UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER'S THESIS

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DETERMINANTS OF ASSET RETURNS IN TIMES OF INCREASED UNCERTAINTY

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AUTHORSHIP STATEMENT

The undersigned Domen Pavlič, a student at the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), author of this written final work of studies with the title Determinants of Asset Returns in Times of Increased Uncertainty, prepared under supervision of prof. dr. Igor Lončarski PhD.

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LIST OF ABBREVIATIONS

n. d.	No Date
ACAR	Average Cumulative Abnormal Return
AMEX	American Stock Exchange
AR	Abnormal Return
BMP	Boehmer, Musumeci, and Paulson
CAPM	Capital Asset Pricing Model
CAR	Cumulative Abnormal Return
CBOE	Chicago Board Options Exchange
CRSP	Center for Research in Security Prices
DITM	Deep In-Of-The-Money
DOTM	Deep Out-Of-The-Money
EMH	Efficient Market Hypothesis
ETF	Exchange Traded Fund
ETN	Exchange Traded Note
FRED	Federal Reserve Economic Data
GFC	Great Financial Crisis
LTCM	Long-Term Capital Management

NASDAQ	National Association of Securities Dealers Automatic Quotation System
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
SAR	Standardized Abnormal Return
SCAR	Standardized Cumulative Abnormal Return
VAR	Vector Autoregression
VIX	CBOE Volatility Index
VXO	S&P 100 Volatility Index

INTRODUCTION

The American mathematician John Allen Paulos once wrote that uncertainty is the only certainty there is (Paulos, 2003). Investors are particularly aware of this because the value of their investments is determined, at least in part, by the current state of uncertainty. Its ever-changing nature provides jobs for those who protect financial institutions from the associated risks and creates opportunities for those brave enough to seize them. Periods of low volatility are followed by strong movements and vice versa. Political unrest, market shocks, and natural disasters are just a few catalysts that can suddenly heighten market participants' fears and drive the rise in risk premiums. These problems are exacerbated by the "correlation breakdown" phenomena, which refers to return patterns that diverge significantly in uncertain times from those in calmer times (Loretan & English, 2000). In other words, when the full force of a storm hits the markets, valuations fall substantially and the risk management processes that normally ease the pain become obsolete.

There is much research on the relationship between market returns and uncertainty. DeLisle, Doran and Peterson (2010) argue that a sharp increase in market volatility is associated with a considerable decline in stock prices. However, according to their findings, the relationship does not work in reverse – there is no correlation between a decline in the VIX index and future returns. In general, an increase in uncertainty is associated with negative returns and increased volatility. For example, French, Schwert and Stambaugh (1987) concluded that when expected risk premia are positively correlated with predictable volatility, an unexpected positive change in volatility lowers current stock prices. Market participants often use the tool of implied volatility to measure the extent to which the price of the observed asset is likely to fluctuate in the near future. Many have found that current implied volatility can be a relatively accurate estimate of future realised volatility. For example, Poon and Granger (2003) analysed the methods and empirical results of ninety-three papers that dealt with volatility forecasting. They found sixty-six relevant studies, some of which compared only one pair of forecasting approaches and others that covered several. They concluded that option standard deviation models based on the Black-Scholes model and its various generalisations provided the best forecasts of future volatility. The discoveries presented in these papers triggered a revolution in finance and led to the emergence of a new asset class. Today, investors can bet on volatility with various financial instruments. Perhaps best known is the exchange-traded VIX volatility index of the Chicago Board Options Exchange (hereafter CBOE), whose value is watched daily by many. It contains the implied one-month volatility of options on the overall market index S&P 500 (Andersen, Bollerslev, Christoffersen, & Diebold, 2005). In the literature, the VIX is often seen as an indicator of market and macroeconomic risk and panic, as the emergence of fear increases implied volatility. At the same time, calmness lowers it (Aharon & Qadan, 2019).

In other words, extremely high VIX values indicate considerable anxiety among market participants and are considered a bullish indicator for long-term investors. These considerations are based on the concepts of behavioural economics. In times of financial turmoil, investors tend to overreact to bad news and indiscriminately sell their holdings to increase liquidity and limit their risk (Giot, 2005).

On the other hand, low values indicate high risk appetite and are considered a bearish indicator (Cipollini & Manzini, 2007). The VIX index value is in many ways comparable to the price of an insurance contract, the premium of which is also not constant over time and depends on various factors. For example, if one takes out fire insurance, the value of one's home is protected in the event of a fire. If the likelihood of a fire in the neighbourhood increases, the insurance agent will likely charge higher premiums. Portfolio insurance works similarly. Events that negatively affect the market outlook affect both supply and demand. Those who need insurance are willing to pay more for it, while increased risks force insurance sellers to charge higher premiums.

As mentioned earlier, many researchers have studied the relationship between market returns and contemporaneous changes in implied volatility. For example, Cipollini and Manzini (2007) found that the VIX signals market direction with some limitations. When implied volatility is elevated, the signal is "loud and clear" – future market returns tend to be high. In times of low implied volatility, on the other hand, their model was less effective. The authors also developed and implemented an asymmetric buy-and-hold trading strategy with a three-month holding horizon for the S&P 500 index, which can be considered a proxy for large-cap stocks. This approach performed better than the long-only strategy for this index. In addition, Ding, Mazouz and Wang (2021) also investigated the predictive power of the VIX index. They regressed portfolio returns on one-day lagged VIX values and various risk factors to investigate whether the closing value of the VIX can help predict the next day's stock returns. The sensitivity to the previous day's VIX value is negative in five out of sixteen portfolios, with a statistical significance of at least ten per cent, indicating the presence of a profitable trading rule.

There also seems to be a connection between the change in implied volatility and the size factor. When the change in the VIX index is positive, the S&P 500 index outperforms the S&P 600 index, which measures the performance of US small-cap stocks. However, when the change is negative, small-cap stocks tend to outperform (Copeland & Copeland, 2016). Statistically significant relationships were also found between the cross-section of industry returns and the impact of uncertainty represented by the VIX. The authors found that different moments of the cross-sectional distribution of industry returns were related to the change in the VIX and its value (Copeland, Copeland, & Copeland, 2018).

The existing literature uses various techniques to measure the effects of changes in anxiety. For example, Cipollini and Manzini (2007) used dummy variables to quantify the impact of crises. They also ranked the changes in the VIX and then calculated the impact of each rank on the returns of the S&P 500 index. Sometimes multivariate time series models, such as vector autoregression (hereafter VAR), are also used. One such example is the work of

Durand, Lim and Zumwalt (2011). Another frequently used method, which is also used in this thesis, is the event study approach. For example, Chowdhury and Abedin (2020) applied it in studying the volatility of stock indices in the early days of the COVID-19 pandemic.

Nevertheless, its popularity, which facilitates comparability with other studies, is not the only reason for choosing it. Such an approach also allows the decomposition of returns into a "normal" model-based component and an "abnormal" component that refers to the unexplained part of the return. The ability to disaggregate was thus another essential factor in favour of this method, as the analysis of abnormal returns (hereafter AR) will be the central objective of this thesis. In other words, the essence of using the event study method is its ability to remove the normal or expected part from raw returns. This leaves the researcher with only the abnormal or event-specific component, i.e. the actual impact of the event on the valuation of the company. ARs can also be used as a basis for comparing the impact of events on different securities.

Although the literature addressing the relationship between changes in fear proxies and market returns is extensive, there seems to be a gap in how various firm-specific factors affect returns when uncertainty suddenly increases. Addressing it will be the central aim of this master thesis. Its empirical section revolves around analysing the abnormal performance of differently sorted portfolios in times of sudden uncertainty increase. Firms are classified into bivariate sorted portfolios based on size, book-to-market ratio, operating profitability, and investment, with only portfolios at the extreme ends of the distribution considered. The next step involves the determination of the event dates, where the daily changes in the VIX volatility index serve as the primary input. They are then used to estimate the individual ARs, which are later aggregated at the portfolio level. The detailed analysis of them will be the main contribution of this thesis to the existing literature, as these estimates of abnormal performance will show how individual factors affect performance during the outbreak of uncertainty. For example, do companies with higher market capitalisation survive the period immediately after the shock better than those with lower capitalisation? How do highly profitable companies fare compared to those with low earnings potential? The results are essential both for empirical research, as they represent an important cornerstone that will help to advance knowledge on how different factors influence returns in stress situations, and for practical application in the asset management industry. The latter can use the results for risk management purposes and portfolio allocation strategies, as the analysis of different event windows meets the needs of both areas.

Overall, the results suggest that when markets suddenly become more uncertain, not all assets are affected equally. When portfolios are sorted by size, large companies tend to have higher ARs than smaller companies in the first days after the event. When the book-to-market ratio is the observed sorting factor, growth stocks tend to be a safer investment than value stocks. Similarly, companies with robust operating profitability generate higher ARs than those with weak profitability. Sorting by asset growth, on the other hand, produces mixed results.

The remainder of this thesis is structured as follows: Section 1 discusses the relevant theoretical concepts on the relationship between investor sentiment and asset returns, such as the efficient market hypothesis (hereafter EMH) theory and the relationship between risk aversion and asset returns. Section 2 provides a detailed description of the VIX volatility index and describes the origin of the factors used in the analysis. Section 3 presents and discusses the data used for the analysis. Section 4 provides a detailed description of the methodology used. Section 5 presents the results. The sixth section concludes and provides directions for future research.

1 RELATIONSHIP BETWEEN INVESTOR SENTIMENT AND ASSET RETURNS

Empirical finance researchers generally agree that there is a link between investor sentiment and asset returns. Brown and Cliff (2004), for example, studied the relationship between movements in broad market indices and sentiment indicators. The latter include the American Association of Individual Investors' weekly survey, which asks randomly selected investors for market forecasts for the next six months, and the Investor Intelligence Index, whose editors scan investors' newsletters weekly to gauge their general sentiment. The authors of the study concluded that the relationship between changes in the sentiment index and market returns implies a strong contemporaneous effect.

This section takes a closer look at the relationship between uncertainty and market returns. First, the background of the EMH is presented, followed by the theoretical concepts that describe this apparent deviation from the EMH. At the same time, the factors that determine the cross-section of returns in uncertain times are discussed.

1.1 Efficient market hypothesis

The existence of ARs should also be considered from the perspective of the EMH, which postulates that a company's current share price reflects all available public and private information and denies the existence of alpha-generating opportunities. Accordingly, this theory rejects the existence of under- and overvaluation and assumes that the market value of an asset equals its fair (intrinsic) value at all times. In such an environment, consistent market outperformance should not be possible and increasing exposure to riskier assets is the only way to achieve higher nominal returns. Accepting the strong form of the EMH may be challenging, but its adjustments are more consistent with actual market behaviour. The semi-strong form incorporates publicly available information into the current market price, while the weak form only considers past prices. The latter negates the ability of technical analysis methods to produce above-market risk-adjusted returns, while the former also denies the predictive power of company fundamentals (Fama, 1970). In short, if investors' assumptions were rational, their interactions would lead to an equilibrium in which all asset prices are equal to their fundamental value. Even if a certain proportion of investors behave irrationally, the theory implies that the inefficiencies will be offset by their rational competitors through arbitrage, bringing prices back into equilibrium (Baker & Wurgler, 2006).

In summary, any unexpected event that provides new information of great economic value and changes the company's profit expectations should lead to an adjustment in the share price. The magnitude of the change should therefore serve as an estimate of the economic value of the event (Agrawal & Kamakura, 1995). Although proponents of classical finance theory assume that market participants act strictly rationally, behavioural economists often disagree and question the existence of the EMH. They believe that investors often act irrationally. A classic example of their psychological bias is over- or underreaction to new information, which opens up possibilities for empirical research. As mentioned above, the EMH assumes that new information should be fully priced into the value of the asset immediately, which means that the return pattern should resemble a random walk structure. In reality, however, there is often a serial correlation in asset returns, which contradicts the EMH. Moreover, the peculiarities of the local market structure, combined with the institutional framework and its constraints, pose an additional challenge to the implementation of the EMH (De Bondt & Thaler, 1985).

1.2 Why do share valuations fall in times of heightened uncertainty?

The next logical question is how the rise in uncertainty affects the cross-section of returns. Does the decline in sentiment affect all assets equally, or is there some heterogeneity between them? Some authors, such as Giot (2005), describe selling behaviour during periods of heightened uncertainty as "indiscriminate", implying that investors' main objective then is to shift their holdings into safe assets. Under these circumstances, the investment-specific characteristics that distinguish between good and bad in normal times are of secondary importance.

On the other hand, Baker and Wurgler (2006) suggest that a state of heightened anxiety affects stocks differently, as those that are more difficult to value and more complex to arbitrage should perform worse. Factors that the authors believe influence returns include size, age, past volatility, profitability, dividend policy and book-to-market ratio. Smaller companies are considered riskier than large ones (this phenomenon is often referred to as the size effect). Younger firms have less data, more uncertainty about their prospects and higher growth expectations, and are more vulnerable to economic downturns than their older, more established peers. As a result, they are considered riskier and should underperform in uncertain times. Past profitability and volatility should also influence the risk of an investment. Companies with higher volatility and lower profitability should perform worse than their peers on the other side of the spectrum. The book-to-market ratio should also serve as an indicator of how investors view a company's prospects. A low value of this ratio indicates distress, while a high value represents high expectations. Both sides of this spectrum should be penalised when sentiment deteriorates, as investors then prefer safer and more reliable investments (Baker & Wurgler, 2006).

Baker and Wurgler (2006) conclude that the cross-section of future stock returns depends on sentiment indicators at the beginning of the period. When uncertainty is high, future returns on stocks that are attractive to speculators tend to be low, while the opposite is true when uncertainty is low. The authors also note that conditioning on sentiment reveals several return patterns that are not visible in unconditional models.

Ding, Mazouz and Wang (2018) developed a model and formalised the intuition presented by Baker and Wurgler (2006) that assets that are prone to mood swings are also more difficult to arbitrage. Their model assumes that two assets respond differently to market sentiment and hypothesises that the sentiment-prone asset is more sensitive to changes in market sentiment than its sentiment-immune counterpart. For example, if fear spreads among investors, these assets should fall more. By decomposing investor sentiment into long- and short-term components, the authors found that the relationship between the returns of the long-short portfolio, which finances purchases of sentiment-prone stocks by shorting sentiment-immune stocks, is positive when the short-term sentiment component, defined as the incremental change in investor sentiment, increases. In other words: When investor sentiment falls (i.e. the level of fear and uncertainty rises), the returns of such a portfolio should be negative on average. The latter measure, used in the Ding, Mazouz and Wang (2018) paper, is derived from the Baker and Wurgler index, which uses the first principal component whose inputs include several variables representing investor sentiment. Several of these factors are also analysed in this thesis, albeit with a different approach (Ding, Mazouz, & Wang, 2018).

1.3 Is investors' risk aversion constant over time?

The notion of a constant expected return on an asset over time has long been disproved. The most basic form of the non-constant expected return model of assets depends on the evolution of the excess return of the market. Merton (1980) points out the difficulty of basing the estimation of expected returns on past realisations, since the assumption of constant returns requires long series to obtain accurate estimates, while the assumption of time-varying expected returns complicates the estimation further.

Merton proposes several models that attempt to estimate expected returns, including an approach that applies the concept of risk aversion. Since market exposure is by definition not risk-free, a risk-averse agent requires compensation above zero to invest his money in risky assets unless the expected market return is equal to the risk-free rate. If risk aversion is assumed to be non- constant over time, then its changes can affect the level of risk premium required. An increase (decrease) in investors' aggregate risk aversion only leads to an unchanged level of the market risk premium if aggregate risk decreases (increases).

Therefore, its increase should positively influence market risk and increase the required return (Merton, 1980).

Guiso, Sapienza, and Zingales (2018) propose two forces responsible for the change in aggregate risk aversion. It can change when either the risk aversion of the typical investor or the distribution of wealth among investors with different risk aversion changes. In this paper, the authors investigated whether the great financial crisis (hereafter GFC) of 2008 increased the risk aversion of individual investors. The survey of investors revealed that the experience of the crisis left deep scars and changed their risk perception (i.e. their risk aversion increased after the crisis).

What is the connection between time-dependant risk aversion, its consequences for the expected risk premium and this thesis? Classical empirical finance theory states that the current market value of an asset is equal to the sum of the present values of its future cash flows. Therefore, changes in market capitalisation should be exclusively related to adjustments in the company's future cash flow generation opportunities. However, changes in the company's prospects are not the only channel through which its market capitalisation is affected. This is where the degree of risk aversion of investors comes into play. Its sudden rise may not have a long-term impact on the value of the company's future cash flows, but the market capitalisation can still fall. This happens when investors' overall risk aversion increases, which translates into higher required risk premia. In other words, a sudden increase in risk aversion should contemporaneously lower asset valuations. How do investors behave in such an environment? An increase in uncertainty reduces their risk appetite – they reduce their exposure to risky assets (Aharon & Qadan, 2019).

1.4 "Flight-to-safety" as an explanatory factor for the cross-section of returns

The so-called "flight-to-safety" concept is another mechanism that could explain some of the differences in ARs in the differently sorted portfolios. The generally accepted definition of this term, which can to some extent be used interchangeably with the "flight-to-quality" concept, explains the behaviour of risk-averse investors who shift their portfolios from equities to safer asset classes in times of market turmoil. These assets include precious metals such as gold and silver, government bonds and high-quality equity investments (Sarwar, 2017).

This area has been analysed extensively, with researchers focusing on the relationships between the return dynamics of assets considered risky or safe when markets are under significant stress. For example, Jubinski and Lipton (2011) have examined the link between an increase in implied volatility, bond yields and spreads. They concluded that the response is consistent with theoretical expectations, as government and high-quality corporate bond yields fall when equity market volatility rises. Similarly, Durand, Lim and Zumwalt (2011) argue that market risk and the value premium in the Fama-French three-factor model respond to fluctuations in the VIX, suggesting that a rise in volatility is associated with a flight to safety. They use the VAR method to obtain impulse responses to test the response of factors consisting of different extreme portfolios to a one standard deviation shock to the VIX index. The cumulative impulse responses show that the changes in market risk premia caused by this shock are consistent with theoretical expectations. A rise in the VIX initially led to a fall in the market risk premium of about fifty basis points.

The reader should be aware that the terms "flight-to-safety" and "flight-to-quality", both of which refer to investors' preference for safer and higher-quality assets in stress situations, are defined somewhat differently in this thesis than in the conventional literature. These terms are used when referring to the specific relationship between portfolios, as shown by Durand, Lim and Zumwalt (2011). Their analysis concludes that a one standard deviation innovation in the relative changes of the VIX index has a positive effect on the value-growth premium (HML factor), suggesting that investors prefer value stocks over growth stocks when uncertainty increases. On the other hand, the initial response of the SMB factor is somewhat mixed. After four days, however, the size premium decreases, suggesting that investors prefer to hold shares in larger companies rather than small ones in stress situations. Therefore, portfolios consisting of large, value stocks should be considered safer than their small, growth alternatives in times of heightened uncertainty. Note that the data in the study cover the period from February 1993 to the end of July 2007 (Durand, Lim, & Zumwalt, 2011).

2 DETERMINANTS OF ASSET RETURNS

The importance of implied volatility, usually represented by the VIX index, for asset returns in modern, well-developed capital markets has already been discussed in the previous sections. The same applies to factors commonly used to explain the cross-section of asset returns. Nevertheless, little has been said about the methods used to determine said implied volatility measures and factors. This will be the main objective of this section. The first part deals with the procedure for determining the values of the VIX index. Secondly, the origin of the factors used as sorting criteria in this analysis and the method required to calculate them will be presented.

2.1 VIX index – measure of investor uncertainty and fear

When traders try to assess market conditions, they often check the value of the VIX volatility index, commonly referred to as the "fear index" and better known by its ticker symbol "VIX". It is also considered an indicator of investor sentiment. Like other indices, for example the S&P 500 and the German DAX, the VIX is also readily available and easily accessible. However, the VIX differs from the above-mentioned indices in one important respect. The latter measure the price movements of the underlying assets, whereas the VIX index measures implied volatility (Whaley, 2009).

The VIX index is a financial benchmark created using the average of the bid and ask prices of options on the S&P 500 index to provide a real-time market estimate of the expected (implied) volatility of the S&P 500 index. In other words, the VIX index value can be viewed as a projection of the expected future volatility of the S&P 500. It is intended to provide an immediate annualised estimate of the expected thirty-day volatility of the S&P 500 index following each VIX index tick. Note that it is not possible to invest directly in the VIX index. However, it is possible to gain exposure through the use of financial derivatives[1] (Whaley, 2009). In this thesis, the VIX index is used to determine event days.

At this point, the aforementioned concept of implied volatility should be addressed. Algorithms such as the famous Black-Scholes formula used for option pricing determine the theoretical option price based on the combination of the market value of the underlying security, its volatility, and other relevant factors. However, the theoretical price of an option is rarely identical with its actual market price. The latter should reflect market participants' assumptions about future volatility, while the former is usually based on volatility parameters derived from historical data. This is where the concept of implied volatility comes into play. If market liquidity is assumed, the implied volatility parameter can be determined by equating the observed market price of the option contract with the price calculated using the chosen option pricing method (Mayhew, 1995).

When the VIX Volatility index was first introduced in 1993, the CBOE had two main objectives. First, the newly introduced index was to serve as a basis for predicting short-term market volatility. The minute-by-minute readings were based on index option prices going back to early January 1986 to facilitate a comparison of the then-current VIX level with historical volatility levels. Secondly, the VIX should also serve as a benchmark for the valuation of volatility futures and options contracts. Originally, the index values were not derived from the option prices of the S&P 500 index (with the ticker symbol SPX), as is the case today, but from the option prices of the S&P 100 index (with the ticker symbol OEX). There is a simple explanation for this. OEX options were the most actively traded index options in the United States at the time. The original VIX index had another unique feature: it was based on the at-the-money (hereafter ATM[2]) prices of only eight index calls and options (Whaley, 2009).

