3**	**-7.3**	**3.5**	**33.8**	**0.0**	**-14.6**

Table 6.2 Characteristics of stocks that perform well in periods of bad times. The table shows trends in the characteristics of quintiles sorted on performance, where the first quintile consists of the lowest performing stocks and the fifth quintile of the highest performing stocks. In Panel A the performance is based on excess returns, and in Panel B on CAPM alpha. The factors are measured as percentile ranks, where a low value means the quintile has an imbalanced distribution towards stocks with low exposure to the factor. The percentile rank is estimated by grouping consecutive quarters of bad times into eight different periods and calculating the percentile ranks of factors for each of the quintiles separately for the eight periods. The ranking presented in the table is the weighted average of the percentile ranks in all eight periods, where the weight is based on the number of quarters in the period. The purpose of the table is to identify characteristics of the stocks that historically have performed well in the periods of bad times. For example, by looking at the column for momentum it can be observed that high performing stocks disproportionately contains high momentum stock. Based on CAPM alpha, which measures risk adjusted returns, the factors with the strongest trends are book-to-market, growth and momentum. Additional factors with observable trends are size, price to earnings and bid-ask spread.

6.3 Performance of Characteristics in Bad Times

The third step is to evaluate the performance of the characteristics and factors in bad times. Long-short factor portfolios are constructed based on the findings in the previous step. The long leg invests in stocks with high bad time alpha and the short leg in stocks with low bad time alpha. The long and short positions are based on the trends identified in Panel B of table 6.2. The reason for constructing long-short portfolios rather than long-only is to use the knowledge of the relative performance within each factor. The portfolios are constructed to produce positive alpha rather than excess return, as the objective is to generate risk adjusted returns. The alpha of each long-short factor portfolio is estimated using regression analysis, and the results are separated between bad time, good time and overall performance.

The long-short factor portfolios are constructed, as described in section 5.3, by investing in stocks ranked in the highest and the lowest 30% within each factor. For example, the momentum factor is long in stocks that have a momentum ranked above the 70^{th} percentile and is short in stocks that have a momentum ranked below the 30^{th} percentile. Table 6.3 presents the excess return for the long and short leg of each long-short factor portfolio. In the table the excess return of the market has been deducted in order to display how each factor performs compared to the market portfolio. The three factors identified to have the strongest trends in section 6.2 were low book-to-market, high growth and high momentum. Looking at table 6.3, it can be observed that all of these positions have an excess return above the market in both periods of good and bad times. The result supports the motion that these factors could be effective when hedging against bad times. However, it should be noted that the trend is in part due to the fact that the opposite side of the factors are amongst the lowest performing in the sample. Low growth and low momentum are for example the only two factors apart from high risk stocks that have a negative excess return in bad times. The table also shows that low risk stocks generate strong returns in bad times. As discussed earlier, this is mainly the result of low beta exposure. The additional factors that displayed trends in table 6.2 were large size, high P/E and low bid-ask spread. These are all factors with excess returns above the market in both periods of good and bad times.

Low Factor Values

Small/Low	Size and Value: Size	Size and Value: BM	Good Fundamentals: P/E	Good Fundamentals: Growth	Low Risk: Beta	Low Risk: Volatility	Low Risk: World Beta	Momentum: Momentum	Illiquidity: Turnover	Illiquidity: Bid-Ask Spread
Above market return good times	-1.1%	1.4%	-0.2%	-1.9%	-1.9%	-1.8%	-1.8%	1.1%	0.0%	0.0%
Above market return bad times	4.4%	4.1%	3.7%	-1.6%	8.0%	5.9%	6.5%	-3.6%	3.9%	2.0%
Sharpe ratio good times	0.37	0.43	0.46	0.22	0.42	0.38	0.40	0.35	0.53	0.42
Sharpe ratio bad times	-0.78	-0.88	-0.56	-1.14	-0.48	-1.17	-0.78	-1.03	-0.92	-1.02

High Factor Values

Big/High	Size and Value: Size	Size and Value: BM	Good Fundamentals: P/E	Good Fundamentals: Growth	Low Risk: Beta	Low Risk: Volatility	Low Risk: World Beta	Momentum: Momentum	Illiquidity: Turnover	Illiquidity: Bid-Ask Spread
Above market return good times	0.3%	-1.7%	1.7%	0.5%	1.8%	6.1%	1.6%	0.0%	3.4%	-1.7%
Above market return bad times	4.2%	1.6%	8.2%	5.8%	-5.5%	-4.2%	-4.1%	2.0%	2.9%	3.1%
Sharpe ratio good times	0.48	0.00	0.48	0.50	0.31	0.45	0.34	0.37	0.54	0.32
Sharpe ratio bad times	-0.89	-0.88	-0.40	-0.56	-1.21	-1.00	-1.12	-0.73	-0.82	-1.33

Table 6.3 Excess return for each leg of the long-short factor portfolios. The table displays the excess return for each leg of the long-short factor portfolios displayed in table 6.4. The excess return of the market has been deducted in order to display how each factor performs compared to the market portfolio. Panel A displays the above market excess return for stocks in the lowest 30% of each factor, referred to as low factor values. Panel B displays the above market excess returns for stocks in the highest 30% of each factor, referred to as high factor values. The six factors identified to have observable trends in table 6.2 were large size, low book-to-market, high price to earnings, high growth, high momentum and low bid-ask spread. As seen in the table, all of these positions have an excess return above the market in periods of both good and bad times. This table is used to see which leg to long and which to short in table 6.4.

Table 6.4 presents the summary statistics for the long-short factor portfolios. The top row displays the excess return of the portfolios for the entire sample period, while the rows below display the excess return separated into good and bad times. The bottom row of the table displays the portfolios long and short positions, described in Table 6.3. The tail return is the performance of the portfolio in the quarters where the excess return of the market is in the worst 10% of the sample. The tail return indicates how the portfolios performs in the absolute worst period of financial bad times. Of the three factors with the strongest trends, both growth and momentum have high and statistically significant excess return in bad times. These two factors also have exceptional tail returns, and actually performs the best in periods of large drawdowns. Book-to-market on the other hand has a much lower and statistically insignificant excess return in bad times, but compensates with a high return in good times. The growth factor also has a positive return in good times, while the momentum factor displays a fairly large negative return. The results are that both the book-to-market and the growth portfolios generate positive returns over time, while the momentum factor generates a slightly negative return over time.

The results are less compelling for the additional factors discussed in section 6.2. The size factor has a minor negative return in bad times, and does not seem to perform particularly well over the full sample period either. Bid-ask spread performs even worse, with a relatively substantial negative return in bad times and a low portfolio return. P/E on the other hand displays a positive return in bad times, and a decent return for the full sample. In conclusion, out of the six factors identified in 6.2, book-to-market, P/E and growth tend to perform the best over time. It is also found that momentum earns high returns in periods of bad times, and that both momentum and growth have large tail returns. However, it should be noted that all of the portfolios underperform the market over time. The average excess return of the market is 2.6% per quarter, where the highest excess return of any portfolio is 1.8%. At the same time, all of the portfolios significantly outperform the market in periods of bad times and specifically in the tail return. The average excess return of the market in bad times is -11.6%, and the tail return is -21.3%.

The findings in Table 6.4 might not be surprising when comparing to the market portfolio, since the long-short factor portfolios bring down the volatility and provide good bad times returns by construction. The interesting takeaways from the table lie in the relative performance among the factors themselves. As is evident, momentum which from Table 6.2 was believed to be a factor of interest is shown to underperform when looking in the long-term compared to other alternatives. The two factors that have both a positive bad times return and a statistically significant overall portfolio excess return are book-to-market and growth. While turnover has a statistically significant positive overall excess return, it has a negative bad times return and no trend present in table 6.2 from which one could draw any conclusions. As a result from table 6.4, book-to-market and growth seem to be two of the most interesting candidates for long-term portfolio construction with focus on exhibiting favourable bad times performance.