This was appropriate as these types of options were the most actively traded at the time. On the other hand, options that were deep out-of-the-money[3] were thinly traded and also had

[1] Market participants who wish to obtain exposure to the VIX in order to, among other things, gain directional exposure and diversify their portfolio, typically buy exchange-traded notes (ETNs). The most popular are the short- and medium-term VIX tracking ETNs, which trade under the tickers VXX and VXZ, respectively (Alexander & Korovilas, 2012).

[2] If the exercise price of an option is equal to the current market price of the underlying security, it is called an at-the-money option (ATM) (Hull, 2012).

[3] If the strike price of a call option is below (above) the current market price of the underlying security, the option is called in-the-money (out-of-the-money) or ITM (OTM). For put options, the reverse logic applies. A call (put) option is called deep in-the-money (DITM) if the current market price is significantly below (above) the option's strike price. For the deep-out-of-the-money options (DOTM), the reverse is true (Hull, 2012).

large bid-ask spreads. Over the years, the parameters used to calculate the index changed mainly due to two general market trends. First, the SPX options market became the most active index options market in the United States. Second, the use of OTM and ATM put options became popular for portfolio insurance purposes, reducing the earlier problems of low liquidity. The most notable change in the index calculation method occurred in September 2003, when the CBOE decided to replace the prices of the OEX options with those of the SPX. At the same time, the basket of options used in the calculations was also expanded – they included OTM options in the index calculation model. Today, the original index, which is based on the option prices of the S&P 100 index, is traded under the ticker "VXO". The price development of this index is available from 1986 until today. This thesis uses the volatility index, known by the abbreviation VIX (Whaley, 2009).

2.1.1 How is the VIX index calculated?

The following section shows how the value of the VIX index is calculated. First, the estimator of implied volatility is needed. Equation (*1*) shows how to obtain it:

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \tag{1}$$

where T stands for the time to expiry, F corresponds to the forward index level derived from the prices of the index options, K_0 is the first strike price below the forward index level F, K_i is the strike price of the i^{th} OTM option (call if $K_i > K_0$, put if $K_i < K_0$ and both put and call if $K_i = K_0$), R represents the risk-free rate, $Q(K_i)$ is the average of the bid and ask prices for each option with strike K_i and ΔK_i is the interval of the strike price calculated using the following formula (CBOE, 2022):

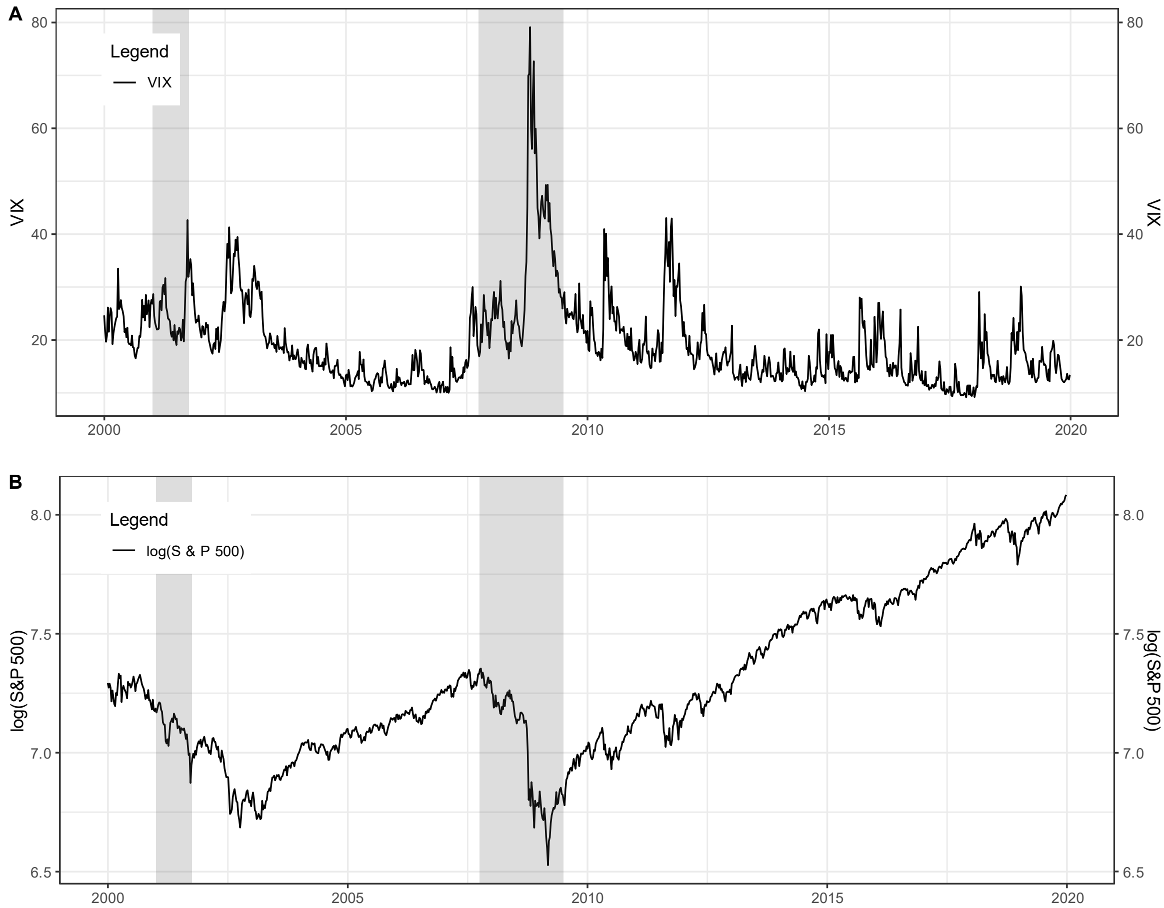
$$\Delta K_i = \frac{K_{i+1} + K_{i-1}}{2} \tag{2}$$

Finally, the value of the VIX index results from the value of σ expressed in equation (*1*), where $VIX = \sigma * 100$. The above model leads to the following conclusion: an increase (decrease) in $Q(K_i)$ should, ceteris paribus, lead to an increase (decrease) in the value of the VIX. The following section deals with the technical details of the individual components. As mentioned above, the VIX measures the expected 30-day volatility of the S&P 500 index. The risk-free rates are based on the yield curve of US Treasury securities. The yields of bonds with non-tradable maturities are extrapolated using the cubic spline model. How are the options used to calculate the VIX index selected? The model derives the value of the VIX from the SPX option chain. The selected OTM SPX put and call options are centred around the at-the-money strike price K_0. The model considers all actively traded OTM put and call options and stops only when two consecutive option contracts with a bid price of zero are found. The reader should bear in mind that the model assumes that both put and call options are considered when the strike price is equal to K_0, while for any other strike price only one option is selected (CBOE, 2022).

2.1.2 Relationship between the S&P 500 index and the VIX volatility index

Historically, the record level of the VIX was reached during the 1987 stock market crash. After that, it only came close to that level twice – at the peak of the GFC in October 2008 and in March 2020, during the chaos caused by the COVID-19 virus outbreak. Figure 1 shows the development of the VIX and the S&P 500 index during the analysed period (Whaley, 2009).

Figure 1: The CBOE Volatility Index (VIX) is often referred to as the "fear index" [4]



Source: own work.

The reader should note that the VIX value often makes large jumps when the stock indices fall. There have been many swings in its history. Apart from the spikes already mentioned, the VIX rose, for example, in response to global financial market disruptions such as the Asian currency crisis in 1997, the collapse of Long-Term Capital Management (LTCM) after Russia's default in 1998, and the European sovereign debt crisis (Whaley, 2009).

[4] The shaded area represents recession as defined by FRED (2022).

The reader should be aware that while there is a strong negative relationship between the VIX and the S&P 500, which is commonly used as a proxy for the market portfolio, this relationship is not linear. Giot (2005) calculated the relationship between the one-day relative changes of the VIX index and the S&P 100 index in three different periods: the 1994-1997 bull market with low volatility, the 1997-2000 bull market with high volatility, and the 2000-2003 bear market with high volatility. The author found a negative non-linear relationship between the returns of the S&P 100 index and the movements of the VIX index. Positive returns for the market index are associated with smaller relative changes in the value of the VIX index than negative returns for the stock index. Moreover, Giot (2005) shows that the strength of this relationship depends on the volatility environment. When volatility is low, volatility indices react more strongly to negative market returns than when volatility is high.

2.2 Origins of the factors used in the analysis

The portfolios analysed in the empirical part of the thesis are sorted by various factors that are generally assumed to explain the part of the cross-section of returns that remains unexplained after controlling for the market return factor. Two models are presented in this section. First, Fama and French's original three-factor model, followed by its extension to include profitability and investment factors. The latter considers all factors relevant to the sorting procedures in this thesis.

Although almost three decades have passed since the publication of Fama and French (1993) famous paper in which they identified five common factors for stock and bond returns – three factors for the former and two for the latter. Their findings are still valid today and are often used in empirical applications. For example, Amin, Al Mamun and Rahman (2021) studied the response of the Australian stock market to the uncertainty caused by the COVID-19 outbreak and the impact of the government's stimulus package on restoring market confidence. They used the Fama-French three-factor model alongside the Carhart four-factor model, which includes the momentum factor in addition to the original three factors, and the one-factor market model to test the robustness of the ARs. In addition, Nasri and Sutrisno (2018) applied the CAPM and the Fama-French three-factor model to the Indonesian market and examined the performance of the models. They concluded that the latter has better explanatory power. Additional robustness checks, such as using equally weighted portfolios (they originally tested the models with value-weighted portfolios) and controlling for the global financial crisis period, were consistent with the original results.

The popular Fama-French three-factor model is an extension of the CAPM model developed in the early 1970s, which relates the excess returns of equities to the sensitivity of the market risk premium. The latter model is based on the idea that there are two categories of risk in any investment – systematic and specific. The former refers to market risks that cannot be diversified away, while the latter describes company-specific risks that do not correlate with market movements and can be mitigated through diversification. Despite its relative straightforwardness, Fama and French (1993) show that the CAPM alone explains little cross-sectional variation in average returns and present an extended model that also takes into account size (market capitalisation, which is the product of share price and number of shares outstanding) and the book-to-market equity factor (BE/ME)[5], which significantly increases the explanatory power of the CAPM model (Fama & French, 1993).

There is also an economic reason for this choice. Fama and French (1995) note that a high BE/ME or low market capitalisation to book value ratio indicates a long period of poor profitability. In other words, stocks with a high BE/ME tend to be less profitable before and after the valuation date. Essentially, a low BE/ME ratio is associated with companies that on average have a high return on capital (growth stocks). In contrast, distressed companies often have a high BE/ME ratio. The sensitivity of the size factor is also related to the company's profit opportunities – the size of companies is positively related to their profits. The three-factor model for controlling size and value is formulated as follows:

$$R_{it} - R_{Ft} = \alpha_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + e_{it};\ t = 1, 2, \cdots, T, \qquad (3)$$

where $R_{it} - R_{Ft}$ denotes the excess return calculated as the difference between its nominal return and the interest rate on a one-month Treasury bill (or an alternative substitute for risk-free assets). $RMRF_t$ stands for the excess market return, which is calculated as the difference between the return of the market portfolio and the return of the risk-free proxy rate. The original paper by Fama and French (1993) used the one-month Treasury bill rate. SMB and HML denote factors reflecting size and book-to-market equity, respectively.

Fama and French (1993) constructed six portfolios based on size and book-to-market to calculate the relevant factors. Specifically, two size groups, small and large, and three book-to-market groups were formed. Changes in the SMB (small minus big) factor, also known as the size or small company effect, are intended to replicate the size-related return premia. It was originally calculated as the difference between the simple average returns of the three small stock portfolios and the three large stock portfolios. The calculated difference should be free of book-to-market factor influences and instead focus on the different return patterns of small and large stocks. The HML (high minus low) factor is used to explain the difference in returns between assets with high and low book-to-market ratios. It is calculated as the difference between the simple average of the returns of two portfolios with a high book-to-market ratio and the simple average of the returns of two portfolios with a low book-to-market ratio (Fama & French, 1993).

[5] The book-to-market ratio is one of the most important financial ratios. It compares the book value of the company, calculated using historical accounting values, with its market value. Financial analysts often refer to this ratio when determining whether the market views a particular company as growth or value oriented. A high (low) value classifies it as a value (growth) company. They can end up in a value range for a variety of reasons. Often this happens because of persistently low profitability. Therefore, a high value of BE/ME can also indicate distress. Low BE/ME values, on the other hand, are often found in companies that have shown high profitability in the past and have a bright future ahead of them (Fama & French, 1998).

However, the race to identify new relevant explanatory factors did not end with the publication of the three-factor model. Since then, many alternative models have been published. For example, a four-factor model was developed and published in 1997, adding momentum[6] to Fama and French's original three-factor model (Carhart, 1997). In empirical finance, the Carhart model is often referred to as the Fama-French-Carhart model (FFC). Interested readers should consult, for example, the paper by Durand and Rath (2015), which decomposes several factors and shows that the analysed model components are related to the financial policies of individual companies.

Note that Carhart did not discover the momentum factor. One of the first papers to look at the explanatory power of past returns was published by Jegadeesh and Titman (1993). They have shown that buying short-term winners and selling short term losers of the past, where short-term is defined as a period of one year or less, and holding the position for up to one year within the observed period leads to high abnormal performance. For example, the most thoroughly analysed strategy in their study, where stocks were selected based on their past six-month returns and held for six months, produced an average excess return of more than 12 per cent per year. The authors also find that the ability to achieve positive ARs declines after one year (Jegadeesh & Titman, 1993). In contrast, DeBondt and Thaler (1985) show that portfolios built on long-term past returns that span three to five years have high future returns, while winners with high past returns have low future returns.

Nearly two decades later, Fama and French developed and published an expanded version of the original three-factor model. The so-called five-factor asset pricing model includes profitability (RMW) and investment (CMA) factors in addition to the original three factors (Fama & French, 2015). The extended model is estimated as follows:

$$\begin{gathered} R_{it} - R_{Ft} = \alpha_i + b_i RMRF_t + s_i SMB_t + h_i HML_t + r_i RMW_t \\ + c_i CMA_t + e_{it};\ t = 1, 2, \cdots, T, \end{gathered} \tag{4}$$

where $RMRF_t$, SMB_t, HML_t are constructed in the same way as in the original by Fama and French (1993). RMW_t is the difference between the returns of diversified portfolios of stocks with high and low profitability, while CMA_t is the difference between the returns of diversified portfolios of companies with conservative and aggressive investment policies, respectively. In addition, b_i, s_i, h_i, r_i, c_i represent the corresponding coefficients or sensitivity of individual stocks (portfolios) to certain factors (Fama & French, 2015). The four sorting factors, namely size, value, investment, and operating profitability, used in this thesis were derived from these models.

[6] In the literature, the momentum factor is sometimes referred to as UMD, which stands for Up-minus-Down (Durand & Rath, 2015).

3 DATA

This section presents the data used in the empirical part of the thesis. Before the calculation of the ARs could begin, the event data had to be determined. For this purpose, the daily changes of the CBOE volatility index VIX were retrieved from the Bloomberg database. For a visual representation of the event dates, see Appendix 3. For this thesis, the daily closing values of the VIX index from the beginning of 2000 to the end of 2019 were used. Figure 1 shows its development over time.

Table 1 presents the descriptive statistics of the VIX index and its changes over the observed period. Large fluctuations can be seen, with the peak exceeding the mean by a factor of four. The maximum value corresponds to the peak of the global financial crisis at the end of 2008, while the minimum value was reached in November 2017[7].

Once the events were defined, the second step of data collection began, as the excess returns[8] of the differently sorted portfolios were needed. The return data for the portfolios analysed in this thesis, calculated as the difference between the value-weighted average return of all CRSP[9] companies traded on the NYSE, AMEX or NASDAQ and the interest rate of a one-month Treasury bill, are taken from the database published on Kenneth R. French's website (French, n.d.). Within the period studied, the lowest daily excess market return of almost minus nine per cent was achieved on 1 December 2008. This happened in the midst of a highly volatile period following the collapse of the US investment bank Lehman Brothers. As luck would have it, the day with the highest excess market return in the period under consideration fell during this period. It reached 11.4 per cent on 13 October 2008.

Table 1 shows the relevant descriptive statistics for the market excess return. The "VIX Index" line contains the descriptive statistics of the CBOE volatility index in levels, while the second line describes its relative changes. The last row contains the descriptive statistics of the market's excess return proxy in per cent. The data covers the period from the beginning of 2000 to the end of 2019 and is provided in a daily format. The latter is calculated as the difference between the market return and the risk-free rate. The Mean column indicates the average change of each variable, the Median column the mean change, SD the standard

[7] A few months after reaching the observed low, an abrupt jump in the VIX value brought the "VIX shorting era" to an abrupt end. Between the first half of 2013 and the end of 2017, the value of the VIX index fell steadily, prompting many market participants to bet against it. They built exposure by selling financial derivatives that generated positive returns when the value of the VIX index fell. Due to the negative trend of the VIX index, this strategy generated high returns. The returns of the two most popular exchange-traded funds (ETF): VelocityShares Daily Inverse VIX short-term ETF (XIV) and ProShares Short VIX short-term futures ETF (SVXY), were over a thousand per cent. However, on the fifth of February 2018, the sudden sharp rise wiped out many who had built wealth using this strategy. This event later became known as "Volmageddon" (Augustin, Cheng, & Van den Bergen, 2021).

[8] Please note that the terms "return" and "excess return" are used interchangeably and refer to the excess return of portfolios, assets or market indices unless otherwise stated.

[9] Center for Research in Security Prices.

deviation, while Min (Max) represents the lowest (largest) value and the change in the VIX index and market excess return, respectively.

Table 1: Descriptive statistics of the daily VIX index values and the corresponding daily changes

	Mean	**Median**	**SD**	**Min**	**Max**
VIX index	19.956	17.655	8.940	9.140	82.690
Changes of VIX index in %	-0.002	-0.502	7.014	-35.059	76.825
Excess Market Return in %	0.025	0.060	1.203	-8.950	11.350

Source: own work.

As defined in the introductory part of the thesis, the analysis of ARs is performed with equally weighted and double-sorted portfolios downloaded from Kenneth R. French's website. Note that only the portfolios located at the extreme ends were included in the analysis. Therefore, four portfolios are considered for each bivariate combination, resulting in a total of 24 portfolios. The data range from the beginning of 2000 to the end of 2019 and are available in daily format. The decision to omit data for the period after 2020 is based in part on the authors' belief that the highly abnormal market behaviour following the COVID-19 virus outbreak, which initially led to a sharp decline in market valuations and was followed by a strong recovery, would significantly alter the outcome of the study. Due to lack of space, the robustness test to check the validity of this assumption was not carried out and was postponed to future research (French, n.d.).

The portfolios, which consist of all securities actively traded on the NYSE, AMEX, and NASDAQ, were double sorted according to four criteria. Namely size, book-to-market ratio, operating profitability and investment. Each pair of sorting criteria thus results in 25 sorted portfolios, and as mentioned earlier, only the portfolios with a highest or lowest value of the sorting criterion are considered. Therefore, the following six sorting types were used for the analysis (French, n.d.):

- size and book-to-market,
- size and operating profitability,
- size and investment,
- book-to-market and operating profitability,
- book-to-market and investment,
- and operating profitability and investment.

The following paragraphs discuss the different types of sorted portfolios and their characteristics. The insights gained from the following discussion serve as a starting point for analysing ARs, which are compared with theoretical expectations. First, the factors of size and book-to-market ratio are addressed.

What are the causes of these factors? Empirical researchers discovered the anomaly associated with size and value long ago. The basic asset pricing model, which despite its shortcomings, still shapes the strategic decision-making process of boards today[10], assumed that the factor measuring sensitivity to market returns was sufficient to explain the cross-section of expected returns. This thesis was relatively quickly disproved. One of the most significant advances was made by the work of Banz (1981). In his study, he examined the empirical relationship between returns and the total market value of NYSE common stocks and coined the term "size effect". The latter stands for the market anomaly in which small companies tend to have higher risk-adjusted returns than large ones, even when controlling for market returns. In other words, shares of small (large) companies achieve higher (lower) returns on average than their respective market sensitivity factor would suggest.

Isolating the size effect, however, was not the only major breakthrough in empirical finance in the 1980s. Around the same time that Banz (1981) published his work, another team of researchers was investigating different market anomaly. Lanstein, Reid and Rosenberg (1985) found that statistically significant ARs can be obtained by constructing a zero-investment portfolio that finances the purchase of stocks with high book-to-market ratios ("value stocks") – i.e. stocks whose share price is low relative to the book value of their assets – by shorting stocks of companies with low book-to-market ratios ("growth stocks"). Note that the term "zero-investment portfolio" refers to a trading technique in which two tradable securities (winners and losers) are identified and the differences in their returns are calculated. The main idea behind this theoretical concept is that the investor does not need any funds of his own, as the proceeds of the short position are used to finance the purchase of the long position. In practise, however, several limitations restrict the applicability of such an approach. Among others, trading costs, short selling restrictions and intermediary margin requirements have to be considered (Alexander, 2000). Despite these limitations, the approach is frequently used in empirical applications. Interested readers should consult, for example, Chen, Huang, Wu (2021) who used the zero-investment strategy to analyse the cross-section of market returns of real estate investment trusts (REIT) and showed that such a trading strategy generates momentum in the medium term and reversals in the long term. The authors define the book value per share as the value of common equity, including intangible assets, per share.