	Size and Value		Good Fundamentals		Low Risk			Momentum	Illiquidity	
Factor	Size	BM	P/E	Growth	Beta	Volatility	World Beta	Momentum	Turnover	Bid-Ask Spread
Portfolio excess return	0.80%	**1.77%**	1.09%	**1.51%**	-0.54%	**-2.77%**	0.69%	-0.08%	**1.44%**	**0.64%**
	(1.94)	(2.89)	(1.84)	(3.15)	-(0.73)	-(3.02)	(0.84)	-(0.12)	(2.80)	(2.04)
Excess return good times	**0.9%**	**1.8%**	0.9%	**1.2%**	-1.4%	**-4.0%**	1.7%	-0.5%	**1.7%**	**0.8%**
	(2.06)	(2.73)	(1.45)	(2.38)	(-1.11)	-(4.05)	(1.92)	-(0.73)	(2.99)	(2.46)
Excess return bad times	-0.1%	1.3%	2.2%	**3.7%**	**4.5%**	**5.0%**	**-5.3%**	**2.8%**	-0.5%	-0.5%
	-(0.10)	(0.92)	(1.38)	(2.39)	(3.10)	(2.87)	-(3.05)	(2.02)	-(0.79)	-(0.59)
Sharpe ratio good times	0.21	0.28	0.15	0.22	-0.18	-0.37	0.19	-0.07	0.30	0.23
Sharpe ratio bad times	-0.03	0.25	0.37	0.56	0.75	0.68	-0.74	0.48	-0.21	-0.14
Tail return*	0.49%	0.14%	1.18%	4.47%	9.13%	9.92%	-10.95%	5.18%	-3.03%	-2.85%
Confidence Interval (95%)										
Lower bound	-0.01%	0.57%	-0.07%	0.57%	-2.33%	-0.97%	-0.93%	-1.36%	0.43%	0.02%
Upper bound	1.62%	2.96%	2.25%	2.45%	1.14%	-4.57%	2.32%	1.20%	2.45%	1.26%
Sharpe ratio	0.18	0.28	0.17	0.27	-0.07	-0.26	0.08	-0.01	0.26	0.17
Volatility	4.4%	6.4%	6.3%	5.6%	8.0%	10.7%	9.0%	0.08	0.05	0.04
Skew	0.04	2.41	1.56	-0.41	-0.72	-2.12	0.90	-0.57	3.34	-0.82
Kurtosis	1.69	13.83	7.35	3.50	3.42	10.13	3.51	7.31	21.27	3.68
Position in the portfolio										
Long leg	large	low	high	high	low	low	high	high	high	low
Short leg	small	high	low	low	high	high	low	low	low	high

*Tail return is the return of the portfolio in quarters where the excess return of the market is in the worst 10% of our sample. The tail return indicates the return in the absolute worst period of financial bad times.

Table 6.4 Performance of long-short factor portfolios. The table displays the excess returns of the long-short factor portfolios with belonging t-stats in brackets below. The long-short factor portfolios are constructed by investing in stocks that are ranked in the highest and the lowest 30% within each factor. For example, the size portfolio is long stocks with the 30% highest market capitalisation and short stocks with the lowest 30% market capitalisation. The portfolios are value-weighted and are refreshed and rebalanced every quarter. The three factors with the highest excess returns are book-to-market, growth and turnover. In periods of bad times, low beta and volatility earn the highest excess return and also demonstrate exceptional tail returns. However, this is only the effect of low market exposure and both of the factors have negative returns in good times. The highest excess returns in bad times amongst the other factors are present in P/E, growth and momentum. Of these, growth and momentum have the highest tail returns.

The shortcoming of looking at excess returns is that it will to some extent always reflect the portfolios exposure to the market. In order to adjust for beta, the excess return of the long-short factor portfolios is regressed against the market using the following equation:

$$\mathrm{R_p} = \alpha_a + \beta(\mathrm{r_m} - r_f) + e \tag{3}$$

The regression estimates the overall alpha for each factor portfolio, which measure the risk adjusted return over the full sample period. The result is presented in Panel A of table 6.5. The growth factor has the highest overall alpha, and is the only factor with a statistically significant result at the 5% level. The factor with second highest overall alpha is book-to-market, which is statistically significant at the 10% level. None of the other factors have statistically significant results. The finding indicates that book-to-market and growth have the highest risk adjusted returns over time. To estimate the alpha in bad times, a dummy variable is included in the regression as shown by the equation:

$$\mathrm{R_p} = \alpha_a + a_b D_b + \beta(\mathrm{R_m} - r_f) + e \qquad (4)$$

The dummy variable in the extended regression assumes the value of one if the quarter is defined as bad times, and zero otherwise. The result is presented in Panel B of table 6.5. The top row displays the good time alphas, which is the alpha earned in good times. The bad time dummy shows the additional alpha earned in bad times, and the bad time alpha is the total alpha earned in periods of bad times. As seen in the table, the two factors with statistically significant bad time alphas are P/E and growth. These are also the two factors with the highest bad time alphas, together with book-to-market. However, book-to-market is only statistically significant at the 10% level. Another interesting observation is that multiple factors have positive alphas in both good and bad times. This would indicate that outperformance in bad times not necessarily come at the cost of underperformance in good times. At the same time, it was shown in table 6.4 that the excess return of these factors were significantly below the market portfolio. The reason why factors display positive alphas and low excess return is because of low beta exposure. As seen in table 6.5, factors with positive good and bad time alphas also have beta values close to zero.

The conclusion from the analysis of the excess return and the regression is that book-to-market and growth are the two factors that generates the highest returns over time, while P/E and growth are the two factors that performs the best in periods of bad times. The results are used in the next step when choosing what factors to include in the bad times portfolios.

Panel A											
	Size and Value		Good Fundamentals		Low Risk			Momentum	Illiquidity	
Factor	Size	BM	P/E	Growth	Beta	Volatility	World Beta	Momentum	Turnover	Bid-Ask Spread
Overall alpha	0.3%	1.1%	0.7%	**1.7%**	0.7%	-1.5%	-0.5%	-0.1%	0.8%	0.2%
	(0.78)	(1.82)	(1.15)	(3.58)	(1.17)	-(1.89)	-(0.86)	-(0.21)	(1.48)	(0.88)
Panel B										
Good time alpha	0.2%	0.7%	0.1%	**1.5%**	0.9%	-1.6%	-0.9%	-0.2%	0.7%	0.0%
	(0.35)	(1.04)	(0.18)	(2.71)	(1.33)	(1.86)	-(1.34)	-(0.31)	(1.18)	(0.03)
Bad time dummy	0.9%	2.2%	3.3%	1.5%	-1.2%	1.1%	2.2%	2.3%	0.3%	1.4%
	(0.67)	(1.13)	(1.70)	(0.92)	-(0.63)	(0.42)	(1.22)	(1.05)	(0.21)	(1.58)
Market Beta	**0.13**	**0.19**	**0.14**	-0.07	**-0.60**	**-0.48**	**0.57**	-0.06	**0.18**	**0.17**
	(3.31)	(3.28)	(2.39)	-(1.50)	-(10.96)	-(6.81)	(10.75)	-(1.02)	(3.67)	(6.67)
Bad time alpha	1.1%	2.9%	**3.5%**	**2.9%**	-0.3%	-0.6%	1.3%	2.0%	1.0%	1.4%
	(0.90)	(1.71)	(2.00)	(2.11)	-(0.17)	-(0.26)	(0.83)	(1.08)	(0.72)	(1.78)

Table 6.5 Regression on long-short factor portfolios. The table shows the CAPM alphas for each of the long-short factor portfolios with belonging t-stats in brackets below. Panel A shows the overall alpha, estimated by regressing the excess return of the market on the excess return of the portfolios in a simple linear regression:

$$\mathrm{R_p} = \alpha_a + \beta(\mathrm{R_m} - r_f) + e$$

The growth factor has the highest overall alpha, and is the only factor with a statistically significant result at the 5% level. The second highest overall alpha is present in book-to-market, which is statistically significant at the 10% level. None of the other factors have statistically significant results. In Panel B the CAPM alpha is separated between good and bad times, using a dummy variable:

$$\mathrm{R_p} = \alpha_a + a_b D_b + \beta(\mathrm{R_m} - r_f) + e$$

The dummy variable in the extended regression assumes the value of one if the quarter is defined as bad times, and zero otherwise. The top row of Panel B displays the good time alphas, which is the alpha the portfolios earn in good times. The bad time dummy shows the additional alpha the portfolios earn in bad times, which is simply the difference between the good and bad time alpha. Two factors have a statistically significant bad time alpha at the 5% level, P/E and growth. These are also the two factors with the highest bad time alpha, together with book-to-market that has a statistically significant alpha at the 10% level. Several of the portfolios have positive alphas for both good and bad times, however these portfolios also have noticeably low beta values. The low market exposure is why the excess return of the portfolios are below the market portfolio regardless of their alpha.

6.4 Building Bad Times Portfolios

As a fourth step to the analysis, this section applies the findings in previous sections to construct portfolios. The first portfolio is built to perform well over time, and is therefore primarily based on the overall alpha. The second portfolio focuses solely on performance in bad times, and is therefore instead based on the bad time alpha.

Out of the six factors that demonstrated clear trends in bad times, the analysis in section 6.3 identified book-to-market and growth as the two factors with the strongest overall performance.

The factors produce both the highest excess return and overall alpha, which measures the risk adjusted performance over time. They are also the only two factors with statistically significant and positive overall alphas. Based on these findings, book-to-market and growth are selected as the two factors best suited for the long-term portfolio. Once the factors have been chosen, the portfolio is constructed by going long in each of the respective long-short factor portfolios. The performance of the long-term portfolio is presented in figure 6.2.

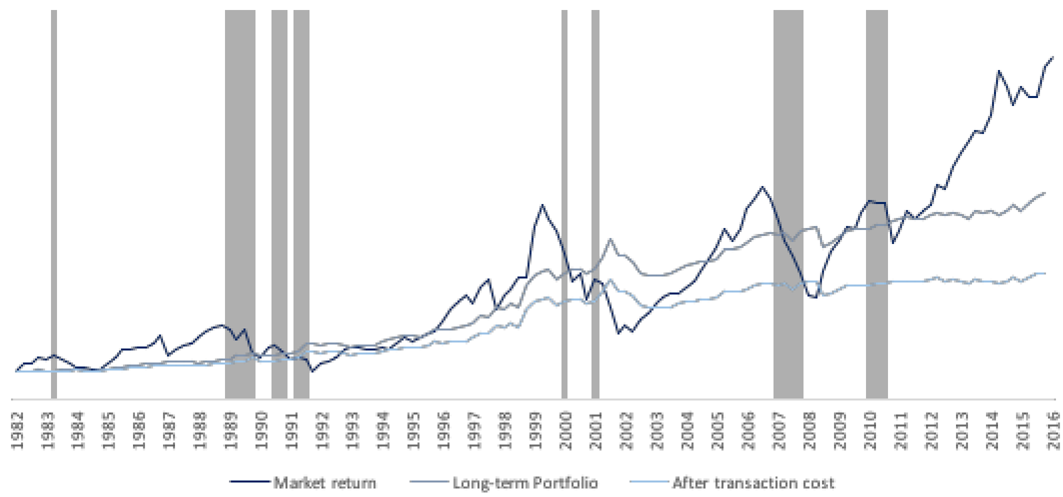

Figure 6.2 Excess return of the long-term portfolio. The figure displays the excess return of the long-term portfolio compared to the market portfolio. The portfolio is invested in the book-to-market and growth long-short factor portfolios. The bottom line is the excess return of the long-term portfolio after a transaction cost of 1.44% per annum have been deducted. The grey bars are periods defined as bad times. The long-term portfolio fails to beat the market portfolio over time, however the returns are less volatile and the portfolio performs significantly better in bad times. When transaction costs are included the return of the long-term portfolio is significantly worsened.

When analysing figure 6.2 it is important to consider that the long-term portfolio is not only constructed to perform well in bad times, but also in periods of good times. As seen in the graph, the long-term portfolio fails to beat the market portfolio over time. However, the returns in bad times are considerably better than the market return, and the portfolio also manages produce positive returns in good times. In other words, the long-term portfolio achieves what it was designed for. In addition, the returns are far less volatile than the returns of the market. This is by all means expected, as the long-short portfolio reduces volatility by construction. In the bottom line of the graph a transaction cost of 1.44% per annum has been deducted from the excess return of the portfolio. The deduction is a proxy of the real transaction cost combined with holding and rebalancing the portfolio. Obviously, the real transaction cost would depend on the positions the portfolio holds and at what frequency it is rebalanced. The reduction is thus only an indication of the real cost, which is very hard to estimate for short positions.

The transaction cost is included in the graph to illustrate that the actual return of the portfolio over time would be substantially lower if all costs are considered.

The second portfolio is constructed to maximise returns in bad times. The two factors identified to have the highest and statistically significant bad time alphas are P/E and growth. Both factors have high excess returns in bad times and the intercept of the dummy variable indicates strong alphas in bad times. They are also the two factors with the highest bad time alpha. The bad times portfolio is a zero cost long-short portfolio that is constructed by investing in stocks that are in the highest 50% of both P/E and growth, and shorting the market. The excess return of the bad times portfolio is presented in figure 6.3.

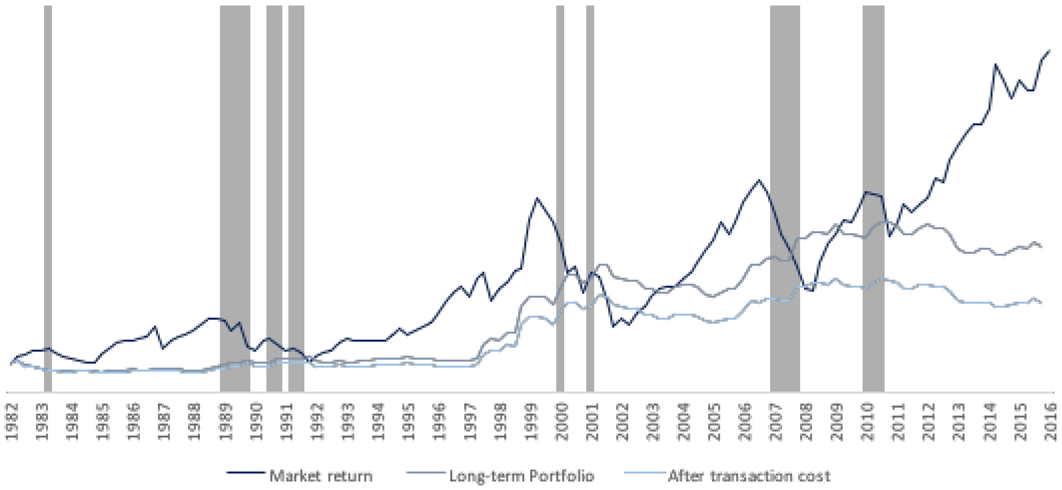

Figure 6.3 Excess return of the bad times portfolio. The figure displays the excess return of the bad times portfolio compared to the market portfolio. The portfolio is invested in the P/E and growth factors and is short the market. The bottom line is the excess return of the bad times portfolio after a transaction costs of 1.44% per annum have been deducted. The grey bars are periods defined as bad times. The bad times portfolio underperforms the market portfolio over time, but as can be seen in the graph the portfolio generates positive returns in bad times. The overall performance is reduced when transaction costs are considered, but the returns in bad times remain positive.

As seen in the graph the bad times portfolio generates positive excess return in periods of bad times. The portfolio underperforms compared to the market over time, but the graph indicates that the portfolio actually outperforms the market during downturns. The portfolio manages to surpass the market in every recession, and it has only been severely beaten by the market under the last five years. The returns are also far less volatile than the market return, making it a more stable portfolio to hold over time. However, once the transaction costs are considered the excess return of the portfolio is almost constantly below the market excess return.

Even if the transaction costs have to be adjusted to properly determine the return of the portfolio, it indicates the importance of considering all aspect when evaluating investment strategies. To better assess the performance of the two portfolios, the excess return for each of the portfolios is regressed against the market. The results are presented in table 6.6.

Panel A		Portfolio 1		Portfolio 2	
	Market return	Long-term	w/ transaction costs	Bad Times	w/ transaction costs
Portfolio return	2.62%	1.57%	1.21%	1.49%	1.13%
Excess return good times	4.8%	1.4%	1.0%	1.2%	0.7%
Excess return bad times	-11.6%	2.7%	2.4%	4.6%	4.3%
Tail return	-21.26%	3.16%	2.80%	8.0%	7.7%
Sharpe ratio good times	0.44	0.33	0.24	0.15	0.09
Sharpe ratio bad times	-1.11	0.57	0.50	0.64	0.59
Panel B					
Overall alpha	N/A	**1.58%**	**1.22%**	**2.11%**	1.27%
		(4.17)	(3.22)	(2.56)	(1.89)
Good time alpha	N/A	**1.31%**	**0.95%**	1.39%	0.69%
		(3.05)	(2.22)	(1.50)	(0.91)
Bad time dummy	N/A	1.63%	1.63%	4.25%	0.04%
		(1.33)	(1.33)	(1.64)	(1.62)
Market Beta	N/A	0.02	0.02	-0.03	-0.01
		(0.50)	(0.50)	-(0.46)	-(0.12)
Bad time alpha	N/A	**2.9%**	**2.6%**	**5.6%**	**0.7%**
		(2.69)	(2.36)	(2.45)	(2.18)

Table 6.6 Excess returns and alpha values of portfolios. The table shows the excess return and the alpha values for each of the two portfolios. The first portfolio is constructed to create high overall returns and is invested 50/50 in the book-to-market and growth long-short factor portfolios. The second portfolio is constructed to generate high returns in bad times, and is invested in stocks with P/E and growth in the highest 50% and short the market. Alpha values are estimated using multiple variable regression including a dummy variable for bad times:

$$R_p \quad = \alpha_a + a_b D_b + \beta(R_m - r_f) + e$$

The dummy variable assumes the value of one if the quarter is defined as bad times, and zero otherwise. The excess return of portfolio 1 is only marginally higher than for portfolio 2, while the overall alpha is in fact higher for portfolio 2. Furthermore, portfolio 2 has a considerably higher bad time alpha and performs better in periods of bad times. Both portfolios have a market beta close to zero.

The table shows that the excess return of portfolio 1 is positive over time, even if it is a full percentage point below the excess return of the market. More interesting, the excess return of the portfolio is positive 2.7% in bad times compared to the markets negative -11.6%. This result is further amplified when looking at the tail returns, which is positive 3.16% for the portfolio and negative -21.26% for the market. The overall alpha is 1.58% and statistically significant, which means the risk adjusted return is positive over time. On top of this, the portfolio earns additional

1.63% alpha in bad times and has a statistically significant bad time alpha of 2.9%. The performance of the portfolio is well in line with the objective of generating positive returns in bad times while maintaining an upside in good times. The results are to some extent negatively affected when considering transaction cost, but not enough to alter the conclusion.