But why do differences in size and book-to-market ratios affect returns? Chan and Chen (1991) suggested that firms with high book-to-market equity ratios should be called "marginal firms". The latter implies that the market has punished their poor performance and inefficient production processes by reducing their value. Moreover, a high book-to-market ratio suggests that they may have cash flow and debt challenges. Such companies tend to be

[10] Bancel and Mitto (2014), for example, have shown that the CAPM model is used to estimate the cost of equity by four out of five European financial experts surveyed. This is comparable to the Graham and Harvey (2001) survey, which showed that 73.5 per cent of CFOs surveyed use the CAPM to determine the cost of equity. The use of this model is not widespread only in industry but also in academia. Welch (2008) shows that three quarters of the American business professors surveyed derive the cost of equity from the CAPM model.

more sensitive to changes in the economic environment. A decline in economic sentiment, accompanied by a deterioration in credit market conditions, would likely put them in deep trouble and reduce their chances of survival. In the event of economic shocks such as that associated with the recent COVID-19 outbreak, the GFC that began in 2008, or the European sovereign debt crisis that followed a few years later, market participants initially tend to remove assets classified as risky from their books and restrict the financing options of troubled companies more than those classified as less risky. Consequently, higher risk implies higher expected returns, which partly explains the apparent difference in returns (Chan & Chen, 1991). The hypothesis that value firms suffer more than growth firms when economic sentiment deteriorates was also supported by Chen, Petkova and Zhang (2008), who pointed out that the value premium has countercyclical tendencies.

In addition, some research, such as that of Fama and French (1992), suggests that a high value of the book-to-market ratio indicates financial distress. Under this assumption, investors expect higher returns (i.e. higher cost of capital from the firm's perspective) to compensate for the risk associated with holding such assets, compared to firms with lower book-to-market ratios, which are considered more promising. The data are consistent with the theoretical assumptions. Fama and French (1993) show that firms with high book-to-market ratios tend to have persistently low profits in the five years before and after the ratio is calculated. An alternative explanation for why "value" stocks outperform "growth" stocks has been proposed by Lakonishok, Shleifer and Vishny (1994), who argue that trading strategies exploiting value anomalies outperform not because of higher risk, but because of suboptimal investor behaviour. In layman's terms, market participants extrapolate future returns from the past and therefore overestimate (underestimate) the future earning power of past winners (losers). Accordingly, low (high) future returns are a correction of the past misjudgement. Since both high and low book-to-market ratio stocks tend to be considered risky, future research should also include the performance of mid-book-to-market ratio stocks, since they are not classified as either "growth" or "value". Such a portfolio was not analysed in this thesis, as only the portfolios at the extreme ends of book-to-market ratio were considered.

The theoretical interpretation of the size effect puzzle is somewhat related to the effect described in the previous paragraph. Small companies tend to be less profitable than their large counterparts. Like stocks with high book-to-market ratios, they tend to underperform in times of economic downturn, requiring additional compensation for risk. Other hypotheses that attempt to explain their abnormal performance are the neglect factor, liquidity, and age. The first is that the cost of analysing and tracking the performance of small companies is too high, leading to neglect by large institutional investors. Second, trading small companies might be expensive due to their low trading volume. Finally, young companies have a shorter operating history, while at the same time much of their value is based on the long-term potential of their business model. Such a structure is often vulnerable to economic shocks or a tightening of credit market conditions, which increases uncertainty among investors. The last reason is also one of the explanations for the higher risk of stocks with a low book-to-market ratio compared to those with a medium ratio (Malahin & Matar, 2019). In addition, the January effect is often cited as a reason for the small companies' premium. The latter describes the anomaly that market returns tend to be high in the first month of the year. The increase in demand is often attributed to the typical December price decline, which is due to investors selling their loss-making positions to realise tax losses and offset realised gains, thereby reducing their net tax expense. Previous empirical research has shown that returns in January, especially in the early days, are much higher for small companies than for large companies (Friend & Lang, 1988).

These portfolios are drawn up each year at the end of June. The companies are sorted into five portfolios according to their size, measured by market equity (ME), and into five portfolios according to the book-to-market ratio (BE/ME). Each portfolio represents a distinct intersection of factors. While the value of companies, the market capitalisation, is readily available and can be derived from current stock market quotations, the same is not true for the book value of equity. The latter is calculated using accounting data, which is usually published quarterly. French calculates the ratio BE/ME for June of year t by dividing the value of the book value for the last fiscal year by the market value in December of year $t-1$. All firms without accessible data on market capitalisation and with a negative book value of equity are also excluded (French, n.d.). The four portfolios analysed are:

- small size, low book-to-market,
- small size, high book-to-market,
- large size, low book-to-market,
- large size, high book-to-market.

Table 2 shows the descriptive statistics of the four portfolios, sorted by size and book-to-market ratio, and estimated regression parameters of excess portfolio returns regressed on excess market returns. The latter show some general portfolio-specific dynamics. First, the mean returns of the extreme portfolios are briefly discussed. They are consistent with the expectations and assumptions of empirical finance theory. Large stocks tend to have lower average returns than their smaller counterparts, which is also the basis for the size factor developed by Fama and French. The high BE/ME portfolio representing value companies also has a higher expected return than the growth stocks represented by the low BE/ME portfolio, which is again consistent with the theoretical expectations of Fama and French (1992).

The following descriptive statistics tables also show the portfolio-specific sensitivity to the excess market return factor, denoted β, in the entire sample. A similar study was conducted by Fama and French (1993) for 25 stock portfolios sorted by size and book-to-market ratio. Note that Table 2 is similar in structure to the descriptive statistics tables of other combinations of sorting criteria in this section (French, n.d.).

Fama and French (1993) also show that large firms tend to have lower betas than smaller ones when the value quantile is fixed and that value firms have lower betas on average than growth firms when size is fixed. Surprisingly, the correlations found in this thesis differ from the original work. Results show that small growth firms have the lowest beta, while large value stocks have the highest sensitivity to market factor in the sample used in this work. In other words, the data show that large companies tend to be more sensitive to excess market returns than small ones. At this point the question arises as to the reason for this divergence, for which there are several possible explanations. First, there are many differences between the methodology used by Fama and French and the methods used in this thesis. For example, the original study used monthly returns, while this thesis uses daily percentage changes. Second, the components of the market factor are not equally weighted but are based on their value at the time the index was formed. Therefore, companies that are typically characterised as "large value stocks" drive market returns (Fama & French, 1993).

The level of concentration fluctuated considerably throughout the observation period. At the peak of the dot-com bubble, the five largest companies accounted for about 18 per cent of the total market capitalisation of the S&P 500 index. After that, the share slowly declined and reached a low of just over 15 per cent in 2015. Since then, the share of the five largest companies has steadily increased, reaching a quarter of the total market capitalisation by the end of 2019. This means that the largest companies dictate the movements and changes in the index when using value-weighted market returns as a market proxy. Since the S&P 500 index is the value-weighted index of the largest US companies, their influence is also transmitted to the excess returns of the broad market index developed and used by Kenneth R. French (Eitelman & Wharton, 2020).

The structure of the proxy for the market return factor is also reflected in the values of the coefficient of determination[11]. It should come as no surprise that the large value companies have the highest coefficient of determination, as they determine market returns. Their R^2 coefficient is over ninety per cent. On the other hand, the market factor alone explains less than sixty per cent of the variation in the portfolio of the small growth companies. The apparent heterogeneity across portfolios raises the question of whether the value weighted excess market return factor applied in Fama and French (1993) paper is appropriate for measuring beta coefficients, given the concentration and the increasingly important role of the largest index components. Since the market model used to calculate the normal return requires an approximation to the actual market, the author considered it appropriate to use the value-weighted excess return factor on the assumption that it adequately reflects the actual market situation. This assumption opens the door for future research that could use the equal-weighted excess market return as a proxy for the market portfolio to test the robustness of the results obtained in this thesis.

[11] For reasons of space, the coefficient of determination is not included in the table of descriptive statistics but can be viewed on request from the author.

Time-varying market betas could be another explanation for the differences in reported betas. Fraser and Groenewold (1999) note that the classical CAPM model assumes that parameters are stable over time. In empirical applications, however, this assumption is often rejected, leading to instability in market betas over time – hence the relatively short estimation periods in practise. Fraser and Groenewold (1999) also estimated the betas of 23 sectors using three different estimation methods: rolling regression, Kalman filter, and recursive regression, and they showed that they change over time.

The seemingly low explanatory power of market returns was one of the main reasons for the development of Fama and French's three-factor model. Fama and French (1993) hypothesised and demonstrated that the additional explanatory factors – size and value – "have the best chance of having marginal explanatory power" (Fama & French, 1993, p. 19).

Table 2 shows the four extreme portfolios mentioned above. For example, the members of the "Small ME, low BE/ME" portfolio are best described as small growth stocks. The Mean column represents the average daily nominal return of each portfolio over the observation period, which includes daily returns from the beginning of 2000 to the end of 2019 in percentage terms. SD represents the standard deviation of returns, and Min (Max) shows the lowest (highest) return of the portfolio over the observation period. β stands for the sensitivity of portfolio returns to the excess market return factor. The other tables in this section are similarly structured.

Table 2: Descriptive statistics of the portfolios sorted by size (ME) and book-to-market (BE/ME)

Portfolio	**Mean**	**SD**	**Min**	**Max**	**β**
Small ME, low BE/ME	0.047	1.396	-11.050	9.930	0.909
Small ME, high BE/ME	0.093	0.917	-6.120	6.220	0.585
Large ME, low BE/ME	0.037	1.359	-10.780	14.140	1.084
Large ME, high BE/ME	0.043	1.650	-17.670	14.740	1.179

Source: own work.

Secondly, the companies were sorted into portfolios according to size and operating profitability. Here the stocks are sorted into five portfolios by size and five by operating profitability. The latter is defined as the difference between annual sales and cost of sales, interest expense and selling, general and administrative expenses divided by book equity for the last fiscal year ending in $t-1$. Companies for which market value, book value or other accounting data point required for the calculation of operating profitability was missing were excluded from the sample (French, n.d.). According to Fama and French (2006), firms with a higher expected return on equity (net profits compared to the average book value of equity in year t) should have higher stock returns, while the opposite is true for less profitable firms. The four portfolios analysed in this section are:

- small size, low operating profitability,
- small size, high operating profitability,
- large size, low operating profitability,
- large size, high operating profitability.

Table 3 provides basic descriptive statistics on the portfolios sorted by these criteria. The attentive reader will note the discrepancy between the theoretical returns and the actual observations. Although the relationship between average returns and profitability should generally be positive[12], empirical work sometimes produces puzzling results. For example, Fama and French (2008) find that when using extreme portfolios to construct a trading strategy, average hedge portfolio returns are weakest when stocks are sorted by profitability. At the same time, they find little evidence that average returns and profitability are positively correlated when controlling for market capitalisation and book-to-market ratio.

The search for a suitable yardstick for evaluating profitability could be one reason for this behaviour. Although net profit seems to be the natural method, there is empirical evidence to contradict this. The further down the income statement one moves, the greater tends to be the deviation from true economic profitability. With this knowledge in mind, the best indicator of true economic performance seems to be gross profit (Novy-Marx, 2013, pp. 2-3).

On average, small firms with low operating profitability have generated higher nominal returns over the observed period than portfolios of small firms with high operating profitability. Note, however, that the average nominal returns of portfolios of large companies are in line with theoretical expectations. A portfolio of such companies with high operating profitability performs better than its counterpart with low operating profitability. Furthermore, the size effect is also present. Comparing size and holding operating profitability constant, the portfolio of small companies delivers higher average nominal returns than the one with large companies at both low and high operating profitability.

The last column shows the size of the market factor sensitivity parameter. Again, portfolios consisting of large firms have greater explanatory power. There is also a difference in the explanatory power of the market factor between portfolios of large companies with low and high operating profitability. The simple market model explains 91 per cent of the variation in the case of high operating profitability. In contrast, a market factor explains slightly less than 82 per cent of the fluctuations in returns for portfolios with low operating profitability. The difference in explanatory power between portfolios with low operating profitability appears to be insignificant.

[12] For more see Fama and French (2015).

Table 3: Descriptive statistics of the portfolios sorted by size (ME) and operating profitability (OP)

Portfolio	Mean	SD	Min	Max	β
Small ME, low OP	0.079	1.135	-8.520	8.380	0.739
Small ME, high OP	0.058	1.264	-8.650	9.570	0.830
Large ME, low OP	0.019	1.795	-12.730	16.300	1.351
Large ME, high OP	0.044	1.213	-11.080	14.190	0.964

Source: own work.

Next, the portfolios sorted by size and investment were analysed. In this form of sorting, companies are divided into five quintiles according to size and investment. Those with low asset growth are assigned to portfolios with low investment activity, while those with high investment activity receive the reverse treatment. Investment is defined as the annual growth rate in the balance sheet value of assets between the fiscal year ending in year $t - 2$ and the fiscal year ending in year $t - 1$ (French, n.d.). The four portfolios analysed in this section are:

- small size, low investment,
- small size, high investment,
- large size, low investment,
- large size, high investment.

The idea behind measuring the investment effect on stock returns goes back to the dividend discount valuation formula originally presented by Miller and Modigliani (1961):

$$V(t) = \sum_{\tau=1}^{\infty} \frac{E\big(Y(t+\tau)\big) - E\big(\Delta B(t+\tau)\big)}{(1+\rho)^{\tau}}, \quad (5)$$

where, $V(t)$ represents the market value of the observed firm at the end of the period, $Y(t)$ represents the income received in period t after interest and taxes, and $\Delta B(t+\tau)$ represents the change in the book value of equity between the two periods, which can be calculated as $B(t+\tau) - B(t)$. According to the authors, the change in book value can be also interpreted as an increase in the value of assets or investments. Finally, ρ stands for the discount factor. When equation (5) is divided by the book value of the company's equity, it would be reasonable to expect a positive correlation between future stock returns, the company's current book value and expected future profitability, while the correlation between future stock returns and expected growth in book value (investment) should be negative (Miller & Modigliani, 1961).

Table 4 shows the descriptive statistics of the portfolios sorted by size and investment. The average nominal portfolio returns are consistent with the theoretical expectations that companies with low investments generate higher returns than those with high investments. The size effect is also reflected in the fact that large companies deliver lower average returns to their small counterparts.

Table 4: Descriptive statistics of the portfolios sorted by size (ME) and investment (INV)

Portfolio	Mean	SD	Min	Max	β
Small ME, low INV	0.095	1.161	-9.140	8.430	0.733
Small ME, high INV	0.046	1.196	-8.290	9.520	0.810
Large ME, low INV	0.050	1.304	-10.250	14.170	1.015
Large ME, high INV	0.025	1.615	-12.560	15.720	1.254

Source: own work.

The behaviour of the book-to-market and the operating profitability of the portfolios is observed next. The following four portfolios were analysed:

- low book-to-market, low operating profitability,
- low book-to-market, high operating profitability,
- high book-to-market, low operating profitability,
- high book-to-market, high operating profitability.

Table 5 shows the descriptive statistics of a quartet of extreme portfolios, sorted by book-to-market ratio and operating profitability. The dynamics of growth versus value stock returns are consistent with the theoretical expectations of Fama and French (1992) – a portfolio of stocks with a high book-to-market ratio outperforms its counterpart with a low book-to-market ratio.

Table 5: Descriptive statistics of the portfolios sorted by book-to-market (BE/ME) and operating profitability (OP)

Portfolio	Mean	SD	Min	Max	β
Low BE/ME, low OP	0.040	1.640	-12.740	11.720	1.098
Low BE/ME, high OP	0.051	1.239	-9.980	11.710	0.981
High BE/ME, low OP	0.090	1.042	-6.980	7.300	0.691
High BE/ME, high OP	0.077	1.853	-10.580	25.490	0.830

Source: own work.

While growth stocks with high operating profitability outperform a portfolio with low profitability, the opposite is true for value stocks. There, a portfolio consisting of stocks with low operating profitability achieves a higher average return than a portfolio with companies that have high operating profitability.

In fifth place comes the analysis of the portfolios, sorted by book-to-market value and investment. In this section, the behaviour of the following four portfolios was analysed:

- low book-to-market, low investment,
- low book-to-market, high investment,
- high book-to-market, low investment,
- high book-to-market, high investment.

Table 6 shows the descriptive statistics of the portfolios sorted by book-to-market and investment criteria. The return dynamics show similarities with the returns of the portfolios sorted by size and investment. The daily return of a low-investment growth equity portfolio is, on average, 2.7 basis points higher than that of its high-investment counterpart. The difference in average returns between low and high investments is even more pronounced for value stocks. Here, a low-investment portfolio, on average, achieves five basis points higher daily return than a high-investment portfolio. Note that there is also evidence of a "value" effect. A portfolio of stocks with a low book-to-market ratio performs worse on average than a portfolio of stocks with a high book-to-market ratio, which is in line with Fama and French (1992).

Table 6: Descriptive statistics of the portfolios sorted by book-to-market (BE/ME) and investment (INV)

Portfolio	**Mean**	**SD**	**Min**	**Max**	**β**
Low BE/ME, low INV	0.056	1.408	-11.080	10.550	0.963
Low BE/ME, high INV	0.029	1.575	-10.640	11.810	1.161
High BE/ME, low INV	0.108	1.131	-7.530	6.850	0.709
High BE/ME, high INV	0.058	1.142	-8.200	8.000	0.754

Source: own work.

Finally, the extreme portfolios, sorted by operating profitability and investment, were analysed. Here, the behaviour of the following four portfolios was observed:

- low operating profitability, low investment,
- low operating profitability, high investment,
- high operating profitability, low investment,
- high operating profitability, high investment.

Table 7 offers interesting insights into the dynamics of the equity portfolio, sorted by operating profitability and investment. The highest mean return is achieved by a portfolio containing stocks with low operating profitability and low investments, followed by a portfolio consisting of stocks with high operating profitability and low investments. In contrast, the lowest average return is achieved by a portfolio consisting of stocks with low operating profitability and high investments. The operating profitability dynamics with fixed investments again show mixed results, similar to other portfolios containing this factor. On the other hand, for both portfolio types, the companies with low operating profitability achieve higher average returns than the counterpart with high operating profitability.

Note that the regression of portfolio returns on the market factor shows that, on the basis of the adjusted coefficient of determination, the portfolio containing stocks with high operating profitability and high investment is best described by Kenneth R. French's excess market return factor. The corresponding value of the coefficient is equal to 0.83.

Table 7: Descriptive statistics of the portfolios sorted by operating profitability (OP) and investments (INV)

Portfolio	Mean	SD	Min	Max	β
Low OP, low INV	0.091	1.239	-9.560	8.440	0.814
Low OP, high INV	0.032	1.475	-9.880	10.190	1.029
High OP, low INV	0.073	1.297	-9.180	10.260	0.928
High OP, high INV	0.049	1.395	-11.200	12.670	1.059

Source: own work.

In order to better understand the dynamics of returns in times of a sudden rise in fear, on which the empirical part of the thesis will focus, nominal returns on the day of the event are first analysed. The later sections of the thesis will focus on the ARs. But first, Appendix 2 shows the average nominal returns for each portfolio on the day of the event. All had negative returns on average on the day of the event, albeit with different second moments. Furthermore, the distribution of returns appears to be skewed to the left – the negative sign of the third moment dominates for the differentially sorted portfolios. The fourth moment, Kurtosis, which tests for the presence of fat tails, also suggests that the distribution of nominal returns of the portfolios on the day of the event is influenced by them (Fraser & Groenewold, 1999).

Surprisingly, the portfolio consisting of large stocks with low operating profitability shows the largest average decline of 2.3 percentage points on the day of the event. One could rightly assume that the "size effect" would favour such a portfolio. On the other side of the spectrum is the portfolio of small value companies, which on average lost "only" 1.1 percentage points of its market value. The latter means that all portfolios experienced negative nominal returns on average. However, determining the average nominal impact is not the goal of this thesis but only a step along the way. Next, the procedure for calculating ARs is presented, and then the analysis follows. The reader should note that there are a variety of factors that influence portfolio performance. Processes such as risk adjustment can alter returns and final results. Therefore, the results in Appendix 2 should be treated with caution and interpreted as a general indication of trends on event days rather than solid facts, as the above adjustments were not made.

4 METHODOLOGY

Next, the methodology used in this work will be discussed. As mentioned earlier, the core of the analysis will revolve around the event study approach. First, the methodological details will be discussed, followed by a description of the algorithm used to isolate the events. Thirdly, the specifics of the AR calculation and aggregation procedure will be discussed.

This thesis tried to answer the following questions:

1. Does a sudden sharp increase in fear, as measured by the VIX index, cause cross-sectional effects in ARs when different portfolio sorting criteria are applied. In other words, is the response to a spike in fear in terms of abnormal performance the same across all firm-specific criteria examined?
2. Are returns only affected on the day of the event or can ARs also be detected in other event windows?
3. Are the ARs achieved consistent over time or do they change from one period to another?

4.1 Event study methodology

Analysing the impact of a particular event on the prices or returns of securities is one of the main tasks of financial economists. For example, it may be of interest to measure the impact of the announcement of quarterly earnings or an unexpected monetary policy decision on stock returns. The event study approach to measuring such effects has a long tradition in the finance literature. The first academic papers using this methodology were published as early as the first half of the 20th century. One of the pioneers was Dolley (1933) who analysed the effects of stock splits on the performance of company shares (MacKinlay, 1997).