The second portfolio generates a somewhat lower excess return over time, but compensates with better performance in bad times. The excess return is up to 4.6% and the tail return is at an impressive 8%. The alpha attributed to bad times is 4.25% and the bad time alpha is 5.6%, which is higher than for any of the individual factors. Surprisingly, the overall alpha of the portfolio is 2.11% and statistically significant. The stronger performance in bad times is to be expected, however the higher overall alpha was not anticipated and means the second portfolio outperforms the first in almost every aspect. The returns of the two portfolios are similar in good times, while the second portfolio generates much higher returns in bad times. This shows that it is possible to construct high performing portfolios by focusing on performance in bad times. The one advantage of the first portfolio is the lower volatility, which is reflected in the higher Sharpe ratio in good times. This indicates that the long-term portfolio provides more stability when held over time which becomes evident when considering the transaction costs. The transaction costs practically erase any alpha earned in bad times. Another interesting observation is that both of the portfolios have a market exposure close to zero. The low beta value indicates that neither of the two portfolios are affected my market movements, which is one of the qualities that where desired when constructing the portfolios. The analysis concludes that it is possible to construct a portfolio that generates positive returns in bad times without the cost of underperformance in good times.

6.5 Out of Sample Robustness Test

In the fifth and final step of the analysis the empirical results from the out of sample test are presented and investigated. As described in Section 5.5 the entire study is basically redone using the same methodology, but changing the sample period in order to see how well the proposed strategy would perform during the financial crisis. The sample is split in 2004, and the results found in the first sample is tested on the later sample. The aim is of course to see whether the way of going about portfolio construction will hold in a more timeless matter and whether it is fit for a future crisis rather than just the previous ones.

6.5.1 Repeating the Process

The results found for the first three steps in the out of sample robustness test are displayed in figure 11.7 and tables 11.1, 11.2 and 11.3 found in the Appendix. While it is unnecessarily ceremonious to go through the results in detail, some of the most important differences are interesting to highlight. The quarters defined as bad times closely resemble that of the main sample but with a slight difference as one might expect. The disparity is due to the fact that the sample is smaller and thus slightly different quarters will belong to the bottom quantile of returns. Furthermore, when observing the percentile ranks of the stocks divided into quintiles, the trends are very similar to those in the full sample. The main difference is perhaps that the factor P/E has a clearer positive trend for increasing alphas. This trend would lead one to expect to find better explanatory results for the P/E factor in the out of sample test, compared to the original test.

In the third step the empirical results from the out of sample long-short factor portfolios are evaluated. The tables are presented in the Appendix as mentioned in the previous paragraph, and there are several key differences observed when comparing to the previous results. First of all, the size factor looks much more interesting for portfolio construction. Not only does size have a significant and positive overall excess return along with a positive overall alpha but also most importantly a positive and significant bad times alpha on the 10% level. At the same time the P/E factor does not provide any conclusive or statistically significant results in the out of sample test as it did in sample. P/E no longer seems to be a candidate for constructing portfolios when changing the time frame for observations. Notable is also that there seem to be several negative tail return results from the long-short factor portfolios. This is indicative that they do not perform as well in truly bad times as one would have liked and as they seemed to perform in sample. Other than this the results for the long-short factor portfolios resemble that which was found and analysed previously in sample.

6.5.2 Evaluating the Out of Sample Portfolios

One of the most important steps for drawing conclusions based on this thesis is conducted by evaluating and analysing the results from the out of sample portfolio strategy. Two portfolios are selected based on the same procedure as described in section 6.4. Portfolio 1 is just as before selected on the factors with the highest and most significant overall alpha and double checked by considering the overall excess return of the long-short factor portfolio. While the factor beta has a positive overall alpha, which put it up for consideration when constructing out of sample portfolio 1, no trend was identified in the previous step and is therefore excluded. When reproducing portfolio 2 for the out of sample test it is clear that only size and growth have both positive and significant bad time alphas.

Consequently, it turns out that both portfolios are constructed on the size and growth long-short factors. This differs from in sample, which in itself is a warning sign, and leads one to question the reliability of the findings in section 6.4. If the portfolio strategy proposed in sample were to hold then one would have hoped to find the same factors for portfolio construction out of sample. Looking at the two graphs presented below one can begin to draw the conclusion that the out of sample portfolios do not perform well. First of all, it seems like they have negative returns and that they do not perform particularly well in bad or good times. In each graph there are two lines presented in addition to the market portfolio, one for implementing the strategy in 2004 and one for implementing it in 2006. It is evident that market timing seems to be very important in defining how well the strategy does which is not at all intended and not a good result for protecting risk averse investors from bad times.

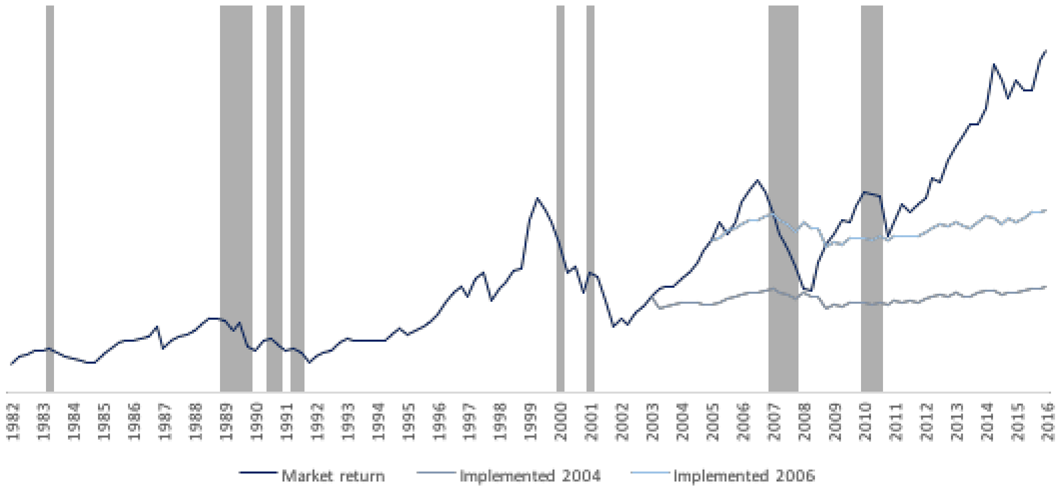

Figure 6.4 Out of sample long-term portfolio. The table displays the excess return of the out of sample long-term portfolio, when implemented in 2004 and 2006. The portfolio is invested in the long-short factor portfolios for size and growth. The portfolio does not produce positive returns in bad times and underperforms the market over time. The way of creating portfolio strategies in bad times suggested in this thesis does not hold up when tested out of sample.

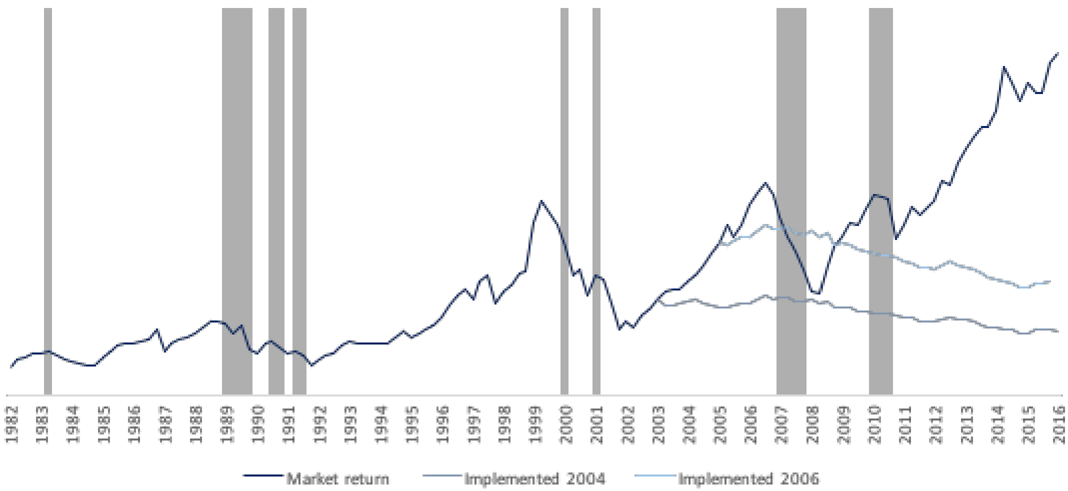

Figure 6.5 Out of sample bad times portfolio. The table displays the excess return of the out of sample bad times portfolio, when implemented in 2004 and 2006. The portfolio is invested in the size and growth factor and short in the market. The portfolio significantly underperforms the market over time. The methodology suggested in this thesis fails at generating positive returns in bad times when tested out of sample.

The results for the out of sample robustness test do not seem any better when looking closer at the numbers from the regressions in table 6.7. In fact, the numbers strongly point towards the fact that the strategy does not hold up whatsoever when conducted out of sample. Both portfolios have negative bad time alphas and negative portfolio excess returns during bad times, although less negative than the market. Portfolio 2 even has a negative overall portfolio return while portfolio 1 is close to zero. Both portfolios do however display market betas close to zero similar to the in sample testing which is the intention. The low market betas do however not outweigh the downsides. It seems to be the case that the hope and intention of identifying characteristics indicating strong bad times performance in a future crisis based on historical performance is discarded. Unfortunately, the positive and strong results analysed in section 6.4 that lead one to believe that something of significance was found are strongly rejected when they do not hold up out of sample.