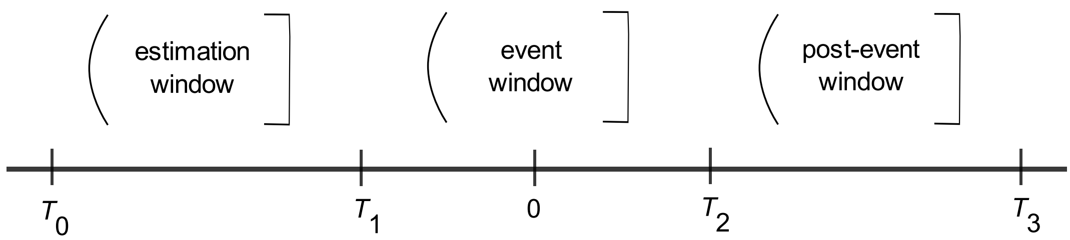
Over the years, increasing computing power simplified quantitative analysis and increased the popularity of this methodology. Another breakthrough occurred a few decades later when Fisher, Jensen, Roll (1969) published a paper whose main objective, according to Fama (1991), was to make extensive use of the newly created NYSE monthly CRSP file to demonstrate its utility and justify its future funding. Later, event studies became an important aspect of finance, especially corporate finance. Fama (1991) notes that before the popularisation of such an approach "there was little evidence on the central issues of corporate finance. Now we are overwhelmed with results, mostly from event studies ... on all counts, the event-study literature passes the test of scientific usefulness" (p. 1600). When Kothari and Warner (2004) examined articles published between 1974 and 2000 using the event study methodology, they found that more than 560 of them were published in leading financial journals.

This section discusses the approach and summarises the work of Kothari and Warner (2007), MacKinlay (1997), Campbell, Lo and MacKinlay (1997), and Brown and Warner (1980 and

1985), whose work forms the cornerstone of event impact measurement. This methodology is also used in this work. First, the general idea is presented, followed by an explanation of specific models, such as the widely used market model. Third, the general factor model is derived in matrix form, followed by a description of the AR extraction and aggregation procedures. Next, the process for obtaining the Patell and BMP test statistics, which can be applied when the returns are not normally distributed, is explained. Finally, the design of the non-parametric generalised sign test, which assumes no distribution, is shown.

To initiate an event study, three crucial components are needed. Namely, observation period, event window and estimation period. The first describes the periodicity of a variable (e.g. daily or monthly observations), the second is composed of days before and after the event (the largest event window in this thesis extends from three days before the event to three days after), and the last refers to the period before the event window in which the parameters of the chosen normal return model are estimated. The event(s) may cluster around a specific time, occur at different times, or be a combination of both. Figure 2 graphically illustrates the timeline of the event study and the location of the critical time points. The labelling used in Figure 2 is consistent with that used by MacKinlay (1997). Assuming that τ represents the time of the event, the event date is defined as $\tau = 0$. The period between $\tau = T_1 + 1$ and $\tau = T_2$ represent the event window. In other words, $L_1 = T_1 - T_0$ and $L_2 = T_2 - T_1$ are the lengths of estimation and event windows. In some cases, the time window after the event is also analysed. This is usually done in event studies with a long time horizon. However, this does not apply to this thesis, as the largest event window covers seven trading days. The latter is called the post-event window.

Figure 2: Event study timeline



Adapted from Campbell, Lo and MacKinlay (1997).

Before calculating ARs, the appropriate model for estimating normal return must be formed. Models for determining normal performance are generally divided into two subgroups. It can be either statistical or economic. The latter is based on statistical and economic assumptions, while the former is based solely on statistical assumptions. Thus, the potential advantage of economic models is the ability to reduce the uncertainty of normal returns through economic constraints. Let R_t be an $(N \times 1)$ vector of asset returns at time t. Assuming joint multivariate normality and independent and identical distribution of returns, the vector R_t has mean μ and constant variance-covariance matrix Ω (MacKinlay, 1997).

The return, R_{it}, of the observed security for period t during the event window can be calculated as:

$$R_{it} = K_{it} + e_{it}, \tag{6}$$

where K_{it} represents the normal or expected return obtained by applying the given normal return model, and e_{it} represents the unexpected or AR component. The following subsections present different approaches to calculating K_{it}. By reordering the equation (6), the AR formula can be obtained. It is equal to the difference between the actual return of the i-th asset at time t and the “normal” return. In other words, AR is equal to the unexpected change in market value at time t in the equation (7) (Kothari & Warner, 2004).

$$AR_{it} = e_{it} = R_{it} - K_{it}, \tag{7}$$

The complexity of normal return models knows no upper limit. However, the most basic ones are usually quite simple and intuitive. The most commonly used models are presented below, including the one used in the empirical part of the thesis.

4.1.1 Constant mean return model

Campbell, Lo and MacKinlay (1997) define this model as the most basic one used in the analysis of ARs. As the name implies, the mean of the i-th asset return is constant over time. Let μ be an $(N \times 1)$ vector of mean asset returns. The i-th element of such a vector, denoted by μ_i, represents the i-th mean asset return. Under this assumption, the constant mean return model can be specified as follows:

$$R_{it} = \mu_i + \xi_{it}, \tag{8}$$

where R_{it} is the i-th element of R_t or the return of security i in period t. ξ_{it} is the disturbance term with $E[\xi_{it}] = 0$ and $Var[\xi_{it}] = \sigma^2_{\xi_i}$. Note, that the term $\sigma^2_{\xi_i}$ refers to the (i, i) element of Ω. The ARs of the i-th asset at time t can be calculated as:

$$AR_{it} = \xi_{it} = R_{it} - \mu_i, \tag{9}$$

4.1.2 Market adjusted model

The next logical step in calculating ARs is to compare the performance of the security with the performance of the general market. Following Campbell, Lo and MacKinlay (1997), the market-adjusted model assumes that the expected returns for the observed securities are not necessarily constant but are the same across the market. If M represents the market portfolio of all securities, then it follows that the expected return in the event window, $E(\tilde{R}_{it})$, for each security i is equal to the expected return of the market portfolio, denoted $E(\tilde{R}_{mt})$. The actual ARs can be determined by replacing the market return with the actual return of the i-th asset and are obtained from the following equation:

$$AR_{it} = R_{it} - R_{mt}. \tag{10}$$

4.1.3 Market model

If the assumption that systemic risk equals one is relaxed and the factor β_i is allowed to vary between securities, then the basis for the market model is established. Such a model is given by:

$$R_{it} = \alpha_i + \beta_i \mathrm{R}_{mt} + \epsilon_{it}. \tag{11}$$

Here R_{mt} and R_{it} are the returns of the market and the i-th security for period t, while ϵ_{it} is the disturbance term with mean zero and variance equal to $\sigma^2_{\epsilon_i}$. In such an environment, the factor β_i represents the sensitivity of the i-th asset to the evolution of the market return. Moreover, the intercept term α_i is constant over time and varies across firms. The intercept term indicates the level of return an investor can expect when the returns of the factors are zero. Its value can either be interpreted as a risk-free interest rate or it indicates that there is still a risk factor priced in that was not considered in the model.

Practitioners typically use the S&P 500 index, the value-weighted or equal-weighted CRSP index, or another broad-based stock market index as a market portfolio proxy. In such a model, the AR of the i-th security at time t is calculated as:

$$AR_{it} = R_{it} - \alpha_i - \beta_i \mathrm{R}_{mt}, \tag{12}$$

The market model could be a further development of the concept of constant average returns, since the addition of the return component associated with the variation in market returns leads to a reduction in the variance of ARs. This can be shown algebraically by comparing the variances of the constant average return and market return models AR. The variance of the first model can be calculated as follows:

$$Var[\xi_{it}] = \sigma^2_{\xi_i} = Var[R_{it} - \mu_i] = Var[R_{it}] - Var[\mu_i] = Var[R_{it}] \tag{13}$$

while the variance of the market model AR can be derived as:

$$\begin{aligned} Var[\epsilon_{it}] = \sigma^2_{\epsilon_i} &= Var[R_{it} - \alpha_i - \beta_i \mathrm{R}_{mt}] \\ &= Var[R_{it}] - Var[\alpha_i] - {\beta_i}^2 Var[\mathrm{R}_{mt}] \\ &= (1 - R^2) Var[R_{it}], \end{aligned} \tag{14}$$

where R^2 is the coefficient of determination of the regression of the i-th securities market model and lies in the interval between zero and one. The reduction in variance is therefore represented by the following formula:

$$\sigma_{\epsilon_i}^2 = (1 - R^2)\sigma_{\xi_i}^2. \tag{15}$$

This derivation implies that the AR variance is lower or equal when using the market model than when using a simple constant mean model. Lower variance leads to higher precision of estimates. Intuition suggests that the inclusion of additional risk factors would lead to an even more precise result. However, empirical application often shows that the gain in model accuracy when adding new factors is often relatively small (Campbell, Lo, & MacKinlay, 1997).

At this point, the economic models should be briefly discussed. They differ from statistical ones primarily in that they contain additional restrictions. The two economic models most frequently used in the literature are the Arbitrage Pricing Theory (APT) and the Capital Asset Pricing Model (CAPM). In the first one, the expected return is the linear combination of several risk factors. In contrast, the second one is based solely on the expected return of the market portfolio. Two important limitations cast a shadow on the adequacy of such models. The validity of the CAPM was questioned after its weaknesses were exposed in the form of deviations from the imposed restrictions. APT models suffered from a lack of explanatory power. Once the most important factor, which behaves like a market proxy and contributes most of the variation, is controlled for, the marginal explanatory power of additional factors drops significantly. Therein lies the reason for the gradual decline in the popularity of economic models (MacKinlay, 1997).

Moreover, economic models suffer from the joint hypothesis problem. Kothari and Warner (2007) point out that when economic models are used, all tests become joint tests. By using the economic model to measure AR, the presence of AR and the correctness of the model specification are tested simultaneously. Consequently, the rejection of the null hypothesis that there is no AR could be the result of market inefficiency, an incorrect asset pricing model or both (Fama, 1991).

Finally, the reference portfolio approach should be addressed. Normal returns can be calculated from the returns of the reference portfolio, which consists of stocks filtered into different portfolios that best match the structure and characteristics of the target based on specific criteria – for example, size or book-to-market ratio. This technique does not require an estimation period, as the returns of the observed assets are compared with the performance of the reference portfolio. Interested readers should consult Barber and Lyon (1997). They analyse the empirical significance and specification of test statistics in long-term event studies aimed at identifying long-term abnormal stock returns. They show that test statistics constructed using a reference portfolio are misspecified. Furthermore, Ritter (1991) uses reference portfolios sorted by size to measure the long-term performance of IPOs.

Despite their simplicity, the quality of the results obtained with simple or sophisticated models is usually quite similar. So which model is the best? The analysis of Brown and Warner (1980) provides some valuable conclusions: "Beyond a simple, one factor market model, there is no evidence that more complicated methodologies convey any benefit. In fact, we have presented evidence that more complicated methodologies can actually make the researcher worse off ... But even if the researcher doing an event study has a strong comparative advantage at improving existing methods, a good use of his time is still in reading old issues of the Wall Street Journal to determine event dates more accurately" (p. 249). Apart from the fact that the goodness of fit is not significantly improved, the extension of the basic market model by introducing new explanatory variables carries the risk that the new regressors are not statistically significant and at the same time generate unwanted noise in the results (Becchetti, Ciciretti, & Hasan, 2009).

4.1.4 Matrix estimation of normal return models

The estimators of the parameters in the market and factor models are usually obtained using the ordinary least squares (OLS) method. The following section presents the matrix form of a general factor model. Note that the derivation of such a model is an extension of the basic market model and is based on the market model of Campbell, Lo and MacKinlay (1997). In general, the estimation period of the factor model can be expressed as follows:

$$R_i = X_i \theta_i + \epsilon_i, \tag{16}$$

where $R_i = \left[R_{i,T_0+1} \ \dots \ R_{i,T_1}\right]'$ is an $(L_1 \times 1)$ vector of returns of the estimation window and $X_i = [X_1 \dots X_N]$ is an $(L_1 \times N)$ matrix with N vectors of factor realisations, where X_1 is a vector of ones. Then, $\theta_i = [\theta_1 \ \dots \ \theta_N]'$ represents an $(N \times 1)$ vector of parameter estimates, where θ_1 is equal to the intercept term. Campbell, Lo and MacKinlay (1997) then define the OLS estimators of the factor model as follows:

$$\hat{\theta}_i = (X_i' X_i)^{-1} X_i' R_i, \tag{17}$$

$$\hat{\epsilon}_i = R_i - X_i \hat{\theta}_i \tag{18}$$

$$\sigma_{\epsilon_i}^2 = \frac{\hat{\epsilon}_i' \hat{\epsilon}_i}{L_1 - N} \tag{19}$$

$$Var\left[\hat{\theta}_i\right] = \sigma_{\epsilon_i}^2 (X_i' X_i)^{-1} \tag{20}$$

Once the parameters have been estimated, they can be used to obtain ARs. In other words, the parameters estimated during the estimation period are applied to the actual event window data. If $\hat{\epsilon}_i^*$ is taken as the $(L_2 \times 1)$ AR vector of company i in the event window, then AR can be defined as follows:

$$AR_i = \hat{\epsilon}_i^* = R_i^* - X_i^* \hat{\theta}_i, \tag{21}$$

where $R_i^* = \left[R_{i,T_1+1}^* \ldots R_{i,T_2}^*\right]'$ is an $(L_2 \times 1)$ vector of event window return realisations and X_i^* is an $(L_2 \times N)$ matrix with a vector of ones in the first column and event window realisations of factors in the other columns.

Up to this point, the general model for calculating ARs has been presented in matrix form. From this point on, however, the formulae are adapted for the market model used in this thesis to calculate the parameters for normal returns.

The sensitivity to the excess market return in the market model for the event (company) i described in equation (12) can be calculated using the OLS approach with the following equation:

$$\hat{\beta}_i = \frac{\sum_{\tau=T_0+1}^{T_1}(R_{i\tau} - \hat{\mu}_i)(R_{m\tau} - \hat{\mu}_m)}{\sum_{\tau=T_0+1}^{T_1}(R_{m\tau} - \hat{\mu}_m)^2}, \tag{22}$$

where $R_{i\tau}$ stands for the excess return of the i-th security at time τ, $\hat{\mu}_i$ is equal to its mean return, $R_{m\tau}$ denotes the market return at time τ and $\hat{\mu}_m$ stands for the average market return. Note that $\hat{\mu}_i$ and $\hat{\mu}_m$ come from the returns of the estimation window. Once the market sensitivity estimator is known, the estimation of the intercept term can begin. The latter is equal to:

$$\hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i\hat{\mu}_m. \tag{23}$$

It should be noted that the OLS estimation method produces estimators that are both efficient and consistent. The former refers to the estimator with the lowest variance among all unbiased estimators of the parameter, while the latter refers to the ability of the estimator to converge to the real value as the sample size approaches infinity (MacKinlay, 1997).

Finally, the AR corresponds to the residual term of the chosen model used to calculate the normal return – i.e. the variation in returns that cannot be explained by the model. Assuming that the market model is the model intended for the calculation of the normal return, AR equals:

$$AR_{it} = \varepsilon_{it} = R_{it} - \alpha_i - \beta_i R_{mt}, \tag{24}$$

where β_i corresponds to the market sensitivity factor from the estimation period, R_{mt} is the market return at time t in the event window and R_{it} stands for the return of asset or portfolio i at time t (MacKinlay, 1997).

Next, the variance estimator is presented. This is often used when significance tests for (cumulative) ARs are to be performed. The variance estimator can be calculated as follows:

$$\hat{\sigma}_{\varepsilon_i}^2 = \frac{1}{L_1 - 2}\sum_{\tau=T_0+1}^{T_1}(R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau})^2. \tag{25}$$

Note that using the market model, the ARs that depend on the market returns of the event window should be jointly normally distributed and have a mean of zero, while the conditional variance of the ARs has two components and is equal to:

$$\sigma^2(AR_{\iota\tau}) = \sigma_{\varepsilon_i}^2 + \frac{1}{L_1}\left[1 + \frac{(R_{mt} - \hat{\mu}_m)^2}{\hat{\sigma}_m^2}\right], \tag{26}$$

where R_{mt} stands for the actual market return at time t in the event window, $\hat{\mu}_m$ denotes the predicted market return and $\hat{\sigma}_m^2$ is the variance of the market returns. The first part of the variance is due to the future disturbances, while the second part represents the additional variance due to the sampling error in $\hat{\theta}_i$. This can be minimised by increasing the size of the estimation window – as L_1 approaches infinity, the sampling error converges to zero. Therefore, the null hypothesis that there are no ARs implies that they are distributed as follows:

$$AR_{i\tau} = N\left(0, {\sigma_i}^2(AR_{i\tau})\right). \tag{27}$$

4.1.5 How are ARs aggregated?

Identifying daily ARs is often not the primary goal of most event studies, but the first step of analysis. Once generated, they are often aggregated over a longer period to obtain cumulative abnormal returns (hereafter referred to as CAR). The latter are used to measure the impact of an event on the share price over time. The steps required to calculate CAR are described below:

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}, \tag{28}$$

where, $CAR_i(\tau_1, \tau_2)$ denotes the sample CAR of security i between τ_1 and τ_2, where $T_1 < \tau_1 \leq \tau_2 \leq T_2$. The variance of CAR is greater than or equal to the variance of a single day AR. When the length of the estimation window is small, researchers should consider the consequences of estimation error, the effects of which are shown in equation (26). However, as the size of the estimation window approaches infinity, the variance of CAR_i converges to:

$$\sigma_i^2(\tau_1, \tau_2) = (\tau_2 - \tau_1 + 1)\sigma_{\varepsilon_i}^2. \tag{29}$$

The distribution of CAR under the null hypothesis that there are no ARs is therefore given as follows:

$$CAR_i(\tau_1, \tau_2) \sim N\left(0, \sigma_i^2(\tau_1, \tau_2)\right). \tag{30}$$

Although a single event CAR can be informative, an increase in the size of the sample is necessary to draw statistically meaningful conclusions. At this point, further aggregation must be done to calculate the average cumulative abnormal return (hereafter ACAR). In general, there are two ways to do this, and both produce numerically equivalent results. Both are described by MacKinlay (1997).

One way to obtain ACARs is to first calculate the average abnormal return (hereafter referred to as AAR) for each period in the event window. If N events are included in the analysis, then the AAR of the sample for period τ is equal:

$$\overline{AR}_\tau = \frac{1}{N}\sum_{i=1}^{N}\overline{AR}_{i\tau}, \tag{31}$$

where the variance is equal[13]:

$$var(\overline{AR}_\tau) = \frac{1}{N^2}\sum_{i=1}^{N}\sigma_{\varepsilon_i}^2. \tag{32}$$

Once the estimates of the AAR for each period and the corresponding variances are calculated, the process of determining the average CAR begins. The estimate of the ACAR is calculated using the following formula:

$$\overline{CAR}(\tau_1,\tau_2) = \sum_{\tau=\tau_1}^{\tau_2}\overline{AR}_\tau, \tag{33}$$

where τ_1 and τ_2 denote the first and last periods of the event window. The variance of the ACAR is also obtained from the AARs. It can be calculated as follows:

$$var\left(\overline{CAR}(\tau_1,\tau_2)\right) = \sum_{\tau=\tau_1}^{\tau_2} var(\overline{AR}_\tau). \tag{34}$$

On the other hand, the ACARs can also be obtained by first calculating the CARs for each security and then aggregating them over time, as shown in the following equation:

$$\overline{CAR}(\tau_1,\tau_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_i(\tau_1,\tau_2). \tag{35}$$

In this case, the variance of the average CAR can be calculated as follows:

$$var\left(\overline{CAR}(\tau_1,\tau_2)\right) = \frac{1}{N^2}\sum_{i=1}^{N}\sigma_i^2(\tau_1,\tau_2). \tag{36}$$

[13] Note that the second component of the conditional variance, due to sampling error, tends to zero only when the estimation window is large. See equation (26) for more information. If the estimation window is small, additional components must be considered.

If these assumptions hold, the ACAR is normally distributed with a mean of zero and a variance equal to $var\left(\overline{CAR}(\tau_1,\tau_2)\right)$. The main objective in aggregating the ARs is to test for the existence of non-zero CARs, with the null hypothesis assuming the distribution of ARs described above[14]. Equation (37) shows the test statistic derived by Mackinlay (1997) for the test of the null hypothesis of zero ACAR:

$$\theta_i = \sqrt{N}\frac{\overline{CAR}(\tau_1,\tau_2)}{\left[var\left(\overline{CAR}(\tau_1,\tau_2)\right)\right]^{1/2}} \sim N(0,1). \tag{37}$$

This test assumes a normal distribution of returns. However, this is only the simplest of the parametric tests. There are many modifications, such as standardisation and non-parametric tests. The procedures described above assume that there is no clustering of events. In other words, the event window of event i must not overlap with the event window of event j if $i \neq j$. When events overlap, additional statistical steps must be taken to control for the side effects (MacKinlay, 1997).

4.1.6 Determining the significance of the estimates when the ARs are not normally distributed

Previously, the basic parametric test for testing the significance of AR and CAR was presented. This test assumes an identical and independent distribution of ARs. In practise, however, the assumption of normal distribution often remains unfulfilled. Therefore, alternative tests for the significance of ARs had to be developed that better describe their behaviour. An important development occurred when Patell (1976) presented his work introducing the standardisation method for ARs, in which each AR was standardised by its estimated standard deviation.

However, the non-normal distribution of ARs is not the only challenge researchers face when trying to determine the statistical significance of estimates. Another problem is event-induced volatility, defined as the increase in the cross-sectional dispersion of stock returns around the event. One of the first to discover this anomaly was Beaver (1968), who analysed the impact of the release of earnings announcements on the market value of the respective companies. His study concluded that "the magnitude of the price change in week 0 is much greater (67 per cent higher) than the average during the period without a report" (Beaver, 1968, p. 81). In other words, an event that contains information important to the company causes an increase in stock price variance around the event date compared to trading days without an event. If a researcher does not control for the increased variance, the null hypothesis of no ARs is too often rejected, leading to Type I errors[15]. One solution to this

[14] Since the actual variance cannot be observed, an estimator should be used. The reader should refer to equations (25) and (26), which show the procedure for determining the variance estimator.
[15] Type I errors refer to the false rejection of the null hypothesis, while type II errors describe the failure to reject the null hypothesis, which is in fact true.

problem is to construct the test statistic using the cross-sectional variance from the event period itself rather than the residual variance from the estimation period (Boehmer, Musumeci, & Poulsen, 1991).