Panel A		**Portfolio 1**		**Portfolio 2**	
	Market return	Long-term	w/ transaction costs	Bad Times	w/ transaction costs
Portfolio return	2.86%	0.25%	-0.11%	-0.74%	-1.08%
Excess return good times	4.9%	0.4%	0.0%	-0.75%	-1.11%
Excess return bad times	-10.3%	-0.7%	-1.0%	-0.66%	-1.02%
Sharpe ratio good times	0.71	0.12	0.01	-0.29	-0.09
Sharpe ratio bad times	-1.37	-0.19	-0.28	-0.31	-0.19
Panel B					
Overall alpha	N/A	0.40%	0.04%	**-0.73%**	**-1.09%**
		(0.80)	(0.08)	-(1.98)	-(2.96)
Good time alpha	N/A	1.01%	0.65%	-0.74%	**-1.10%**
		(1.68)	(1.08)	-(1.63)	-(2.42)
Bad time dummy	N/A	-2.99%	-2.99%	0.07%	0.07%
		-(1.75)	-(1.75)	(0.05)	(0.05)
Market Beta	N/A	-0.13	-0.13	0.00	0.00
		-(1.84)	-(1.84)	-(0.02)	-(0.02)
Bad time alpha	N/A	-2.0%	-2.3%	-0.7%	-1.0%
		-(1.37)	-(1.62)	-(0.61)	-(0.94)

Table 6.7 Performance of out of sample portfolios. The table shows the excess returns and the alpha values for each of the two portfolios. The first portfolio is constructed to create high overall returns and is invested 50/50 in the size and growth long-short factor portfolios. The second portfolio is constructed to generate high returns in bad times, and is invested in stocks with size and growth in the highest 50% and short the market. Alpha values are estimated using multiple variable regression including a dummy variable for bad times.

$$\mathrm{R_p} = \alpha_a + a_b D_b + \beta(\mathrm{R_m} - r_f) + e$$

The dummy variable assumes the value of one if the quarter is defined as bad times, and zero otherwise. Both portfolios generate negative bad time alphas and negative excess returns in bad times. Portfolio 1 has a positive overall alpha, but the return is low and statistically insignificant. Portfolio 2 earns a negative overall alpha, as well as negative excess returns. The results in the table concludes that the findings in section 6.4 do not hold up when tested out of sample.

7 Discussion

In this section the findings from Section 6 are critically examined in the attempt of shedding light on how the results contribute to previous research and the current state of financial investment theory regarding bad times. Furthermore, judgments are made as to what one can learn from this study and to what extent one can draw any reliable conclusions. Emphasis lies on what the findings mean and how valuable they actually are.

7.1 Following Up on the Thesis Question

This thesis is conducted in a manner of analysing and interpreting results step-by-step as described closely in section 6, in order to make critical decision in each instance along the way. As a result, the outcomes and the path to answering the thesis questions differed from what was anticipated. While it was possible to define bad times and find qualities among companies that indicate both positive risk adjusted returns in the long term and strong bad times alphas, some factors deviated from the expectations. One of the more surprising outcomes was that low book-to-market firms were shown to perform well in bad times whereas there was a very clear decreasing trend in alpha for increasing book-to-market. Intuitively one expects the high book-to-market firms to perform well in bad times as they are not overvalued by the market. However, perhaps the low book-to-market firms are correctly priced by the market and in fact should have high market values as they are fundamentally better firms. Another point of surprise was that both size and turnover were expected to show stronger and more significant trends in explaining the cross section of returns in bad times. While it seems intuitive that large companies and high liquidity would do better in bad times this was not as significant as one might have believed. Important to bring up is how the narrow definition of bad times may affect certain factors. The trade-off of finding truly bad times and perhaps going for a broader definition is that it will benefit some characteristics while skewing others. Taking growth as an example, the factor could actually be taking companies that actually grow in the start of financial bad times in consideration since the factor is based on the 12-month growth ex ante. As a result, it may seem as a stronger factor for prediction than it actually is. Since growth was a factor used for the portfolios in section 6.4 this notion would further undermine the positive results.

Following up on the primary thesis question and connecting it to the analysis unmistakably makes one realise that the results found were not in line with the initial hopes. As is evident from looking at both graphs from the suggested portfolios and table 6.6 it is not possible to outperform the market even through the portfolios do well in bad times and have low volatility. Apparently the additional returns in bad times, which provide stability to the portfolio, are not enough to compensate for the low returns during good times. Even prior to conducting the out of sample test it is shown that the portfolios indisputably underperform in the long-term relative to the market

Unfortunately, as the out of sample robustness test makes clear, the portfolios and potential strategies explored do not hold up when tested for timelessness. Looking at the results in the graphs and table 6.7 it does not in any way seem viable to attempt creating such a portfolio. Perhaps one could even believe that analysing the cross-section of returns and alphas based on historical data is not sufficient to predict or hedge against a future crisis. Connecting directly to the secondary sub question asked, this thesis is not able to provide any solid advice on how the risk-averse investor expecting bad times should restructure their portfolio. The only situation in which the portfolio strategies suggested in section 6.4 would make sense is if the investor expects the coming bad times to reflect historical ones. However, making such assumptions is filled with risk which is exactly what the investor in question is trying to avoid.

7.2 Connecting to Previous Research

The study is in part an extension to the research paper Quality Minus Junk by Asness, Frazzini, and Pedersen (2013). As stated in Chapter 2 the authors found positive risk adjusted returns from the QMJ factor and that quality is especially low priced during economic downturns, which should mean that it is especially profitable to buy quality stocks during bad times. The research by Asness, Frazzini, and Pedersen was not only a source of inspiration for this paper but has also been extended and strengthened by looking at the Swedish market. While the hope of the thesis was to clearly identify certain characteristics that indicate high and low quality this turned out to be more difficult than expected. In fact, when conducting the out of sample test it was shown that different factors were found which may indicate that one should conduct additional tests to verify the QMJ factor, at least if one intends to implement it on the Swedish market.

This paper has also been inspired by the similar study conducted on the American market called Rainy Day Stocks by Gormsen and Greenwood (2017), but has come up with quite a different set of circumstances to draw conclusions from. Gormsen and Greenwood were able to create bad times portfolios that both performed better than the market in bad times and in the long-term, which they mentioned was a surprising result. On the other hand, this study found that the bad times portfolios have a positive return in bad times but underperforms relative to the market in the long-term.

Perhaps one could have foreseen that there would be contradictory results when conducting an out of sample test. As the studies from Campbell et al. (2013) indicate, described closer in section 2.2, recessions are very different from one another. With this in mind it seems quite obvious that predicting how to rebalance a portfolio for a future crisis would be hard. However, it was the belief when conducting this study that different bad times would still have some common denominators and thus allowing for a profitable risk-adjusted strategy. As was further described in section 2.3, not only do the recessions differ in the driving underlying factors but also in investor mentality. This thesis validates the fact that recessions differ strongly from one another since it is shown that a future crisis cannot be risk managed while maintaining viable long-term returns.

7.3 Validating the Results

The analysis in section 6 highlights which results are most interesting and which are important to focus on. It is however still important to discuss how valuable these results are in the bigger picture. Looking solely at the results found prior to the out of sample test, one could argue that if the future of the stock market resembles the development from 1983 to 2016, then it is possible to create portfolios with positive bad times and overall returns. Since the Swedish market is inferior in size in comparison to many other markets, resulting in fewer observations, it is harder to achieve a t-stat above 1.96, and thereby statistical significance. Even though this is the case, both of the bad times portfolios in section 6.4 provided a statistically significant positive bad times alpha. This in turn would lead one to believe and validate that the identified factors for creating portfolios in fact do reliably provide positive returns in bad times. Another important question to ask oneself when interpreting the results of many studies is whether one experiences positive returns from portfolios due to a market inefficiency or if it could be that the selected qualities are riskier and therefore have higher average returns. Seeing however that the volatility of the portfolios is low and that they do not outperform the market it does not seem to be the case that they are loaded on risk, but more likely the opposite.

It is however impossible to ignore the contradicting and insightful results from the out of sample robustness test. One of the more important takeaways from the test is that every crisis seems to be different. As is shown in this study, it is possible to find characteristics and portfolios that perform well in historical bad times. However, the basis of the results shifts when the sampled period is changed. In other words, the results are attributed to the specific crises within the sample. In the out of sample test the portfolios were based mainly on information gathered from the bad times of the real estate crisis of 1990-1994 and the IT-crash of 2001. As shown, the information was insufficient to predict and create portfolios for the financial crisis of 2008 and the European debt crisis of 2011. For the results of the methodology to hold over time, each future crisis would have to share its underlying cause with previous crises. This is of course an unreasonable assumption to base any strategy off.

Another question that arises when asking whether any reliable conclusion can be drawn is if the bad times portfolios are in fact mimicking the world index. The reasoning behind this question is as follows; perhaps one could expect that the companies listed on the Swedish Exchange with international business and a majority of incomes arising from activities outside the Swedish market will be the ones who perform best in Swedish bad times. Maybe the companies that do well in the sample are the ones who have revenues and business outside of Sweden. However, these expectations were early on in the study rejected when observing table 6.2 where it is found the world beta in contrast has a clear declining trend for companies with higher returns in bad times. This was further proven when constructing the long-short factor portfolios and calculating the good and bad times returns as can be seen in table 6.4. It was found that the excess returns in bad times were strongly negative at -5.3% (-3.05) and that the positive bad times alpha is not statistically significant.

Another important topic for discussion is if the bad times portfolio strategy is a good idea with regards to the practical matter. Since both portfolios include shorting and adjusting the holdings each quarter one should assume high transactions costs in comparison to simply purchasing an index fund following the market portfolio. Looking at table 6.6 it becomes clear that including transaction costs in the portfolios strongly affects the attractiveness of holding them even further. Another point of discussion is to consider simply shorting the market portfolio as a means of hedging against bad times. While this strategy indeed would hedge against bad times it would not fulfil the criterion of providing respectable returns in good times. On the contrary it would perform very poorly in good times and thus is not an interesting alternative to the long-term investor.

The importance of timing the market is well known to any financial investor and this study is no different. When conducting the out of sample tests and checking for a timeless robustness of the approach to selecting factors for the portfolios it became apparent that the portfolios rely heavily on timing. Having a look at figure 6.4 and 6.5 makes this particularly clear as one can see that there is quite a large difference if one were to have conducted this study and implemented it in 2004 or 2006.

7.4 Trade-offs and Downsides of the Implemented Portfolios

As expected, the portfolios achieve a significantly positive bad times alpha of 2.9% (2.69) and 5.6% (2.45) respectively, but this might seem obvious as this is what the portfolios were intrinsically constructed to do. Intuitively, something must be given up in order to achieve this bad times return. Looking at the results from table 6.6 both portfolios even have positive good times Sharpe ratios, even though somewhat lower than the market, while maintaining very strong and positive bad times Sharpe ratios. The trade-off becomes clearer when looking at figure 6.2 and 6.3. While the portfolios seem to be less volatile and indeed perform well in bad times the catch is that they underperform relative to the market in the long term. Perhaps it is even safe to say that one is better off simply holding the market portfolio if it is truly for the long-term one is investing.

Even though this discussion has directed quite some criticism towards how valuable the findings actually are and how one could find use of them in reality it still holds true that both portfolios maintain stable and positive returns in the long term and in good times as well as bad times in particular. For the risk averse investor or even for the more short-term investor that is expecting an economic downturn this study can help in providing a guideline and an option of portfolio strategy.

8 Conclusion

This thesis studies the cross-section of stock returns during bad times, with emphasis on the performance of certain characteristics and factors. The thesis attempts to create portfolios that perform well during bad times while maintaining positive returns during good times. The primary contributions are made in two steps.

Firstly, trading strategies are suggested that ensure both positive excess returns and positive alphas in bad times. The first strategy focuses on long-term performance by investing in an equally weighted zero-cost portfolio built on long-short positions in book-to-market and growth. The second strategy focuses solely on performance in bad times by investing in a zero-cost portfolio that goes long in high P/E and growth and is short the market portfolio. The strategies are found to generate statistically significant alphas, both in bad times and for the overall sample. However, the portfolios generate lower excess returns than the market portfolio over time due to low market exposure. The result suggests that it is possible to earn positive risk adjusted returns by investing in stocks that perform well in bad times. The suggested strategies could be suitable for the investor who either expects bad times or who values positive returns in bad times highly.

Secondly, the strategies are tested in an out of sample robustness test which finds that the results fall short in predicting returns for a future crisis. Proposing a methodology to risk-adjust investment returns, by placing greater weight on performance achieved during bad times than during good times, would not have held up if one implemented it prior to the financial crisis. As a result, it is safe to say that one should thoroughly question any investor who claims they can create a portfolio based on characteristics and factors from bad times that with certainty will perform well during a future crisis. The conclusion is drawn that one cannot with statistical certainty create risk-adjusted and safe portfolios for future bad times on the Swedish market.

9 Limitations, Extensions and Future Research

In any research conducted nowadays one has to focus the time energy towards certain areas while inevitably leaving out other areas which can be extended and explored further. In this section possible extensions to this research along with some of the limitations are brought up. This section is intended to act as an indicator and suggestion for further research on portfolio strategies and analysing the cross-section of stock returns and characteristics in bad times.

9.1 Robustness Tests on Definitions of Bad Times

Going back to the very beginning of this research one can find areas in which there is further room for exploration, taking the definition of bad times as a first example. It is possible to argue that one should define it differently or even look at financial or economic bad times individually. As mentioned in section 6.1 it is apparent that the bad times definitions of this paper do not fully cover the financial downturns of the market but instead only a portion of each one. An interesting alternative to the out of sample robustness test conducted in this paper would be to instead define bad times differently (rather than defining it the same way but on a different time period) and run the same tests again. It would also have been possible to define bad times on financial times solely and test how the strategy performs in economic bad times or vice versa. Perhaps one would find the same or similar results further strengthening the study or perhaps one would find that in fact is not possible to make any clear deductions.

9.2 Increasing Precision of Characteristics Measures

As described and motivated in Chapter 4 a choice was made to conduct this study based on quarterly data. It is however safe to say that if the time and resources are available to conduct the study on as granular data as possible, monthly or even daily, one would expect to increase the precision of the results even further. While some results may turn out to be the same the statistical certainty of which one could express the results would definitely be higher.

It would be desirable to increase the accuracy of the characteristics and factors, if possible. Suggestions and ways of doing this would be to look at Quality Minus Junk by Asness, Frazzini, and Pedersen (2013) and apply some of the more advanced statistical techniques for factor measurements. For instance, one could calculate the low risk characteristic as the average of beta volatility and compare that to the direct measures of beta, volatility and world beta as in this paper. Even though the calculation of rolling betas was quite thoroughly conducted in this paper one could take this one step further in accordance with the beta estimations of Bawa and Lindenberg (1977) in Downside Risk.

9.3 Improving the Underlying Data

One of the more apparent limitations, and thus areas for possible improvements, of this paper is that most of the data and analysis is based on quarterly results. If one were to conduct the study with even more granular and complete datasets, based on monthly data for instance, then the statistical certainty for drawing conclusions would increase dramatically. Worth mentioning is that while the statistical certainty would in fact rise it is likely that one would find similar results, especially when studying factors based on accounting measures that are only available on a yearly basis regardless of the frequency of underlying data.

One could also look at adding factor specific transaction costs, although this would perhaps be a thesis in itself. Transaction costs depend both on the frequency of trading and the availability and nature of the underlying instrument. As a result, the transaction costs should differ a lot depending on which factors are selected and should be taken into account before recommending a strategy.

9.4 Robustness Check

Another fairly obvious alternative for future extensions to the thesis is by expanding the study to include global markets rather than just Sweden. One could even look closer at the relationship between a company's Swedish market beta and the world beta. Perhaps the companies with both a low Swedish market beta and a high world beta are the ones who perform the best because they are hedged against Swedish bad times in particular. Finally, a suggestion for an additional robustness check is to take the original portfolio strategies in section 6.4 and look at how they perform up until 2014 and after 2014. This could then be compared to the out of sample test conducted in this thesis.

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11 Appendix

11.1 Definition of Bad Times

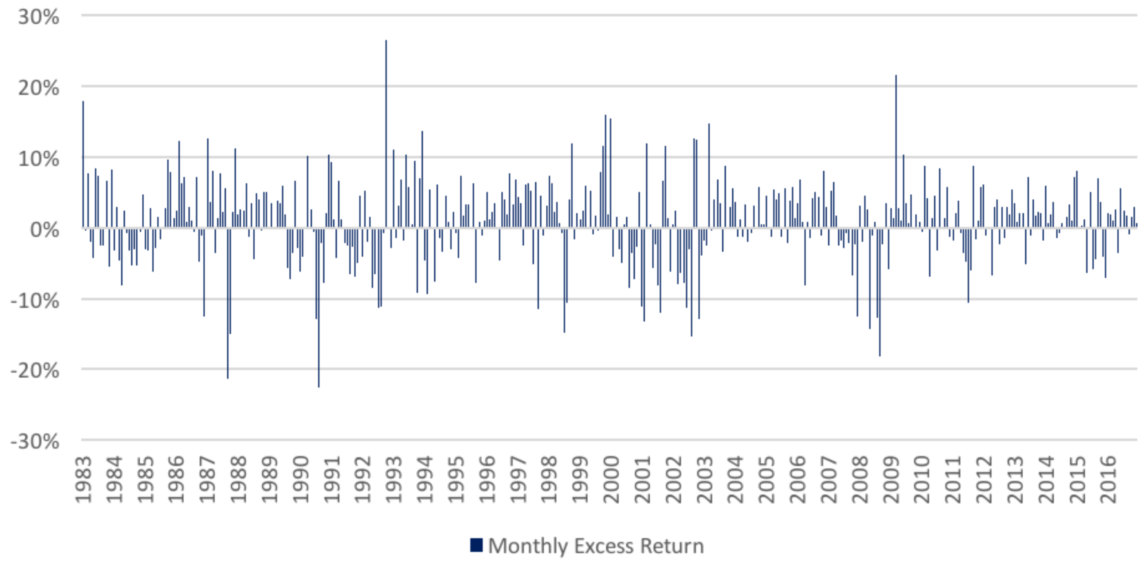

Figure 11.1 Monthly excess returns on the market. The figure shows monthly excess return on the Stockholm Stock Exchange from 1983 through 2016. The graph shows the continuous fluctuations in the stock market and indicates periods of financial bad times.