This was the starting point for the research of Boehmer, Musumeci and Poulsen (1991). They simulated an event with stochastic effects and proved that most common methods too often lead to a false rejection of zero, even if an event only slightly increases the standard deviation of returns. This conclusion served as the basis for the development of a new test procedure, the BMP test statistic. The standardised cross-sectional test statistic is "a hybrid of Patell's standardised residual method and the ordinary cross-sectional approach" (Boehmer, Musumeci, & Poulsen, 1991, p. 256). Next, the procedure for obtaining the Patell test statistic is described first, followed by the presentation of the BMP statistic. These two methods are more popular today than non-standardised test procedures because they have greater statistical power and are easier to apply[16].

The basis for calculating both test statistics is the standardised cumulative abnormal return (hereafter referred to as SCAR), which compares the size of CAR with its standard deviations. Hagnäs and Pynnonen (2014) define SCAR in the following way:

$$SCAR_i(\tau_1,\ \tau_2) = \frac{CAR(\tau_1, \tau_2)}{S_{CAR(\tau_1,\tau_2)}}, \tag{38}$$

where, $SCAR_i(\tau_1,\ \tau_2)$ represents the forecast error-adjusted standard deviation of the CARs, as shown in equation (41) (Hagnäs & Pynnonen, 2014). Next, the average SCAR is calculated as the simple average of the SCAR's. The test statistic of Patell (1976), which has an asymptotic normal distribution, a mean of zero and a variance of one, can be written as:

$$t_{patell} = \sqrt{\frac{N(L_1 - 4)}{L_1 - 2}}\,\overline{SCAR}(\tau_1, \tau_2)\,, \tag{39}$$

where N is the number of events and L_1 is the size of the event window. Event-related variation is accounted for by the BMP test statistic, as explained earlier. In this case, the average SCAR is compared to the standard error of the SCARs, mitigating the problem of misspecification of the usual cross-sectional test. This results in the test statistic that can be applied when testing the null hypothesis of abnormal performance. The BMP test statistic assumes that the residuals used in the calculations are uncorrelated (Boehmer, Musumeci, & Poulsen, 1991). Hagnäs and Pynnonen (2014) specify the BMP test statistic, which is asymptotically normally distributed under the null hypothesis of no abnormal performance, with a mean of zero and a variance of one, as:

[16] Note that these tests can also be applied to clustered event days with some corrections. However, in the context of this analysis, this property is not needed, as clustering of events has been avoided by limiting their repetition to ten days, as described in the methodology section.

$$t_{BMP} = \frac{\overline{SCAR}(\tau_1, \tau_2)\sqrt{N}}{S_{SCAR(\tau_1,\tau_2)}}, \tag{40}$$

where $S_{SCAR(\tau_1,\tau_2)}$ represents the standard deviation of the SCARs, which is defined as:

$$S_{SCAR(\tau_1,\tau_2)} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(SCAR_i(\tau_1, \tau_2) - \overline{SCAR}(\tau_1, \tau_2)\right)^2}. \tag{41}$$

Please note that due to space limitations, the significance of the CARs presented in the results section is only assessed using the BMP test statistic. Patels' test statistics can be obtained from the author upon request.

To verify the results, the non-parametric test was used to further confirm the likelihood of robust results. In addition, the possible presence of outliers in the data could negatively affect the validity of the parametric test. Therefore, the non-parametric test, which is immune to these effects, was needed to provide an additional level of confidence in the obtained estimates of the ARs. The non-parametric and the parametric tests differ in their distributional assumptions. While the latter assume a normal distribution of abnormal returns, the former do not. In other words, the non-parametric tests do not have to assume a certain distribution a priori like the parametric tests. Note that the rank test and the sign test are the most commonly used in the literature (MacKinlay, 1997).

The latter assumes a binomial distribution and independence of ARs with respect to time and cross-section. The test is whether there are more positive CAR events than would normally be expected in the time frame of the event. Under the null hypothesis, the estimated and actual proportions of positive returns should be statistically indistinguishable. Cowan (1992) formulated the generalised sign test as follows.

First, the estimated proportion of positive ARs in the estimation window had to be determined using the following formula:

$$\hat{p} = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{L_1}\sum_{t=T_0}^{T_1} S_{jt} \tag{42}$$

where $\hat{p}$ is the average proportion of positive ARs (error terms) in the estimation window, N is the number of events and L_1 is the size of the event window. S_{jt} is a binary variable with the following conditions:

$$S_{jt} = \begin{cases} 1, & if\ AR_{jt} > 0 \\ 0, & otherwise \end{cases} \tag{43}$$

Finally, the test statistic is defined as:

$$Z_G = \frac{w - N\hat{p}}{\sqrt{[N\hat{p}(1-\hat{p})]}} \tag{44}$$

where w is equal to the number of events with positive CARs. In this thesis, certain assumptions were made regarding the values of $\hat{p}$. Since the estimation window is sufficiently large and the corresponding ARs – the unexplained part of the normal model – are assumed to be normally distributed, it can be assumed that the value of $\hat{p}$ is equal to half. Therefore, the formula for calculating the test statistic will be based on the following specification by MacKinlay (1997):

$$\theta_{sign-test} = \left[\frac{N^+}{N} - 0.5\right]\frac{\sqrt{N}}{0.5} \sim N(0,1), \tag{45}$$

Where $\theta_{sign-test}$ is the value of the sign test statistic, N is the number of all CARs used in the analysis and N^+ is the number of positive CARs. If the number of positive or negative CARs is large enough, the null hypothesis should be rejected with sufficient statistical significance (Cowan, 1992). In the empirical part, for reasons of space, the test is only applied to the event window that extends from the date of the event to the first days afterwards. The structure of such an event window is able to capture the ARs of the days after the event as well. As the Results section will show, there were several portfolios that had large statistically significant ARs in this event window. The null hypothesis is rejected if the absolute value of the test statistic is greater than expected at the specified confidence level. Since the empirical results presented in the last part of the thesis show that the ACAR estimates are predominantly negative, the null hypothesis states that the proportion of positive and negative ACARs is equal, while the alternative states that the proportion of negative ACARs is larger.

Note that in this thesis only the sign test is applied to test the null hypothesis of the absence of ARs. The reason for this decision stems from the various conclusions of those who have tested the performance of these tests. First, the rank test tends to produce a Type I error too often when event-induced variance is present, whereas the sign test remains correctly specified and is thus immune to such anomalies. Second, the generalised sign test is correctly specified when these two tests are confronted with outliers, while the rank test is sensitive to such data. Finally, although the rank test, when correctly specified, better evaluates the statistical significance of the estimator in the short event window, its performance decreases dramatically as the size of the event window increases. However, the generalised sign test remains well specified for the one to eleven day event window (Cowan, 1992).

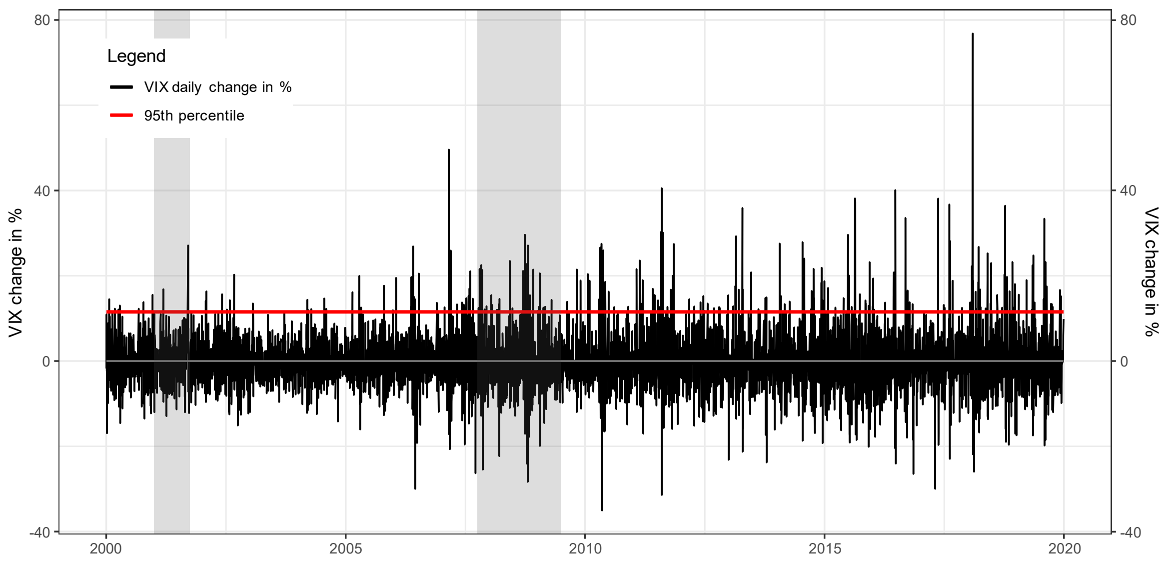
4.2 How were events defined?

Before the analysis can begin, the event dates must be defined. This section describes the algorithm used to select them. In the literature (e.g. Whaley (2009) and Boonchoo, Cheuathonghua, Padungsaksawasdi and Tongurai (2019)), the VIX index is often referred to as a proxy for investor sentiment and is unofficially known as the "fear index". Therefore, it is useful to use it for event dates selection. The following sections provide the details of the procedure described above.

First, the relative changes in the VIX index were calculated using its daily closing values. Then the daily changes were sorted according to their magnitude and the 95th percentile was used as the cut-off value. All data with larger daily changes were considered. Note that an increase in the VIX value is the result of higher implied volatility and thus higher uncertainty.

Figure 3 shows the daily changes in the VIX index over time. The red line marks the 95th percentile, which corresponded to a change of 11.5 per cent. This step required the inclusion of an additional constraint. The analysis of the changes in the VIX index and excess market returns showed that their relationship is not strictly negative. In other words, an increase in the VIX value does not necessarily lead to a negative (excess) market return. Therefore, the VIX change had to be above the 95th percentile and the excess market return had to be negative at the same time for date t to pass the first step in the selection process. The reader is reminded that these limitations prevent episodes of decreasing uncertainty from being considered as potential event data, which is in line with the research objectives of this thesis.

Figure 3: VIX daily changes in %[17]



Source: own work.

[17] The shaded areas represent the time of the crisis, as described by FRED (2022).

The second step in selecting the event dates ensured that the events were not too close together. There are two reasons for such a restriction. The first is statistical and the second is related to the structure of the research question.

Many researchers who use the event study method in their work often focus on the problems caused by the overlap of event windows. The problem of correlations in ARs often arises in event studies where data are combined across many assets or across time. In general, ARs and CARs can be assumed to be independent across securities if the events do not overlap (i.e. if there is no clustering). However, when they do overlap, the distributional results for CARs are not applicable because the covariances between ARs may be different from zero. In other words, if the events overlap but are considered independent, using the least squares method leads to unbiased coefficient estimates but possibly biased standard error estimates, which in turn leads to inaccurate inferences[18] (Campbell, Lo, & MacKinlay, 1997, p. 167).

Moreover, the thesis measures the effects of a sudden outbreak of fear. Therefore, it makes sense to disregard one event if another has recently occurred. This mechanical exclusion provides an additional safeguard against measuring the effects of the same event twice. For example, suppose that a sudden and unexpected event such as the collapse of a major financial institution, the release of weak economic data, or a troubling central bank announcement leads to a sharp increase in the VIX index, followed two trading days later by another increase of a similar magnitude when additional information about the previous event becomes known. In this case, the events are clearly linked and could therefore affect the size of the ARs. Excluding events that occur shortly after the previous ones increases the probability of their independence.

To avoid problems caused by overlapping events, some changes were made and additional filtering criteria were applied in the event selection algorithm. An event (daily VIX change above the 95th percentile) was only selected if it was not preceded by another event in the last ten trading days[19]. This technique not only prevents event windows from overlapping, but also increases the probability that they are independent of each other. The following practical example shows how filtering works. If event A occurred on day 131 and the previous event occurred 15 days ago, an event A would meet the filtering criteria. However, if the previous event occurred three days ago, such an event would be removed from the sample. Such a procedure prevents overlapping event windows, but the problem of overlapping estimation windows remains. After the filtering was completed, 127 events remained. In Appendix 3, the evolution of the VIX index over time is shown visually and

[18] Bernard (1987) describes the negative effects of cross-sectional correlation and provides a framework and some empirical evidence for assessing the extent of inference problems that arise in studies of stock returns when the data exhibit cross-sectional correlation.

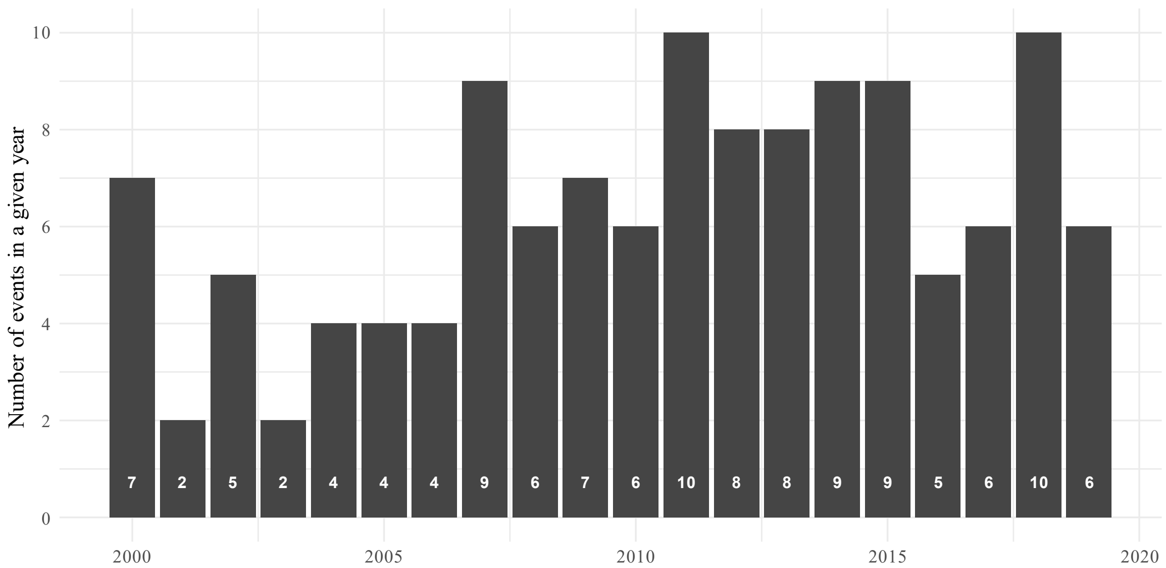
[19] This method is frequently used in the literature. Ichev and Marinč (2018), for example, filter the events according to the method of last and first occurrence. The last criterion starts with the first event in the sample, ignores all events that occur in the next 10 trading days, takes the next event in the sequence, ignores the next 10 days and so on until the entire sample is used. The first selection criterion explicitly excludes the event if another event follows within 10 days of its occurrence.

the event dates are marked. These were used in the next step when the ARs were calculated. On average, the VIX index and the excess market return changed by 16.2 and -1.9 per cent respectively on the day of the event.

Figure 4 shows the distribution of events over time (i.e. how many events took place in a given year). It can be observed that the events occur more frequently in the second half of the sample. An intuitive interpretation of this distribution would imply that markets were much calmer in the first half of the observation period and rarely surprised investors negatively.

As a robustness test, the distribution of events determined in the first step (before the restriction that there must be no similar events in the ten days before the event date) was analysed. Again, a similar pattern was observed. In the first years, the number of sudden increases in market participants' fear was lower[20].

Figure 4: Number of events in a given year



Source: own work.

4.3 How were the ARs calculated and aggregated in this thesis?

The process of converting raw returns into understandable and unambiguous ARs at the portfolio level requires several steps, which are described in this section. Once the return data was cleaned, the normal return model had to be selected. The following two arguments supported the decision to choose the simple one-factor market model among several options. First, a market model is widely accepted in the existing literature to measure normal returns in short event windows. For example, Agrawal and Kamakura (1995) used it to analyse the impact of prominent advertisers on ARs on and around the day of the event. More recently,

[20] The alternative distribution is available on request from the author.

Kotcharin and Maneenop (2020) used it to measure the impact of the COVID-19 virus on the airline industry. Secondly, the reader should be reminded of the conclusions of Brown and Warner (1980) mentioned earlier. They tested various models and concluded that the one-factor market model worked best.

Once the correct model for calculating the normal rate of return had been determined, the parameters had to be estimated. At this stage, the length of the estimation period had to be determined. Armitage (1995) suggests that in practise the estimation window is between 24 and 60 months for studies with monthly data and between one hundred and three hundred days for studies with daily data. Although intuition suggests that a longer estimation window increases the statistical power of the estimated parameters, a trade-off is that lengthening the estimation leads to the coefficients being outdated. In this thesis, the length of the estimation window was set at one hundred days.

As already mentioned in the description of the event-date algorithm, the overlap of event and estimation windows often causes problems for those conducting event studies. The latter is not addressed in the literature as often as the risk of overlapping event windows, but there is still a risk that the earlier event(s) will be included in the estimation period of the current event. Therefore, it was decided to remove the periods of previous event windows that overlap with the current estimation window in order to exclude the possibility that the estimates are influenced by previous events. As a reminder, in order to avoid overlapping event windows and to increase the likelihood that the event dates are independent, the physical constraint that no event may occur in the ten days preceding the event was set.

Although this restriction affects the size of the estimation window, which intuitively should degrade the quality of the estimators, practise shows that such a reduction does not significantly affect the statistical power of the estimators. Corrado and Zivney (1992) tested the change in various parametric and non-parametric tests at different lengths of estimation windows – including 39, 89 and 239 days. One of their main conclusions was that reducing the length of the estimation window from 239 to 89 days had almost no significant effect on the value of the t-statistic, while reducing the estimation period to 39 days resulted in only a slight deterioration in the power of the statistical tests. In view of these results, it was decided not to change the size of the event window based on the previously determined values, as the possibility of excluding the event window period(s) should not significantly reduce the statistical power of the market model estimates.

Once the data conversion was complete, the market model was estimated for each event individually. The parameters obtained were then used to calculate ARs, using the formula described in equation (24). Several different event windows were defined to test robustness and examine the behaviour of ARs in different time periods around the event date. The analysis of the abnormal performance of the event day neglecting the developments on the surrounding days is meaningless because lead-lag behaviour can occur. In other words, even though the event date is clearly defined in this thesis, it is necessary to investigate what happened to the ARs in the days around the event period. Therefore, several event windows were defined, namely (-3, 3), (-3, -1), (0, 3), (-1, 1) and the event day, each bracket representing the beginning and end of the event window period. For example, the event period defined as (-3, 3) starts three days before the event date and ends three days after. Note that the estimation period ends one day before the start of the event window. Therefore, the value of the coefficient estimates of the market model may be different in different event windows. For example, if the event window is defined as $t-1$ to $t+1$, where t is the event date, the estimation period ranges from $t-1-100$ to $t-2$. On the other hand, if the estimation window ranges from $t-3$ to $t+3$, the estimation period ranges from $t-3-100$ to $t-4$.

The (3, -1) event window is used to test whether there are statistically significant ACARs in the days leading up to the event, which could indicate that investors are able to anticipate the sudden increase in fear. The (0, 3) event window tests whether investors need only one day to price in the shock or whether they need several days to do so. The value of the ACAR in the latter event window could be compared to the AAR of the date set by the event window containing only the event date. Finally, (-1, 1) is used to check whether the days around the event provide additional information about abnormal performance in times of stress.

The ARs of the individual portfolios for each event window were then aggregated using the approach of MacKinlay (1997), where they are first summed to obtain CARs for each event, as shown in equation (28), and then averaged over all events, resulting in a CAR that can be used for analysis. This estimate can then be used to analyse the behaviour of the portfolio in the event of a sudden onset of fear, as previously defined.

Once the ACARs were available for the entire observation period, an additional robustness check was performed. First, the sample was split into two subsamples: the pre- and the post-crisis period. There are two main reasons for this step. The calculation of ARs will show whether the estimates between the two subperiods were stable and similar to the estimates for the whole period or whether they changed. In other words, the analysis will show whether the estimates of the response to the event varied between the time periods. Finally, the statistical significance of all estimated ACARs in the first days after the event described by the event window (0, 3) is tested using generalised sign test presented by Cowan (1992).

5 RESULTS

So far, the theoretical concepts and methodology have been presented. Now the focus will be on the analysis of the actual results. This section of the thesis is divided into several parts. First, the results of the method applied to the whole sample are presented. Then, the results of the AR calculation algorithm applied to the different sub-periods are discussed. Third, the expected CARs in the first three days after the event are analysed. They give an indication of what happens to the abnormal performance in the days after the event. The latter serves as an indication of what kind of abnormal performance would be expected if the asset manager missed the first event and only invested in the portfolio under study afterwards. Finally, the results of applying the non-parametric generalised sign test to test the significance of the ARs generated in the (-1, 1) event window are shown.

5.1 Analysis of the ARs for the entire observation period

The reader will see that several results are not statistically significant – i.e. the null hypothesis that there are no ARs is not rejected. In general, there are several reasons that could contribute to this. The absolute value of ACAR could be too small, the variance of ACAR could be too large, or the sample size too small. Finally, a combination of the three factors is also likely. The statistically insignificant estimates should therefore be interpreted as a general indication or tendency rather than a statistically robust estimate.

First, the extreme portfolios are analysed, sorted by size and book-to-market ratio. Table 8 shows the ACARs of each portfolio and the corresponding t-statistics obtained using the BMP method described in the methodology section. The sudden onset of fear hit the small growth stock portfolio hardest on the day of the event. While both high and low book-to-market portfolios are considered more sensitive to changes in investor behaviour than medium book-to-market stocks, the market seems to punish small value stocks less than their growth counterparts, as the negative ACAR of the small value portfolio on the day of the event is less than half that of the small growth portfolio.

Secondly, Table 8 suggests that size matters, as investors tend to penalise small stocks more than large ones when investor sentiment deteriorates. In other words, the market factor tends to explain most of the negative performance of large companies, leaving little room for abnormal movements. This is consistent with the theoretical expectation that small company shares are riskier than large company shares. The former are more exposed to the economic challenges signalled by the VIX index than the latter (Aharon & Qadan, 2019).

The results show that the abnormal performance is also detectable in the days after the event date. It appears that owners of value stocks are able to anticipate the sharp rise in the VIX index, as evidenced by the statistically significant ACAR in the days leading up to the event. Moreover, the data show that once an event occurs, investors tend to stay away from all but the large growth stocks, as the remaining stocks show at least some degree of negative abnormal performance in the days following the sudden VIX rise.

On the other hand, large value stocks seem to be relatively unaffected by the sudden surge in uncertainty on the day of the event, but investors tend to avoid them in the days that follow, as reflected in an ACAR of -12.3 basis points. Sorting companies by size and value shows that the most resilient portfolio is made up of large value stocks, which have the highest ACAR in the minus and plus one day event window, while small growth stocks suffer the most, with an average ACAR of -38.7 basis points. Recall that large value stocks were nominally the most affected during the observation period, losing on average 2.1 per cent of market capitalisation on the day of the event, while small value stocks were the least affected with an average loss of 1.1 per cent (see Appendix 2).

Table 8 shows the ACARs of the four extreme portfolios, sorted by size (ME) and book-to-market ratio (BE/ME). "Small/low" stands for the lowest and "large/high" for the highest quantile. For example: "Low ME, low ME/BM" stands for a portfolio of stocks that are in the lowest quintile for size and book-to-market ratio. The columns represent different event windows, with 0 representing the event date. CARs are expressed as percentages and statistical significance is indicated by asterisks. *** indicates a p-value of less than 0.01, ** indicates a p-value of less than 0.05 and * indicates a p-value of less than 0.10.The other tables in this section are similarly structured.

Table 8: ACARs of portfolios sorted by size (ME) and book-to-market ratio (BE/ME)

Portfolio	(-3, 3)	(-3, -1)	(0, 3)	(-1, 1)	Event day
Average Cumulative Abnormal Return					
Small ME, low BE/ME	-0.767***	-0.101*	-0.595***	-0.387***	-0.195**
Small ME, high BE/ME	-0.279*	0.121	-0.410**	-0.119*	-0.081*
Large ME, low BE/ME	-0.021	-0.068**	0.052	0.020	0.028
Large ME, high BE/ME	0.039	0.132	-0.123*	0.034	-0.010
BMP t-statistic					
Small ME, low BE/ME	-3.225	-1.299	-3.080	-2.671	-2.153
Small ME, high BE/ME	-1.736	-0.043	-2.553	-1.611	-1.637
Large ME, low BE/ME	-0.856	-1.997	0.711	0.291	-0.138
Large ME, high BE/ME	-0.505	0.792	-1.686	-0.363	-0.118

Source: own work.

Table 9 shows the abnormal performance of the portfolios, sorted by market size and operating profitability, around the event dates. The results show that the sudden onset of uncertainty inflicts the most damage in terms of abnormal performance on the portfolio of firms with small market capitalisation and low operating profitability. This is in line with expectations, as both factors exert negative pressure on such stocks. The size effect states that large stocks are considered safer in times of uncertainty, while companies with low operating profitability also tend to be more vulnerable to investor sentiment than their peers on the other side of the operating profitability spectrum. For this combination of factors, the large companies with low operating profitability perform best, achieving an ACAR of 18.2 basis points in the event window (-1, 1). In contrast, the portfolio of small stocks with low operating profitability has an average ACAR of -26.9 basis points in this event window.

Recall that investors holding large-cap stocks with low operating profitability suffered the highest losses on the day of the event, with an average nominal loss of 2.3 per cent, while those holding small-cap stocks with low operating profitability were the least affected, with an average nominal loss of 1.5 per cent of the value of their investment on the day of the event (see Appendix 2).

Table 9: ACARs of portfolios sorted by size (ME) and operating profitability (OP)

Portfolio	(-3, 3)	(-3, -1)	(0, 3)	(-1, 1)	Event day
Average Cumulative Abnormal Return					
Small ME, low OP	-0.528***	0.056	-0.565***	-0.269**	-0.155**
Small ME, high OP	-0.260*	-0.057	-0.202	-0.097	-0.067
Large ME, low OP	0.266	0.210	-0.002	0.182*	0.075
Large ME, high OP	-0.074*	-0.030*	-0.035	-0.043	-0.050**
BMP t-statistic					
Small ME, low OP	-2.690	-0.488	-3.310	-2.419	-2.415
Small ME, high OP	-1.307	-1.140	-0.931	-1.111	-0.638
Large ME, low OP	0.378	1.185	-0.934	1.317	0.406
Large ME, high OP	-1.314	-1.431	-0.448	-1.223	-2.200

Source: own work.

The final sorting of the size portfolio, shown in Table 10, includes the investment factor. As Appendix 2 shows, the large stocks portfolio with high investment had the lowest average nominal return on the event day with a loss of 2.2 percentage points, while the small stocks portfolio with low investment had the best average nominal performance of the quartet with a negative relative change of 1.5 percentage points.

When analysing the size effect, both portfolios consisting of large companies perform better than their counterparts in the small portfolios. Note that even at the ten per cent level, the results for the ACAR's of the large group do not appear to be significantly different from zero in any event window setting, but still show the tendency consistent with theoretical expectations.

When analysing the portfolios from an investment perspective, some inconsistencies become apparent. Among the portfolios of the small companies, the one with the high investments is more affected on the day of the event. However, in the days that follow, the tide turns. The results suggest that companies with lower investments have lower ACARs than the portfolio consisting of companies with high investments. This is not the case for large companies, as the those with high investments have higher ACARs both on the day of the event and the days after (note that the results for these two types are not statistically significant). Using size and investment as two sorting factors, one can conclude that large companies with high investments are the most immune to a rise in fear, generating on average six basis points of ACAR on the day of the event. On the other hand, a portfolio of small stocks with high investments generates the lowest ACAR, on average -14.3 basis points on the day of the event.

The results for the three size variants are consistent with the conclusions of other researchers. Interested readers should, for example, take a look at the paper by Copeland and Copeland (2016), which analysed the relationship between size and the VIX index. As mentioned in the previous section of the thesis, their results suggest that positive changes in the VIX index led to outperformance of large-cap stocks relative to small-cap stocks. Although the conclusions are similar, the reader should note that there are significant methodological differences between that study and this thesis. First, the proxies for portfolio size are different. Copeland and Copeland (2016) use the S&P 500 as a proxy for a large stock portfolio and the S&P 600 as a proxy for a small stock portfolio, while this thesis uses bivariate sorts that include a broader range of stocks. Second, Copeland and Copeland (2016) use monthly returns and changes in the VIX index, while the data in this study are collected daily. Finally, and most importantly, the events are defined differently. Copeland and Copeland (2016) were only interested in positive and negative changes in the VIX regardless of the magnitude of the change, whereas in this study only the most extreme positive daily changes in the VIX that were not preceded by a similar event within ten days were analysed. Despite the different approaches, the message is clear: when market uncertainty increases, investors prefer larger companies to smaller ones, as the latter seem riskier and more vulnerable to negative economic surprises.

Table 10: ACARs of portfolios sorted by size (ME) and investment (INV)

Portfolio	**(-3, 3)**	**(-3, -1)**	**(0, 3)**	**(-1, 1)**	**Event day**
		Average Cumulative Abnormal Return			
Small ME, low INV	-0.559***	0.070	-0.610***	-0.263**	-0.135*
Small ME, high INV	-0.468**	0.012	-0.455***	-0.253**	-0.143**
Large ME, low INV	0.073	0.102	-0.037	0.085	-0.018
Large ME, high INV	0.092	0.010	0.071	0.064	0.060
		BMP t-statistic			
Small ME, low INV	-2.636	-0.407	-3.329	-2.271	-1.943
Small ME, high INV	-2.412	-0.670	-2.746	-2.393	-2.075
Large ME, low INV	-0.435	0.584	-1.063	0.797	-0.885
Large ME, high INV	0.552	0.332	0.448	0.724	0.104

Source: own work.

Table 11 shows the ACARs and the corresponding test statistics of the portfolios, sorted by book-to-market ratio and operating profitability. In this particular case, the portfolio with the lowest ACAR and high statistical significance consisted of growth stocks with low operating profitability. These performed worst in all event windows. Value stocks with low operating profitability showed similar ACAR dynamics, albeit to a lesser extent. The ACAR on the event day is negative and statistically significant, while the underperformance persists on subsequent days. In general, portfolios consisting of stocks with low operating profitability underperform those with high operating profitability. This is consistent with the results in Table 9, which sorts portfolios by size and operating profitability. In addition, Appendix 2 shows that growth stocks with low operating profitability fell the most in nominal terms on the day of the event, by an average of 2.3 per cent, while value stocks with low operating profitability suffered the least. These lost an average of 1.4 per cent of market capitalisation on the day of the event.

Table 11: ACARs of portfolios sorted by book-to-market ratio (BE/ME) and operating profitability (OP)

Portfolio	(-3, 3)	(-3, -1)	(0, 3)	(-1, 1)	Event day
Average Cumulative Abnormal Return					
Low BE/ME, low OP	-0.658***	-0.056	-0.543***	-0.323**	-0.173*
Low BE/ME, high OP	-0.112*	-0.039*	-0.067	-0.071*	0.012
High BE/ME, low OP	-0.272*	0.175	-0.460***	-0.123*	-0.094*
High BE/ME, high OP	0.268	0.152	0.028	0.181	-0.060
BMP t-statistic					
Low BE/ME, low OP	-2.785	-0.792	-2.826	-2.256	-1.905
Low BE/ME, high OP	-1.326	-1.857	-0.379	-1.392	0.577
High BE/ME, low OP	-1.747	0.374	-2.877	-1.727	-1.776
High BE/ME, high OP	0.495	0.940	-0.364	0.137	-0.399

Source: own work.

When stocks are classified into portfolios based on their book-to-market ratio and investments, the results presented in Table 12 show that growth companies with low investments had the worst cumulative abnormal performance on the event date. On average, they had an ACAR of -13.9 basis points when the value of the VIX suddenly rose and an ACAR of -51.7 basis points in the days following the sudden sharp rise in the VIX.

For both value and growth equity portfolios, the size of the investment determines the ACAR – investors seem to penalise the low-investment portfolio more, which is somewhat surprising. One could argue that since a high level of investment reduces the present value of current net cash flows, investors view such companies as riskier and therefore put more selling pressure on them during periods of sharply rising uncertainty, leading to lower ACARs (Miller & Modigliani, 1961). However, if one follows the definition of sudden increase in fear used in this thesis, this theory cannot be confirmed empirically. Moreover, investors remain wary of low-investment stocks in the first days after the event, which is reflected in lower ACAR values of low-investment portfolios for both high and low book-to-market companies. Note that the ACAR values of low-investment portfolios differ only slightly, while a portfolio with low book-to-market stocks performs better in the days following the event than its value-oriented counterpart when analysing high-investment companies. Remember that the latter suffer on average the largest percentage losses in nominal terms on the day of the event, as shown in Appendix 2. On the other hand, value stocks with low asset growth perform best. These companies lose on average 1.4 per cent of their market capitalisation on the day of the event.

Table 12: ACARs of portfolios sorted by book-to-market ratio (BE/ME) and investment (INV)

Portfolio	(-3, 3)	(-3, -1)	(0, 3)	(-1, 1)	Event day
Average Cumulative Abnormal Return					
Low BE/ME, low INV	-0.593***	-0.022	-0.517***	-0.288**	-0.139*
Low BE/ME, high INV	-0.379**	-0.09	-0.254*	-0.167*	-0.039
High BE/ME, low INV	-0.309*	0.178	-0.506***	-0.163*	-0.092*
High BE/ME, high INV	-0.366*	0.018	-0.384**	-0.115*	-0.050
BMP t-statistic					
Low BE/ME, low INV	-3.251	-0.668	-3.663	-2.542	-1.938
Low BE/ME, high INV	-2.043	-1.120	-1.671	-1.692	-0.328
High BE/ME, low INV	-1.779	0.196	-2.746	-1.764	-1.572
High BE/ME, high INV	-1.950	-0.620	-2.537	-1.389	-0.470

Source: own work.

Finally, the ACAR of the stocks, sorted by operating profitability and investment, are analysed. First, however, nominal performance should be considered. In such a sorting combination, the best nominal performance was achieved by a portfolio of stocks with low operating profitability and low asset growth. Such a portfolio lost on average 1.6 per cent in value on the day of the event. On the other side of the spectrum are the companies with low operating profitability and high asset growth, which lost an average of 2.1 per cent in market value on the day of the event, as shown in Appendix 2.

Table 13 shows the results of such a sorting. Assuming that the statistically insignificant ACARs reflect the general behaviour of the analysed portfolios, it can be concluded that a high operating profitability positively influences the abnormal performance of the portfolio in times of stress. In other words, an increase in operating profitability increases a firm's expected ACAR. In contrast, an increase in asset growth lowers the expected ACAR. The results are consistent with the theory of Miller and Modigliani (1961), as they assume that the market penalises high investment growth in such an environment. Note that this is in contrast to the results presented in Table 12, where stocks were sorted by book-to-market ratio and investment. There, the dynamics of ARs showed opposite movements when the book-to-market factor was fixed.

The worst performing portfolio on the event day consists of stocks with low operating profitability and high asset growth, as an average member of such a portfolio generates an AAR of -13.4 basis points, closely followed by its low investment counterpart. Looking at a larger event window, ranging from minus three to plus three days, the worst performing portfolio consists of stocks with low operating profitability and low asset growth. Such a portfolio averaged an ACAR of -53.5 basis points in such an event window. The portfolio consisting of stocks with low operating profitability and high asset growth is the second worst performing portfolio in this environment, as its ACAR averages -40.7 basis points. Note that the former is statistically significant at the one per cent level, while the null hypothesis that the latter portfolio does not generate ARs can be rejected at a confidence level of at least ten per cent.

Table 13: ACARs of portfolios sorted by operating profitability (OP) and investment (INV)

Portfolio	**(-3, 3)**	**(-3, -1)**	**(0, 3)**	**(-1, 1)**	**Event day**
		Average Cumulative Abnormal Return			
Low OP, low INV	-0.535***	-0.668	-0.605***	-0.265**	-0.123*
Low OP, high INV	-0.407*	-1.120	-0.380**	-0.229*	-0.134*
High OP, low INV	-0.057	0.196	-0.075	-0.043	-0.008
High OP, high INV	-0.169	-0.620	-0.207	-0.083	-0.020
		BMP t-statistic			
Low OP, low INV	-2.822	-0.355	-3.610	-2.443	-1.682
Low OP, high INV	-1.842	-0.472	-2.074	-1.804	-1.819
High OP, low INV	-0.418	-0.603	-0.286	-0.662	0.013
High OP, high INV	-1.265	-0.398	-1.260	-1.112	-0.070

Source: own work.

5.2 Abnormal performance in the sub-periods before and after the GFC

The results presented in the previous section are based on a large sample of returns spanning two decades. Both the market and the economic situation have changed over this period. In other words, the original sample includes periods of economic distress and recovery as well as accommodative and restrictive monetary policies, to name a few. These different environments are reflected in the ACARs analysed earlier. The following section attempts to ensure the robustness of the estimates by splitting the data into two economically motivated sub-periods to see how the previously identified relationships hold under different conditions. In other words, the main objective of this exercise is to see if different environments affect the abnormal performance or if it remains constant over time. Note that due to space constraints, the tables of the robustness tests only contain the ACAR estimates, while the corresponding values of the test statistics have been omitted. Nevertheless, the asterisks symbolise the level of statistical significance for each estimate, as before.

To carry out the robustness check, the following steps had to be taken. First, the data was split into a pre- and a post-crisis period, with the crisis period referring to the GFC, which started in the last quarter of 2007. The decision to omit the crisis period was supported by the assumption that the small sample of events would significantly reduce the probability of obtaining statistically significant estimates. The definition of crisis was taken from the Federal Reserve Economic Data (FRED) database (FRED, 2022). The pre-crisis period extended from the last quarter of 2001, when the economic downturn that began at the turn of the millennium ended, to the third quarter of 2007. The post-crisis period began in the last quarter of 2009 and lasted until the end of the sample (FRED, 2022).

The pre-crisis period in the United States was characterised by growth in housing and financial markets, initially supported by accommodative monetary policy, which ended in the later part of the cycle when tightening began. At the end of the third quarter of 2007, the value of the S&P 500 was near its record level. Moreover, this period was also part of a larger trend known as the "Great Moderation", which refers to the era of a significant decline in the volatility of macroeconomic indicators that began in the mid-1980s. The volatility of the business cycle has decreased in many developed countries, not only in the United States (Stock & Watson, 2002).

The severe economic crisis, triggered by a combination of factors (notably the deterioration of the housing market), also led to uncertainty in the financial markets. As a result, many market indices lost a large portion of their value. For example, the Dow Jones Industrial index, one of the most watched indices in the world, fell by more than half between October 2007 and March 2009. It was not until early 2009 that investors regained their confidence and the recovery of the financial markets in the United States began. The recovery was also supported by the actions of the Federal Reserve (FED) and several U.S. government agencies, which took various emergency measures to stabilise the economy and restore confidence in the financial markets. These efforts proved successful, as evidenced by the longest bull market in U.S. history, which was only interrupted in early 2020 by the global outbreak of a pandemic caused by the COVID-19 virus (Foo & Witkowska, 2017). Note that the data sample used in this analysis ends at the end of 2019. Therefore, the impact of the sharp but short-lived economic downturn caused by COVID-19 on the abnormal performance of the different portfolios was not observed.

The post-crisis era also changed some of the established relationships in the market. One of the most obvious changes was the decline of the value premium. For many decades, value stocks had consistently outperformed growth counterparts. The devastating impact of the financial crisis changed that rule. Funds consisting of large value stocks have outperformed funds with growth stocks in only three years over the period studied: 2011, 2014 and 2016. In other words, the value premium seems to have diminished in the post-crisis period, if not disappeared altogether (Arnaut-Berilo, Bevanda, & Zaimović, 2021). The disappearance of the value premium can be observed not only in the US but also in other markets. For example, the study by Cardullo and Gagliolo (2020) shows that the value premium in the Italian market declined significantly after the GFC, but was significant and persistent in the first years of the new century.

Appendix 6, which shows the average daily nominal changes over the observed periods, provides further evidence for this thesis, as the gap between the average return of the value and growth portfolios has narrowed, if not disappeared altogether, in most cases in the post-crisis period compared to the pre-crisis period. When the performance of value and growth companies with high investments is analysed, the gap between these companies has even become negative in the post-crisis period. This suggests that growth companies with high investments have generated higher nominal returns on average in the post-crisis period. Value and growth stocks were not the only ones whose dynamics changed in the post-crisis period compared to the pre-crisis period. The reader should note that the values presented in Appendix 6 is intended as an indicator of the behaviour of the portfolio, since the returns are given in nominal terms and have not been adjusted for risk and other relevant factors. Nevertheless, the results offer some interesting insights into the dynamics of portfolios between the two eras. Value and growth stocks were not the only ones to experience changes in the post-crisis period compared to the pre-crisis period. The spread between small and large companies also narrowed post-crisis, with small (large) companies achieving lower (higher) average daily returns. At the same time, the variance of nominal returns for small companies increased.

The following tables compare the ACARs of the differently sorted bivariate abnormal portfolio returns in the pre- and post-crisis periods. Table 14 first shows the extreme portfolios sorted by size and book-to-market ratio. There are some similarities. As before, the results suggest the presence of a size effect, with portfolios of small companies being more penalised than those consisting of large market capitalisation companies.

Interestingly, large companies had positive ACARs in the pre-crisis period, supporting the thesis that investors perceive them as safer than smaller companies in times of fear. In the post-crisis period, the size relationship remained, with larger companies having higher ACARs, although sometimes not significantly different from zero. Moreover, post-crisis ACARs tended to be lower on the event day than in the pre-crisis period. For example, portfolios of large growth stocks had a positive ACAR of 14.5 basis points in the pre-crisis period and an ACAR of negative 3.8 basis points in the post-crisis period. However, the

AAR of the small value stocks portfolio on the day of the event appears to be relatively unchanged over the periods.

Analysis of ACARs in the post-event period offers further interesting insights. While small firms achieved insignificant AARs in the pre-crisis period on the day of the event, the situation changed in the first days after the event. Thereafter, investors tended to stay away from small-cap stocks – especially small-value stocks, where the ACAR almost reached a negative 71 basis points, while the portfolio of large-cap stocks seemed to perform well, as shown by the positive ACAR.

Several differences emerged in the post-crisis period. First, the statistical significance of the results decreased. Nevertheless, let us assume that the estimates reflect the actual movements. In this case, one can conclude that the size effect is still present, even if the portfolios with large value stocks suffered negative ACARs, while the ACARs of small companies were higher than in the pre-crisis period. In other words, the difference between large and small companies has narrowed after the crisis, which means that the importance of size has decreased. Before the crisis, investors favoured large companies over small ones in times of uncertainty, but after the crisis this relationship is no longer so clear. In addition, the low statistical significance could also indicate a higher variance in ACAR responses in the post-crisis period, implying that the abnormal response to the event was not as clear-cut as in the pre-crisis period.