Figure 11.2 Returns in quarters of financial bad times. The figure shows quarters between 1983 and 2016 in which the excess return on the Stockholm Stock Exchange is in the lowest quintile of the sample. The quarters are used to define periods of financial bad times.

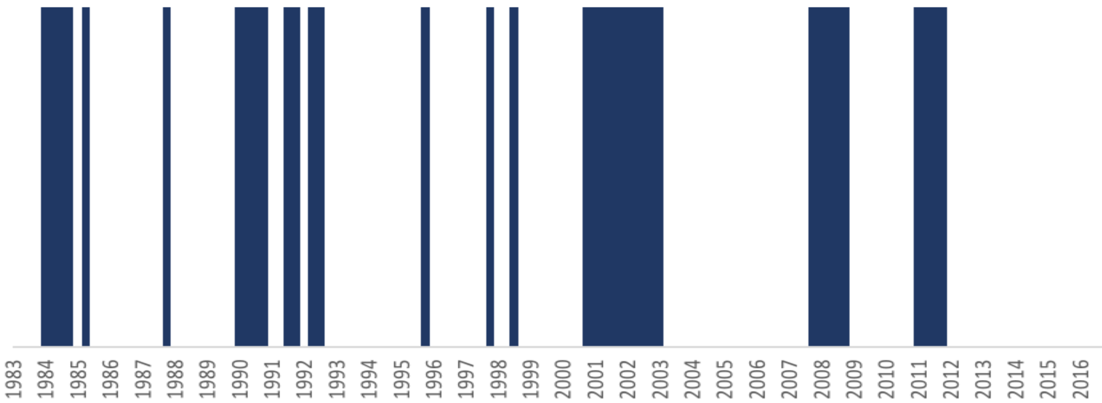

Figure 11.3. Financial bad times. The graph shows quarters defined as financial bad times between 1983 and 2016. Note that not all quarters are included as financial bad times in figure 5.1. This is due to interpolation, which includes periods in which the market as a whole is assumed to be in a financial recession.

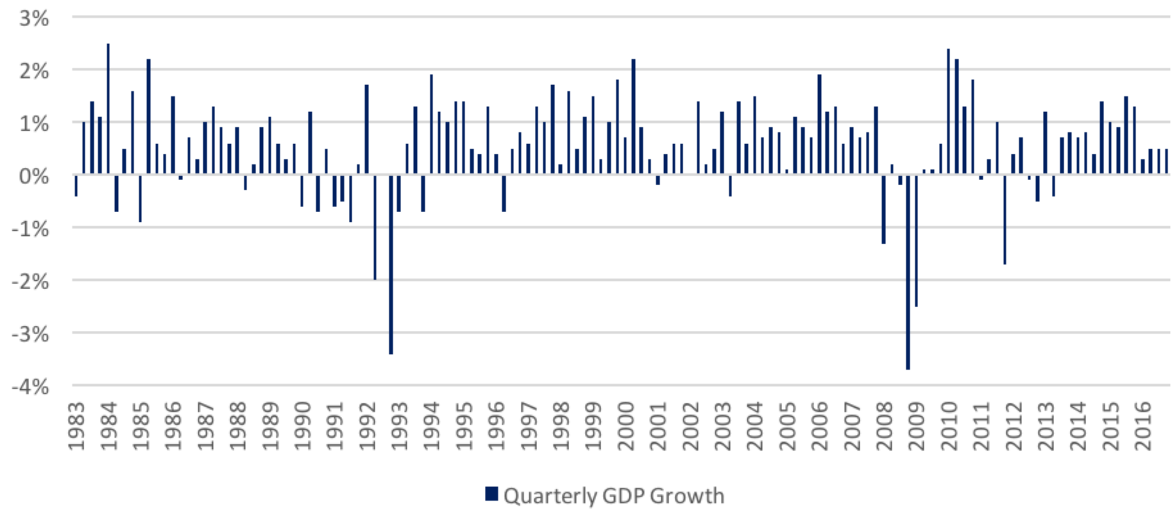

Figure 11.4 Growth in GDP. The graph shows quarterly growth in the Swedish GDP, measured in percentage between 1983 and 2016. The graph indicates periods of economic bad times as well as the length and scale of each recession.

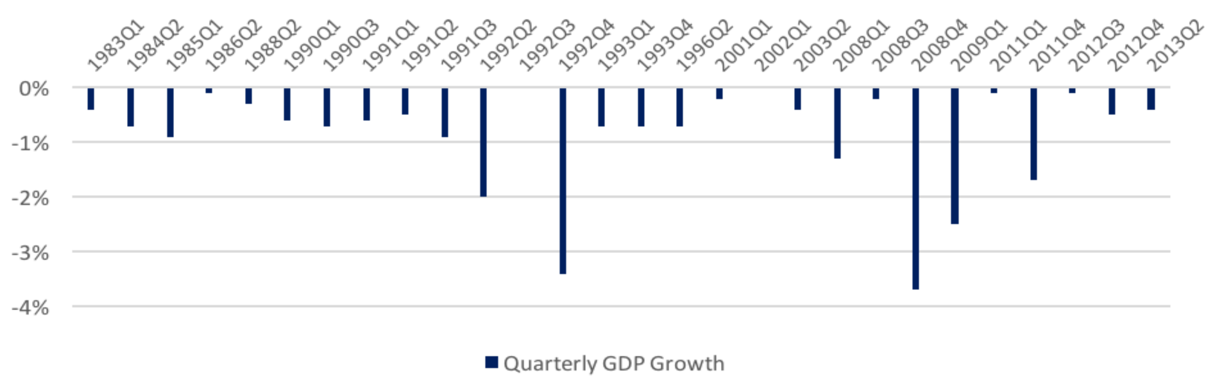

Figure 11.5 GDP in periods of economic bad times. Quarters between 1983 and 2016 in which the growth of the Swedish GDP is in the lowest quintile. The quarters are used for the defining periods of economic bad times.

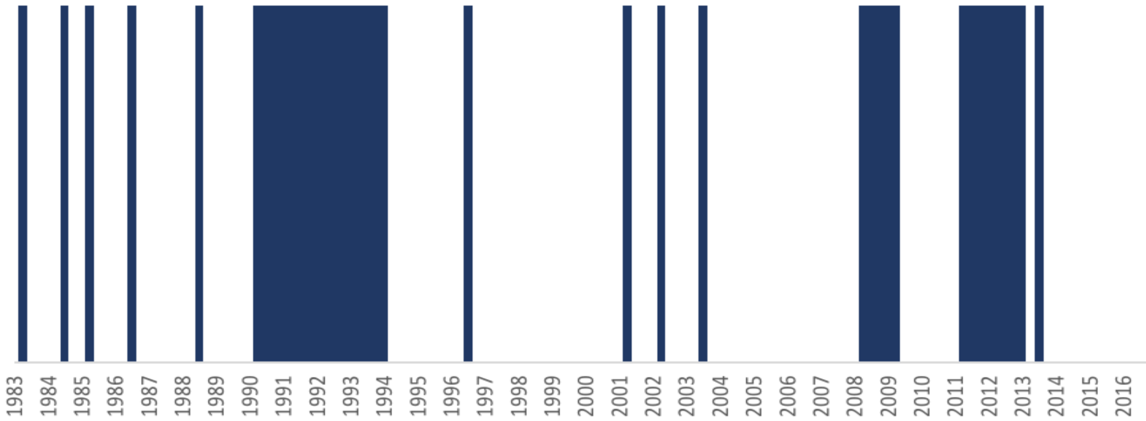

Figure 11.6 Periods of economic bad times. Quarters defined as economic bad times between 1983 and 2016. Note that some quarters are not included as a period economic bad times in figure 5.4. This is due to the interpolation, which includes periods in which the market as a whole is assumed to be in an economic recession.