Interestingly, portfolios consisting of small growth stocks had a statistically significant ACAR of -32.7 basis points in the days leading up to the event in the post-crisis period. A relatively controversial explanation (it contradicts the theory of efficient markets) could be that investors were able to recognise the signs of impending danger and sold such stocks in time. The fact that these types of stocks achieved the lowest ACAR in the post-crisis period is further evidence for such a theory. However, uncovering the exact reasons for this is beyond the scope of this thesis and should be left to future research. In summary, the results show that large growth stocks were the most resilient to fear outbreaks in the pre-crisis period, while large value stocks replaced them in the post-crisis period.

Table 14 shows the four extreme portfolios sorted by size and book-to-market ratio, where "small/low" is the lowest quantile and "large/high" is the highest quantile. For example: "Small ME, low BE/ME" represents a portfolio of small growth stocks. The columns stand for different event windows, where 0 stands for the event date. Pre-crisis means the ACARs of event dates that occurred in the period before the GFC outbreak, while the post-crisis section shows the ACARs in the period after the crisis, as defined by FRED (2022). The ACARs are given as a percentage. Note that the BMP t-statistic was used to test the statistical significance of the ACAR estimates. The structure of the other tables in this section is the same as in Table 14. The asterisks denote the p-value of the estimates. Note that their structure applies to all tables in this section. Furthermore, *** marks a p-value smaller than 0.01, ** a p-value smaller than 0.05 and * a p-value smaller than 0.10.

Table 14: ACARs of portfolios before and after the GFC, sorted by size (ME) and book-to-market ratio (BE/ME)

Portfolio	(-3, 3)	(-3, -1)	(0, 3)	(-1, 1)	Event day
Pre-crisis					
Small ME, low BE/ME	-0.720*	-0.046	-0.647**	-0.379*	-0.020
Small ME, high BE/ME	-0.775**	-0.044	-0.707***	-0.33*	-0.065
Large ME, low BE/ME	0.140	-0.113	0.251*	0.200**	0.145**
Large ME, high BE/ME	0.292	0.149	0.142	0.158	0.261
Post-crisis					
Small ME, low BE/ME	-0.782***	-0.327**	-0.339	-0.438**	-0.198*
Small ME, high BE/ME	-0.214	-0.055	-0.159	-0.121	-0.061
Large ME, low BE/ME	-0.078	-0.060*	-0.002	-0.018	-0.038**
Large ME, high BE/ME	-0.035	0.061	-0.135	0.060	0.072*

Source: own work.

Next, the abnormal performance of the portfolios before and after the crisis, sorted by the factors of size and operating profitability, is discussed. The corresponding results are presented in Table 15. They show that the magnitude and (in some cases) the direction of ACARs changed from one period to another. Prior to the crisis, companies with large market capitalisation and low operating profitability had the highest ACARs, which were 33.6 basis points above the estimates of the normal return model on the event day. This is somewhat surprising, as one would expect investors to punish them more than their peers with high operating profitability, as the latter are theoretically considered safer in times of economic challenges signalled by the VIX index. In the days following the event, the abnormal performance of this portfolio was negative because the ACAR estimate of the event window (0, 3), although not statistically significant, was lower than on the day of the event. In other words, this pattern suggests that investors find them attractive on the first day, but their initial attractiveness decreases in the days after the event.

This pattern is also representative of other portfolios. The results show that most of the negative abnormal performance comes not from the first day, which seems to be well explained by the normal return model, but from the following days. For example, the ACAR estimate of the portfolio consisting of small companies with low operating profitability was not statistically significant at the beginning, but on the following days represented by the event window (0, 3) it performed worse than under normal circumstances. Consequently, the ACAR estimate, which is 73.2 basis points below zero, positions this portfolio type as the worst to hold when analysing size and operating profitability in the pre-crisis period. At the same time, the comparison of the (-1, 1) event window ACAR shows that, with the exception of the portfolio of large and highly profitable companies, all achieved a similarly negative ACAR, which is also statistically significant at the ten per cent level.

In the post-crisis period, the decline in statistical significance of the estimates can be observed. However, assuming that these estimates reflect actual movements, some relationships remained. For example, small firms with low operating profitability continued to be the most affected, while they also had a statistically significant negative AR on the day of the event. The remaining three initially appeared to be relatively unaffected, with the portfolio of highly profitable large companies being the least affected.

What about the developments after the event day? The results show that negative ACARs at the time of the pre-crisis event increased over the years, becoming on average much closer to zero and even positive in the case of portfolios consisting of small companies with high operating profitability. In other words, the initial impact of the shock dissipated and the cumulative abnormal performance was positive on average three days after the event. The decline in response to the sudden increase in uncertainty when stocks are sorted by size and operating profitability is also evident in the largest event window analysed (-3, 3). For small firms with low operating profitability, the ACAR estimate increased by 37.7 basis points in the post-crisis period. The results for the post-crisis period also show that the ACARs of the (-1, 1) are not significantly different from zero, except for the portfolio consisting of small stocks with low operating profitability, which has an ACAR of -34.4 basis points and also had the lowest ARs in the post-crisis period. Nevertheless, the ACAR estimate of the event window (0, 3) is still far above the pre-crisis estimate.

Table 15: ACARs of portfolios before and after the GFC, sorted by size (ME) and operating profitability (OP)

Portfolio	(-3, 3)	(-3, 0)	(0, 3)	(-1, 1)	Event day
Pre-crisis					
Small ME, low OP	-0.846**	-0.080**	-0.732***	-0.312*	-0.044
Small ME, high OP	-0.579*	-0.089*	-0.484*	-0.329*	0.024
Large ME, low OP	0.132	-0.040	0.168	0.368*	0.336**
Large ME, high OP	0.042	0.043	-0.007	-0.091	-0.081*
Post-crisis					
Small ME, low OP	-0.496*	-0.142*	-0.310	-0.344*	-0.163*
Small ME, high OP	-0.086	-0.253	0.173	-0.008	-0.038
Large ME, low OP	0.116	0.120	-0.044	0.095	-0.056
Large ME, high OP	-0.073*	-0.069*	0.007	0.002	-0.008

Source: own work.

Overall, a portfolio of small stocks with low operating profitability seems to be the least attractive combination in the pre-crisis period, followed by its counterpart with high operating profitability. The reader should bear in mind that small stocks with low operating profitability generate higher nominal returns than their counterparts with high operating profitability, as shown in Table 3. Furthermore, as shown in Appendix 6, the average nominal return on portfolios of small firms has declined in the post-crisis period and the gap between large and small firms has narrowed, indicating a reduction in the size premium.

When analysing the ACARs for the portfolios sorted by size and investment for the entire period, the small stocks had on average lower ACAR than the large stocks. However, the analysis of the investment components did not reveal any clear patterns, as shown in Table 16. When the ACARs are split into two sub-periods, the size effect is still present as the small companies tend to have lower ACARs than their large counterparts in both the pre- and post-crisis periods.

The analysis of the investment component is a bit more complicated, as companies with high investments performed better than companies with low investments in the years before the crisis. For example, the portfolio of small companies with high investments achieved a 31.7 basis points higher ACAR than its low-investment counterpart in the early days after the event, while a portfolio of large companies with high investments achieved an ACAR that was 54.3 basis points higher than in normal times. As in the previous sorting example, most of the abnormal performance came from the days after the event in the pre-crisis period. The ACAR of the small investment portfolio is almost eighty basis points lower in the event window, which covers the first few days after the event, than on the day of the event itself. The small stocks with high investments rank second to last with an average ACAR of -58.3 basis points in the first days after the event. The group of large stocks with the highest asset growth performed best, as reflected in a high and positive ACAR.

After the GFC, small companies maintained the existing pattern. In the event window (0, 3), the portfolio of small firms with high investments had a 14.4 basis points higher ACAR than its counterpart with low investments. However, this is not the case for large companies. There, those with low asset growth achieved a higher ACAR in the same event window. The GFC also changed the preferred type of holdings in the group during periods of heightened uncertainty, as the large companies with the highest asset growth were no longer those with the highest ACAR. They were replaced by their low-investment counterparts, which had an ACAR of 1.6 basis points in the post-crisis period. Note that the estimate is not significantly different from zero.

Comparing the ACAR estimates of the two periods, one can again observe the decline in average abnormal performance after the event. While the worst performing portfolio had an ACAR of -90 basis points in the pre-GFC (0, 3) event window, the ACAR of the worst performer after the GFC was -31.4 basis points in the same event window. The weaker reaction to the sudden increase in the VIX is also reflected in the statistical significance of the estimates. The latter decreased after the GFC, as none of the analysed portfolios differed from zero in the event window (0, 3), even at a significance level of ten per cent.

Table 16: ACARs of portfolios before and after the GFC, sorted by size (ME) and investment (INV)

Portfolio	(-3, 3)	(-3, -1)	(0, 3)	(-1, 1)	Event day
Pre-crisis					
Small ME, low INV	-1.029**	-0.084	-0.900***	-0.388*	-0.109*
Small ME, high INV	-0.733*	-0.130	-0.583**	-0.365*	-0.017
Large ME, low INV	-0.060	0.102	-0.146**	-0.053	-0.046
Large ME, high INV	0.385**	-0.188	0.543***	0.325**	0.283***
Post-crisis					
Small ME, low INV	-0.525*	-0.164*	-0.314	-0.322*	-0.110
Small ME, high INV	-0.340	-0.128	-0.170	-0.257*	-0.136*
Large ME, low INV	-0.032	-0.051	0.016	0.090	0.017
Large ME, high INV	0.003	0.073	-0.064*	-0.016	-0.082**

Source: own work.

The allocation of the analysed stocks into portfolios based on book-to-market ratio and operating profitability showed that the book-to-market ratio did not provide an obvious pattern, while companies with low operating profitability had a lower ACAR in both value and growth stock portfolios, as can be seen in Table 17.

When the CARs are aggregated based on the pre- and post-crisis subperiods, the results in Table 17 show that value stocks with high operating profitability achieved the lowest ACAR both on the day of the event, with an average of -11.9 basis points, and in the event window covering the first days after the event, with an ACAR of -76 basis points. In the latter period, value stocks with low operating profitability followed closely with an ACAR of -62.9 basis points. The portfolio with the highest ACAR in the pre-crisis period consisted of growth stocks with high operating profitability.

The data again suggest that most of the abnormal performance occurred outside the event day. An example of the worst performing portfolio consisting of highly profitable value stocks has already been shown, but its counterpart with low operating profitability also shows similar dynamics. On the day of the event, the ACAR appears to be zero, while in the first days after it falls to almost -63 basis points.

After the GFC, this pattern changed. Value stocks with high operating profitability became the "safe haven" in times of stress, as their CAR averaged 43.9 basis points in the days after the event. On the other hand, growth stocks with low operating profitability fell out of favour with investors as they had the lowest ACAR in the post-crisis period. The latter corresponded to -39.8 basis points in the event window (0, 3), with a p-value of less than five per cent. Recall that growth stocks with low operating profitability had the lowest average nominal returns of -2.3 per cent on the day of the event (see Appendix 2), while value stocks with low operating profitability were the least affected in nominal terms, as their average change in market capitalisation on the day of the event was minus 1.4 per cent.

Comparing the two periods, one can draw similar conclusions as before. The statistical significance of the ACAR estimates decreased after the GFC, as only portfolios of growth stocks with low operating profitability provided statistically meaningful estimates. The ACAR estimates were also closer to zero. For example, analysis of the first days after the event shows that the ACAR of the portfolio consisting of value stocks with low operating profitability increased from negative 62.9 basis points before the crisis to negative 23 basis points after the crisis.

Table 17: ACARs of portfolios before and after the GFC, sorted by book-to-market ratio (BE/ME) and operating profitability (OP)

Portfolio	(-3, 3)	(-3, -1)	(0, 3)	(-1, 1)	Event day
			Pre-crisis		
Low BE/ME, low OP	-0.742*	-0.245	-0.456*	-0.140	0.119
Low BE/ME, high OP	-0.210	-0.084	-0.126	-0.101	0.127*
High BE/ME, low OP	-0.651*	-0.003	-0.629***	-0.181	-0.003
High BE/ME, high OP	-0.713*	0.110	-0.760**	-0.666***	-0.119*
			Post-crisis		
Low BE/ME, low OP	-0.710**	-0.210*	-0.398*	-0.444**	-0.259**
Low BE/ME, high OP	-0.107	-0.138***	0.053	-0.052	0.010
High BE/ME, low OP	-0.266	-0.034	-0.230	-0.179	-0.086
High BE/ME, high OP	0.368	-0.197	0.439	0.418*	0.029

Source: own work.

Reversals have been observed not only in stocks sorted by book-to-market ratio and operating profitability, but also in those sorted by investment. Recall that when analysing a whole period, value stocks with high investments had the highest ACAR on the day of the event, while growth stocks with high investments performed best in the first days after it.

Table 18 shows the ACARs before and after the crisis for these portfolios. Before the onset of the financial crisis, high-investment growth stocks had the highest ACAR on the day of the event (33.1 basis points), while low-investment value stocks performed the worst (their ACAR was -10.9 basis points). Interestingly, the positive ACAR of the winner portfolio evaporated as soon as the next few days were considered. The loser portfolio, on the other hand, actually extended its losses in the days following the initial unexpected rise in uncertainty. In the event window, which also considers the days after the event day, the winner remained the same with an almost identical ACAR. The loser portfolio consisted of value stocks with low investments, which had an average ACAR of -83.7 basis points in the days after the event.

The portfolio that performed worst before the crisis, i.e. the portfolio with the low-investment companies, was the most resilient after it. In the days after the event, the high-investment growth stocks achieved the highest ACARs, while their value-oriented counterparts became the second-best alternative for investors. Note that not all post-event ACARs are statistically insignificant. The reader should recall that throughout the entire period, high-investment growth stocks generated the lowest average nominal returns on the day of the event, while low-investment value stocks generated the highest (see Appendix 2). The event day ACAR estimates in the post-crisis period also show a clear initial preference for value stocks, as they have higher ACARs than their growth counterparts. On subsequent days, the relationship remains unchanged for low-investment companies, while both growth and value companies with high investments end up with the similar ACAR estimate. In the pre-crisis period, the dynamics were different. There was no clear pattern on the day of the event. However, the analysis of the (0, 3) event window shows that for both high and low investment companies, value is more penalised than growth.

Table 18: ACARs of portfolios before and after the GFC, sorted by book-to-market ratio (BE/ME) and investment (INV)

Portfolio	(-3, 3)	(-3, -1)	(0, 3)	(-1, 1)	Event day
Pre-crisis					
Low BE/ME, low INV	-0.728*	-0.076	-0.630**	-0.340*	-0.060
Low BE/ME, high INV	-0.314	-0.299	0.002	0.032	0.331***
High BE/ME, low INV	-0.898**	-0.026	-0.837***	-0.299*	-0.109*
High BE/ME, high INV	-0.520	-0.230	-0.302	-0.076	0.194
Post-crisis					
Low BE/ME, low INV	-0.733***	-0.283**	-0.341*	-0.387**	-0.161*
Low BE/ME, high INV	-0.374*	-0.123	-0.191	-0.232*	-0.154**
High BE/ME, low INV	-0.312	-0.065	-0.250	-0.194	-0.039
High BE/ME, high INV	-0.297*	-0.095	-0.194	-0.129	-0.063

Source: own work.

Finally, the ACARs of the two sub-periods are analysed for portfolios sorted by operating profitability and investment activity. Table 19 shows the results for different event windows of each portfolio before and after the crisis. When the entire data sample was used for the calculations, portfolios consisting of companies with high operating profitability had higher ARs in all event windows than portfolios consisting of stocks with low operating profitability. In contrast, there was no such pattern when stocks were considered on the basis of their investment activity (see Table 13). Moreover, the portfolio of companies with low operating profitability and high investment activity recorded the worst nominal return on average on the event date, closely followed by its counterpart with high operating profitability. Compared to the four portfolios sorted by these criteria, the portfolio of stocks with low operating profitability and low investment activity lost the least in nominal terms on average on the event day, namely 1.6 per cent (see Appendix 2).

In this sorting example, elements of alternating patterns can again be observed. But more on this later. First, the pre-crisis results are analysed. Interestingly, all but one portfolio achieved a positive ACAR value on the day of the event, while the negative one was close to zero. The reward for the highest ACAR value on the day of the event goes to the portfolio of companies with high operating profitability and high investment, as it achieved an average ACAR value of 19.2 basis points. In contrast, the lowest ACAR value on the day of the event was achieved by a portfolio of companies with low operating profitability and low investment. After the crisis, however, the positive ACAR values on the event day at least declined, if not turned negative. The worst performing portfolio then consisted of stocks with low operating profitability and high investment. The average CAR of the best performing portfolio before the crisis turned negative and averaged minus five basis points, although this is not statistically significant.

Although portfolios performed well from the ARs' perspective on the day of the event in the years leading up to the GFC, performance deteriorated on average in the days following. For example, the worst performing portfolio had an ACAR of -74.6 basis points in the days after the event, while only the winning portfolio (high operating profitability and high investment) maintained a positive ACAR, although the null hypothesis of no ACAR could not be rejected. After the GFC ended, the worst performing portfolio in the days following the event consisted of stocks with low operating profitability and low investment – similar to the pre-crisis period. On the other hand, the portfolio of companies with high operating profitability and low investment was least penalised in the days after the post-crisis event.

The dynamics of ACARs between periods show that the pattern between high and low operating profitability remained unchanged, while the relationship between ACARs for companies with low and high investment activity reversed after the crisis. In other words, the companies that ranked high on the operating profitability factor achieved higher ACARs on average both before and after the crisis than the companies that ranked in the lowest part of the scale. In contrast, when companies were ranked according to their investment activity, the post-crisis ACAR pattern differed from the pre-crisis pattern. Before the crisis, companies with low asset growth had lower ACARs on average than companies with high investment activity, while the opposite was true after the financial crisis.

Table 19: ACARs of portfolios before and after the GFC, sorted by operating profitability (OP) and investments (INV)

Portfolio	(-3, 3)	(-3, -1)	(0, 3)	(-1, 1)	Event day
			Pre-crisis		
Low OP, low INV	-0.906**	-0.122	-0.746***	-0.234	-0.018
Low OP, high INV	-0.587*	-0.221	-0.341	-0.141	0.123
High OP, low INV	-0.435*	-0.004	-0.422*	-0.302*	0.078
High OP, high INV	-0.002	-0.077	0.058	-0.042	0.192**
			Post-crisis		
Low OP, low INV	-0.575	-0.154	-0.367	-0.366*	-0.117**
Low OP, high INV	-0.335	-0.103	-0.198	-0.290	-0.206
High OP, low INV	-0.031	-0.160	0.122	0.004	0.004
High OP, high INV	-0.167	-0.082	-0.052	-0.093	-0.050

Source: own work.

5.3 Non-parametric test of ACARs

So far, the statistical significance of the estimated ACARs has only been tested with parametric tests that assume the distribution of returns in advance. This section presents the results of the sign test described in the methodology section. The test is used to determine whether the ACAR of each double-sorted portfolio is negative. Appendix 4 shows the ACARs and the corresponding p-value of the test statistic for three observed time periods.

The results indicate that in many cases the null hypothesis of equal proportions of positive and negative CAR cannot be rejected. For example, if the significance level at which the null hypothesis is rejected is arbitrarily set at ten per cent, then the null hypothesis of equal proportions of positive and negative ACARs can be rejected for slightly less than sixty per cent of the portfolios in the entire sample. In the pre-crisis period, the rejection rate was similar, as the null hypothesis was rejected for 54 per cent of the portfolios. The rejection rate for the post-crisis period, on the other hand, suggests that the overall impact of increasing fear, as expressed by a large relative daily change in the VIX index, on the abnormal performance of the differentially sorted portfolios has diminished. In other words: Only one eighth of all portfolios rejected the null hypothesis of an equal distribution of positive and negative CAR in the post-crisis period.

5.4 Performance in the days following the event

At this point, the abnormal performance in the days following the event is addressed. Note that the size of the event window here is somewhat different from what was observed in the previous sections. Here the event window starts one day after the actual event and ends three days after. What is the reason for this shape? Previously, only the movements around the event date were analysed. This section, on the other hand, shows how such an event affects the abnormal performance of the portfolio and is therefore useful for risk and asset management.

In addition to measuring the impact of the event, the event study approach can also be used to backtest trading rules to assess their profitability and reliability. With this in mind, a relatively straightforward hypothesis was developed. It was tested whether differently sorted portfolios generate statistically significant ACARs in the days following the event. Assuming that the event is unpredictable – i.e. that fund managers cannot predict the event itself – such an investigation will reveal the magnitude of the expected ACARs. The result will be applicable in the field of asset management, as statistically significant ACARs are a prerequisite for the development of lucrative trading rules. The proposed event window assumes that the portfolio manager builds a portfolio at the end of the event day and holds it until the end of the third day after the event.

Appendix 5 shows the results of this exercise. For the whole sample, the abnormal performance appears to be relatively strong, as shown by the high statistical significance of the ACARs. Half of the ACAR estimates have a p-value of one per cent or less, while three quarters have a p-value of five per cent or less. In general, the ACARs are negative, suggesting that abnormal performance tends to be negative even after the first day. Sorting the stocks by size and book-to-market ratio, the small growth stock portfolio has the lowest ACARs, while the value stock counterpart is close behind.

The ACARs of the two large portfolios are not significantly different from zero, suggesting the presence of a size effect. The latter was also present when the stocks were sorted by size and operating profitability or investment. Sorting by size and operating profitability also leads to some heterogeneity between portfolios, as portfolios with high operating profitability outperform their counterparts with low operating profitability in terms of ACAR. At the same time, portfolios with high investments achieved a higher ACAR than their counterparts with low investments.

The same trends in operating profitability and investment can be observed when sorted together with the book-to-market factor. However, the book-to-market factor shows a non-constant relationship when different factors are used as a secondary sorting criterion, as shown by the statistically significant estimates of the ACARs. When operating profitability is used, the difference between the ACARs of value and growth companies is relatively small, while growth stocks perform better than value when sorted together with investments.