11.2 Out of Sample Test

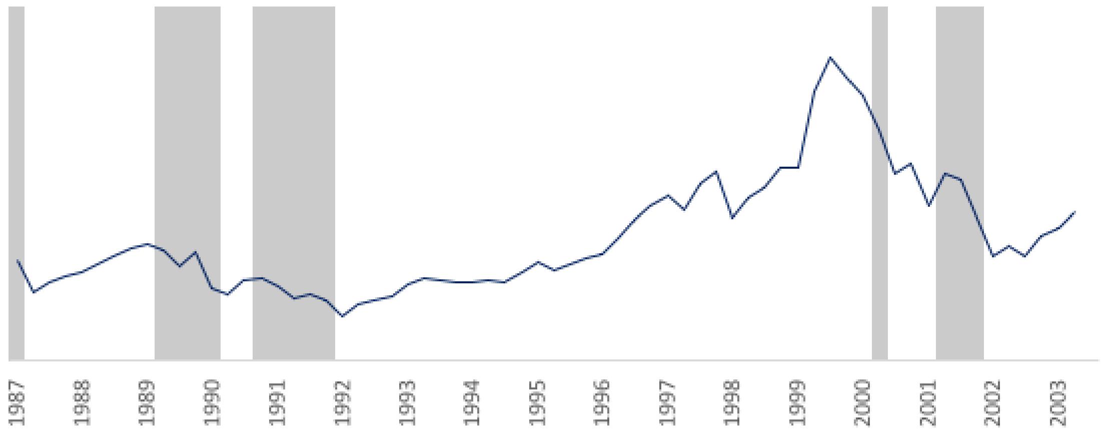

Figure 11.7 Periods of bad times. The figure shows periods defined as bad times and the excess return of the Stockholm Stock Exchange, referred to as the excess return of the market. The blue line is an index of the excess return of the market, and the grey bars indicate periods defined as bad times.

Percentile Ranks sorted on CAPM Alpha

		Size and Value		Good Funadmentals		Low Risk			Momentum	Illiquidity	
	Quintile	Size	BM	P/E	Growth	Beta	Volatility	World Beta	Momentum	Turnover	Bid-Ask Spread
Low returns	*1*	31.4	60.7	37.3	41.2	50.9	61.3	49.2	34.0	56.6	65.1
	2	50.5	56.5	53.5	47.0	47.2	50.6	46.7	49.3	50.3	49.0
	3	59.7	48.8	47.8	48.1	49.3	45.3	48.9	51.4	44.3	44.3
	4	56.5	44.3	45.1	54.2	52.2	40.8	51.9	56.8	48.9	43.5
High returns	*5*	52.0	34.3	64.4	60.6	49.8	50.9	52.8	62.6	50.6	47.6
	5 - 1	**20.6**	**-26.4**	**27.1**	**19.4**	**-1.1**	**-10.4**	**3.6**	**28.5**	**-6.0**	**-17.6**

Table 11.1 Characteristics of stocks that perform well in periods of bad times. The table shows trends in the characteristics of stocks that perform well in bad times. The first quintile consists of the lowest performing stocks and the fifth quintile of the highest performing stocks. The performance is based on CAPM alpha. The factors are

measured as percentile ranks, where a low value means the portfolio have an imbalanced distribution towards stocks with low exposure to the factor. The purpose of the table is to identify characteristics of the stocks that historically have performed well in the periods of bad times. The factors with strongest trends are size, book-to-market, P/E, growth, momentum and bid-ask spread.

	Size and Value		Good Fundamentals		Low Risk			Momentum	Illiquidity	
Factor	Size	BM	P/E	Growth	Beta	Volatility	World Beta	Momentum	Turnover	Bid-Ask Spread
Portfolio excess return	**1.7%**	-1.7%	1.3%	**1.9%**	-1.3%	**-4.0%**	1.8%	-0.2%	-1.6%	**-1.3%**
	(2.49)	-(1.47)	(1.37)	(2.22)	-(0.87)	-(2.06)	(1.32)	-(0.15)	-(1.62)	-(2.33)
Excess return good times	**1.8%**	-1.9%	2.0%	0.8%	-3.0%	**-5.8%**	**3.5%**	-0.8%	**-2.0%**	**-1.5%**
	(2.38)	-(1.41)	(1.72)	(1.70)	-(1.87)	-(2.73)	(2.29)	-(0.53)	-(1.80)	-(2.40)
Excess return bad times	1.0%	-0.7%	-1.5%	**6.9%**	**6.4%**	3.5%	**-5.6%**	2.5%	0.5%	-0.4%
	(0.71)	-(0.41)	-(1.01)	(3.11)	(2.01)	(0.76)	-(2.02)	(0.71)	(0.29)	-(0.32)
Sharpe ratio good times	0.35	-0.21	0.26	0.14	-0.28	-0.41	0.34	-0.08	-0.27	-0.36
Sharpe ratio bad times	0.22	-0.13	-0.32	0.98	0.64	0.24	-0.64	0.22	0.09	-0.10
Tail return*	-1.4%	-2.8%	-2.7%	6.7%	11.0%	11.7%	-10.6%	2.6%	4.8%	-0.4%
Confidence Interval (95%)										
Lower bound	0.4%	-3.9%	-0.6%	0.2%	-4.2%	-7.9%	-0.9%	-3.0%	-3.5%	-2.4%
Upper bound	3.0%	0.6%	3.3%	3.6%	1.6%	-0.2%	4.6%	2.6%	0.3%	-0.2%
Sharpe ratio	0.34	-0.20	0.19	0.30	-0.12	-0.28	0.18	-0.02	-0.22	-0.31
Volatility	5.0%	8.4%	7.2%	6.4%	11.2%	14.4%	10.5%	10.6%	7.2%	4.1%
Skew	-0.15	-1.76	1.80	-0.22	-1.11	-2.04	1.11	-0.58	-2.42	1.17
Kurtosis	1.96	9.69	8.19	1.97	2.59	6.31	2.95	3.83	13.42	4.01
Position in the portfolio										
Long leg	large	low	high	high	low	low	high	high	low	low
Short leg	small	high	low	low	high	high	low	low	high	high

*Tail return is the return of the portfolio in quarters where the excess return of the market is in the worst 10% of our sample. The tail return

Table 11.2 Performance of long-short factor portfolios. The table displays the excess returns of long-short factor portfolios with belonging t-stats in brackets below. The long-short factor portfolios are constructed by investing in stocks that are ranked in the highest and the lowest 30% within each factor. For example, the size portfolio is long stocks with the 30% highest market capitalisation and short stocks with the lowest 30% market capitalisation. The portfolios are value-weighted and are refreshed and rebalanced every quarter. The three factors with the highest excess return are size, P/E, growth and world beta. Of these factors only size and growth have positive returns in bad times. The growth factor have by far the highest excess return in bad times. Low beta and volatility both earn high excess returns in bad times, and have the highest tail returns. However, this is only the effect of low market exposure and both of the factors have high negative returns in good times.

Panel A										
	Size and Value		Good Fundamentals		Low Risk			Momentum	Illiquidity	
Factor	Size	BM	P/E	Growth	Beta	Volatility	World Beta	Momentum	Turnover	Bid-Ask Spread
Overall alpha	1.0%	-0.6%	0.3%	**2.5%**	1.0%	-1.5%	-0.2%	0.1%	-0.8%	-0.9%
	(1.56)	-(0.54)	(0.35)	(2.86)	(1.03)	-(0.87)	-(0.25)	(0.07)	-(0.81)	-(1.67)
Panel B										
Good time alpha	0.3%	0.6%	0.0%	1.4%	1.5%	-1.0%	-0.5%	-0.1%	-0.5%	-0.7%
	(0.44)	(0.42)	(0.01)	(1.35)	(1.24)	-(0.46)	-(0.39)	-(0.30)	-(0.39)	-(1.04)
Bad time dummy	2.7%	-4.7%	1.3%	4.7%	-2.0%	-2.1%	1.0%	0.3%	-1.2%	-1.0%
	(1.41)	-(1.47)	(0.46)	(1.95)	-(0.69)	-(0.40)	(0.34)	(0.60)	-(0.43)	-(0.61)
Beta	**0.20**	**-0.34**	**0.27**	-0.08	**-0.68**	**-0.65**	**0.60**	-0.04	**-0.22**	**-0.12**
	(3.51)	-(3.44)	(3.18)	-(1.17)	-(7.92)	-(4.12)	(6.95)	-(0.27)	-(2.43)	-(2.63)
Bad time alpha	3.0%	-4.1%	1.3%	**6.1%**	-0.5%	-3.1%	0.5%	0.2%	-1.7%	-1.6%
	(1.94)	-(1.56)	(0.56)	(2.99)	-(0.21)	-(0.73)	(0.21)	(0.58)	-(0.72)	-(1.24)

Table 11.3 Regression on long-short factor portfolios. The table shows the CAPM alphas for each of the long-short factor portfolios with belonging t-stat in brackets below. Panel A shows the overall alpha, estimated by regressing the excess return of the market on the excess return of the portfolios in a simple linear regression:

$$R_p \;\; = \alpha_a + \beta(R_m - r_f) + e$$

The growth factor have the highest overall alpha, and is the only factor with a statistically significant result. The factors with second highest overall alpha are size and beta. In Panel B the CAPM alpha is separated between good and bad times, using a dummy variable:

$$R_p \;\; = \alpha_a + a_b D_b + \beta(R_m - r_f) + e$$

The dummy variable in the extended regression assumes the value of one if the quarter is defined as bad times, and zero otherwise. The top row of Panel B displays the good time alphas, which is the alpha the portfolios earn in good times. The bad time dummy shows the additional alpha the portfolios earn in bad times, which is simply the difference between the good and bad time alpha. Two factors have a statistically significant bad time alpha, size and growth. These are also the two factors with the highest bad time alphas.