Finally, if the stocks are grouped by investment and operating profitability, the portfolio of stocks with low operating profitability performs worse than its counterpart with high operating profitability. The response of the investment factor, on the other hand, is not constant, as companies with high (low) investment perform better than those with low (high) asset growth when operating profitability is low (high).

The analysis of the sub-periods allows us to examine the temporal dynamics of the ACAR at the portfolio level in more detail. Immediately striking is the discrepancy in the statistical significance of the ACAR in the different sub-periods. The pre-crisis returns are characterised by negative ACARs, as almost ninety per cent of the portfolios have a negative expected ACAR. At the same time, the p-value of the null hypothesis, which assumes an ACAR of zero, is below one per cent for half of the portfolios and below five per cent for three quarters. In the post-crisis period, the anomaly seems to have disappeared. Although more than half of the ACAR estimates are negative, none of them is statistically significant at the five per cent level or below. Note that only three estimates are statistically significant at the ten per cent level.

The disappearance of statistical significance in the estimates may be puzzling, and uncovering the exact causes is beyond the scope of this thesis. Nevertheless, two very probable ones are briefly discussed in this section. First, it is possible that investors needed more time to fully process the new information in the pre-crisis period than after the crisis. Increased computing power, allowing for better processing of the new information and easier quantification of the impact of the shock, as well as better access to the information, allowing for a timely response to the news, could be the reason for the disappearance of the anomaly in the post-crisis period. Second, it is possible that markets are now more resilient to shocks than before the crisis, which could translate into a lower sensitivity of investors' risk aversion to changes in market conditions.

The magnitude of the anomalies suggests that it is possible to develop a trading strategy that makes the most of them. In the case of negative ACAR, for example, one could build a beta- or market-neutral zero-investment portfolio by shorting the bivariate-sorted equity portfolio and using the proceeds to build a long position in a portfolio with higher ACAR or risk-free investment vehicle.

CONCLUSION

Despite all the technological advances in financial markets in recent decades and the introduction of advanced pricing techniques, investor sentiment remains one of the most important determinants of market returns. This is particularly evident in extreme market states. When fear and anxiety prevail, the cost of capital rises also for the best companies, while in times of greed the most questionable business models have easy access to the capital markets. Ultimately, even the best valuation models can hardly capture the full intensity of investors' emotions. Since the value of their portfolio often declines during times of fear, it is essential to know what drives returns then. A proper understanding of market forces, supported by data-driven decision-making, separates the winners from the losers. The results of this work are an important step towards a better understanding of investor behaviour in stressful situations.

While the existing literature often emphasises that the type of shock that increases uncertainty can have significant industry-specific effects on abnormal performance, the results of this thesis show that some patterns exist regardless of the origin of the shock. The most consistent pattern is related to the size of the observed firm. The ACAR estimates for large companies were higher than those for smaller firms, suggesting higher risk for the latter. The results for other sorting factors often depended on the second sorting criterion. One such example is the book-to-market ratio. For example, when small (large) or low (high) investment companies were analysed, value stocks achieved higher (lower) ACARs than growth counterparts. In addition, sorting by investment factor showed that investors perceive companies with high asset growth as safer when uncertainty suddenly increases. Finally, sorting by operating profitability did not reveal clear and consistent patterns. The latter was not surprising, as this factor often leads to puzzling results, as noted by Fama and French (2008).

The analysis not only focused on the entire sample, but also examined two economically significant sub-periods – namely the years before and after the GFC. The results show that ACAR estimates have changed frequently over time. Although some patterns were maintained (e.g. small firms had lower ACARs on average than large firms for all sorting criteria and across different event windows), several deviations were evident. First, the spread between the two extremes of the sorting criteria often narrowed after the crisis. For example, the difference between the ACAR estimates for large and small firms decreased after the GFC compared to the pre-GFC years. Second, the statistical significance of ACAR estimates has declined in the post-crisis years, reducing confidence in the existence of opportunities to achieve abnormal performance. Finally, much of the abnormal performance was often recorded in the days following the event date. In this respect, the results were somewhat surprising, as the normal return model regularly explained the performance of the first few days relatively well. However, in the following days its explanatory power diminished, leading to statistically significant abnormal performance. This was particularly evident before the GFC, but also applies to the estimates for the entire period.

The statistical significance of the ACAR estimates will surprise EMH fundamentalists because the results contradict the assumption that the market is incapable of producing ARs. However, when the behavioural biases outlined in the thesis are considered, the results make more sense. Although the statistical significance of the estimates has diminished in the post-crisis period, the fact that much of the abnormal performance can be attributed to the days following the event should still be of great value to practitioners in the industry. This is also illustrated by the trading rule presented in this thesis. Normally, a large part of the ACAR is due to the movements on the first day, which does not allow the development of profitable trading strategies (especially considering the costs), as the uncertainty about the future makes the event difficult to predict. In this case, however, there could be an exception. One could construct a zero-investment portfolio by shorting the companies with high negative abnormal performance in the days following the event day (as suggested in the trading rule section) and investing the proceeds in the portfolios with positive abnormal performance or (if none are available) in risk-free proxy investments such as government bonds or money market funds.

For reasons of space, some research ideas had to be shelved. Nevertheless, this work is a good starting point as it opened up several avenues that could be pursued in the future. First, this thesis analysed the behaviour of double-sorted portfolios. Future research could use additional sorting criteria to further fragment stocks, similar to the work of Fama and French (2015), where stocks were simultaneously sorted by four factors. This would further increase the likelihood of accurately pinpointing the characteristics of a company that achieves the highest ACAR during uncertainty spikes. Second, the portfolios in this work consisted only of stocks traded in the United States. In the future, the concepts used in this work could be applied to other markets, such as selected European or Asian. In such a study, markets could also be differentiated according to their geographical location or level of development. Third, for robustness reasons, other models could be used to estimate normal returns. An immediate candidate is the Fama-French five-factor model. Finally, another measure of uncertainty could be used. Changes in the VIX index indicate investors' expectations of future market volatility and are therefore a good indicator of overall uncertainty. Future research should also analyse the abnormal performance of portfolios exposed to specific shocks. For example, one could identify a proxy that measures only political uncertainty. The abnormal performance estimates can then be compared to determine which types of shocks have the greatest impact on each portfolio.

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APPENDICES

Appendix 1: Povzetek (Summary in Slovene language)

Ameriški matematik John Allen Paulos je nekoč zapisal, da je negotovost edina gotovost v življenju (Paulos, 2003). Tega se še posebej zavedajo vlagatelji. Ti se vsak dan spopadajo z nepredvidljivimi tržnimi razmerami, ki lahko v trenutku spremenijo vrednost njihovega premoženja. Politične krize in naravne nesreče sta le dve vrsti dogodkov, ki lahko brez opozorila prestrašijo borzne udeležence. Takšni dogodki upravljavce premoženja pogosto prisilijo v odprodajo tveganih naložb, kar zniža njihovo tržno vrednost. Toda šoki vseh podjetij ne prizadenejo enako. Odziv je namreč odvisen od njihove strukture.

Spremembe vrednosti naložb v obdobju nenadnega povečanja negotovosti so analizirali že številni, a zdi se, da je bila povezava med strukturo podjetij in njihovo kratkoročno dinamiko donosov spregledana. Ugotovitve te magistrske naloge pomembno prispevajo k zmanjšanju te vrzeli, saj ta, s pomočjo metode za študijo vpliva dogodkov (angl. event study methodology), kvantificira abnormalno donosnost podjetij v takšnih obdobjih. Borzna podjetja so razdeljena v različne portfelje glede na njihove karakteristike. Pod drobnogledom se bo znašel vpliv tržne kapitalizacije, razmerja med tržno in knjigovodsko vrednostjo, naložbene dejavnosti in dobičkonosnosti.

Empirični del naloge je razdeljen na dva glavna dela. Prvi preiskuje vpliv nenadnega povečanja negotovosti na opazovane ekstremne portfelje in primerja njihove abnormalne donose v različnih časovnih okvirjih. Rezultati kažejo, da se abnormalna donosnost analiziranih portfeljev ob nenadnem povečanju negotovosti razlikuje. Abnormalne donosnosti pa ni mogoče zaznati le na dan nenadnega povečanja negotovosti, temveč tudi v naslednjih dneh. Drugi del naloge prikazuje abnormalno donosnost portfeljev pred začetkom in po koncu velike gospodarske krize iz leta 2008. Analiza pokaže, da so se po krizi nekatera razmerja na novo definirala.

Appendix 2: Average nominal portfolio return at the time of the event

This table describes the behaviour of each analysed portfolio on the event days. Each row represents a differently sorted portfolio, with a combination of extreme portfolios shown in each case. Avg. Return represents the average nominal percentage return on the event day for each portfolio, while the SD column represents the standard deviation of the returns. The data on portfolio and excess market returns were taken from the database published on Kenneth R. French's website (French, n.d.). ME represents portfolios sorted by market capitalisation, BE/ME represents portfolios sorted by book-to-market ratio, INV represents investment level and OP represents operating profitability.

Portfolio	**Avg. Return**	**SD**	**Min**	**Max**
Excess Market Return	-1.861	1.131	-8.950	-0.400
Size and book-to-market				
Small ME, low BE/ME	-1.937	1.455	-8.580	1.310
Small ME, high BE/ME	-1.149	0.909	-5.650	0.810
Large ME, low BE/ME	-1.911	1.302	-9.720	-0.250
Large ME, high BE/ME	-2.147	1.778	-11.970	0.420
Size and operating profitability				
Small ME, low OP	-1.538	1.120	-6.870	1.160
Small ME, high OP	-1.688	1.221	-8.650	0.600
Large ME, low OP	-2.304	1.709	-12.730	-0.110
Large ME, high OP	-1.785	1.278	-10.460	-0.190
Size and investment				
Small ME, low INV	-1.506	1.141	-5.950	1.550
Small ME, high INV	-1.695	1.183	-7.910	1.040
Large ME, low INV	-1.845	1.254	-10.250	0.300
Large ME, high INV	-2.182	1.556	-11.640	-0.420
Book-to-market and operating profitability				
Low BE/ME, low OP	-2.258	1.629	-9.700	1.060
Low BE/ME, high OP	-1.810	1.214	-9.980	-0.160
High BE/ME, low OP	-1.371	1.029	-6.920	0.690
High BE/ME, high OP	-1.731	1.597	-7.250	1.820

(Appendix 2 continues)

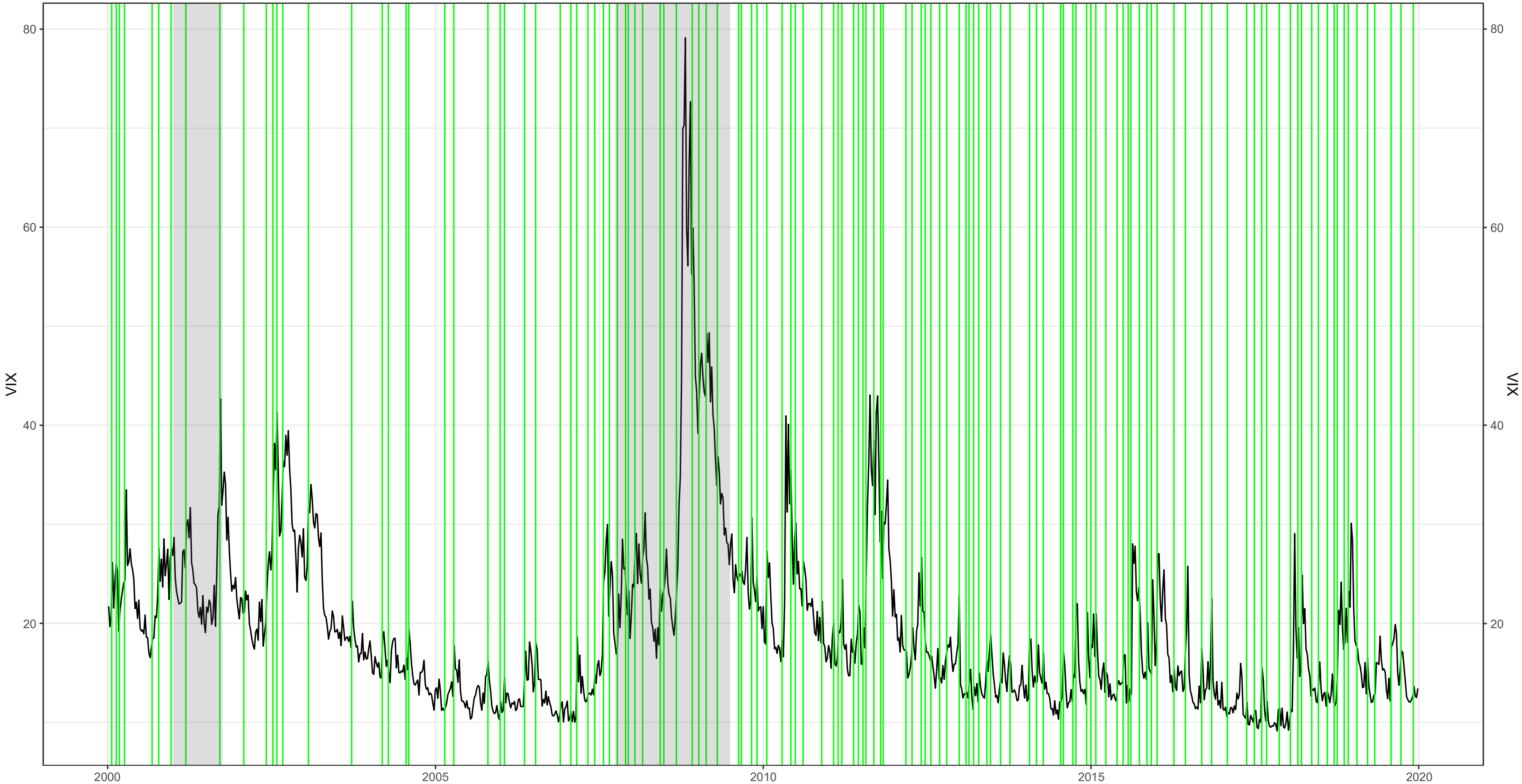
(Appendix 2 continued)

Book-to-market and investment				
Low BE/ME, low INV	-1.969	1.330	-7.680	1.990
Low BE/ME, high INV	-2.230	1.500	-10.640	0.210
High BE/ME, low INV	-1.401	1.149	-6.460	1.210
High BE/ME, high INV	-1.463	1.156	-7.540	0.760
Operating profitability and investment				
Low OP, low INV	-1.639	1.218	-6.470	1.040
Low OP, high INV	-2.069	1.421	-9.070	0.560
High OP, low INV	-1.776	1.270	-9.180	0.290
High OP, high INV	-2.003	1.399	-11.200	-0.090

Source: own work.

Appendix 3: Values of the VIX index over time with corresponding event data

The black line shows the development of the VIX volatility index over time in levels. Green vertical lines mark the event dates. The shaded areas represent the crisis period as defined by FRED (2022).



Source: own work.

Appendix 4: Results of the sign test for the ACARs in the three periods studied

This table shows the ACAR of each portfolio in the event window (0, 3) and the corresponding p-values of the sign test. The table is divided into three sections. The total sample describes the behaviour for the entire observation period, which ranges from 2000 to the end of 2019. The pre-crisis and post-crisis sections in the table correspond to the two periods as defined by FRED (2022). Each row represents a differently sorted portfolio, with each combination of extreme portfolios shown. ME represents portfolios sorted by market capitalisation, BE/ME represents portfolios sorted by book-to-market ratio, INV represents investment level and OP represents operating profitability. The portfolio return data was retrieved from the database published on Kenneth R. French's website (French, n.d.). The ACARs are shown as a percentage.

	Entire sample		**Pre-crisis**		**Post-crisis**	
Portfolio	**ACAR (0, 3)**	**p-value**	**ACAR (0, 3)**	**p-value**	**ACAR (0, 3)**	**p-value**
Small ME, low BE/ME	-0.595	0.074	-0.647	0.115	-0.339	0.500
Small ME, high BE/ME	-0.410	0.103	-0.707	0.007	-0.159	0.672
Large ME, low BE/ME	0.052	0.948	0.251	0.978	-0.002	0.909
Large ME, high BE/ME	-0.123	0.015	0.142	0.500	-0.135	0.060
Small ME, low OP	-0.565	0.002	-0.732	0.007	-0.310	0.187
Small ME, high OP	-0.202	0.035	-0.484	0.022	0.173	0.588
Large ME, low OP	-0.002	0.184	0.168	0.345	-0.044	0.328
Large ME, high OP	-0.035	0.765	-0.007	0.788	0.007	0.672
Small ME, low INV	-0.610	0.009	-0.900	0.002	-0.314	0.412
Small ME, high INV	-0.455	0.074	-0.583	0.054	-0.170	0.588

(Appendix 4 continues)

(Appendix 4 continued)

Large ME, low INV	-0.037	0.294	-0.146	0.054	0.016	0.588
Large ME, high INV	0.071	0.860	0.543	1.000	-0.064	0.500
Low BE/ME, low OP	-0.543	0.035	-0.456	0.115	-0.398	0.253
Low BE/ME, high OP	-0.067	0.052	-0.126	0.212	0.053	0.412
High BE/ME, low OP	-0.460	0.035	-0.629	0.007	-0.230	0.500
High BE/ME, high OP	0.028	0.023	-0.760	0.007	0.439	0.412
Low BE/ME, low INV	-0.517	0.000	-0.630	0.007	-0.341	0.037
Low BE/ME, high INV	-0.254	0.184	0.002	0.655	-0.191	0.412
High BE/ME, low INV	-0.506	0.074	-0.837	0.007	-0.250	0.672
High BE/ME, high INV	-0.384	0.052	-0.302	0.054	-0.194	0.328
Low OP, low INV	-0.605	0.002	-0.746	0.022	-0.367	0.091
Low OP, high INV	-0.380	0.103	-0.341	0.345	-0.198	0.500
High OP, low INV	-0.075	0.359	-0.422	0.022	0.122	0.747
High OP, high INV	-0.207	0.294	0.058	0.885	-0.052	0.500

Source: own work.

Appendix 5: ACARs of the trading rule and corresponding value of the BMP t-statistics

The table shows the values of the ACARs for a trading rule that analyses the abnormal performance of differentially sorted portfolios in the event window of plus one to plus three trading days (1, 3), and the corresponding values of the BMP t-statistic. The table is divided into three sections. The total sample describes the behaviour for the entire observation period, which ranges from 2000 to the end of 2019. The pre- and post-crisis sections in the table correspond to the two periods defined by FRED (2022). Each row represents a differently sorted portfolio, with each combination of extreme portfolios shown. ME represents portfolios sorted by market capitalisation, BE/ME represents portfolios sorted by book-to-market ratio, INV represents investment level, and OP represents operating profitability. The portfolio return data was retrieved from the database published on Kenneth R. French's website (French, n.d.). ACARs are expressed as a percentage. ***p < 0.01, **p < 0.05, *p < 0.1.

	Entire sample		**Pre-crisis**		**Post-crisis**	
Portfolio	**ACAR (1, 3)**	**BMP t-statistic**	**ACAR (1, 3)**	**BMP t-statistic**	**ACAR (1, 3)**	**BMP t-statistic**
Small ME, low BE/ME	-0.382***	-2.743	-0.616***	-2.743	-0.121	-0.540
Small ME, high BE/ME	-0.320***	-3.001	-0.625***	-3.001	-0.093	-0.125
Large ME, low BE/ME	0.018	0.520	0.091	0.520	0.034	0.954
Large ME, high BE/ME	-0.106	-0.793	-0.131	-0.793	-0.204*	-1.815
Small ME, low OP	-0.390***	-2.986	-0.671***	-2.986	-0.125	-0.390
Small ME, high OP	-0.144**	-2.196	-0.517**	-2.196	0.191	1.237
Large ME, low OP	-0.085*	-1.869	-0.184*	-1.869	0.016	0.042
Large ME, high OP	0.023	0.842	0.086	0.842	0.021	0.711
Small ME, low INV	-0.453***	-3.489	-0.769***	-3.489	-0.186	-0.790

(Appendix 5 continued)

(Appendix 5 continues)

Small ME, high INV	-0.298***	-2.819	-0.558***	-2.819	-0.019	0.294
Large ME, low INV	-0.011	-1.265	-0.093	-1.265	0.005	0.093
Large ME, high INV	0.001***	2.760	0.232***	2.760	0.022	0.193
Low BE/ME, low OP	-0.358**	-2.381	-0.572**	-2.381	-0.118	-0.551
Low BE/ME, high OP	-0.087**	-2.350	-0.262**	-2.350	0.028	0.634
High BE/ME, low OP	-0.350***	-2.975	-0.615***	-2.975	-0.131	-0.486
High BE/ME, high OP	0.078**	-2.207	-0.648**	-2.207	0.392	0.729
Low BE/ME, low INV	-0.361***	-2.831	-0.557***	-2.831	-0.162*	-1.378
Low BE/ME, high INV	-0.220**	-2.196	-0.352**	-2.196	-0.033	-0.102
High BE/ME, low INV	-0.396***	-3.044	-0.703***	-3.044	-0.201	-0.689
High BE/ME, high INV	-0.326***	-2.789	-0.515***	-2.789	-0.121	-0.821
Low OP, low INV	-0.459***	-3.437	-0.716***	-3.437	-0.226*	-1.363
Low OP, high INV	-0.235**	-2.051	-0.461**	-2.051	0.026	0.547
High OP, low INV	-0.071***	-2.836	-0.497***	-2.836	0.104	0.760
High OP, high INV	-0.187	-0.889	-0.152	-0.889	-0.002	-0.126

Source: own work.

Appendix 6: Average nominal return and standard deviation of the analysed portfolios before and after the GFC

The table is divided into two periods: before and after the crisis, as defined by FRED (2022). Each row represents a differently sorted portfolio, with each combination of the extreme portfolios shown. ME stands for portfolios sorted by market capitalisation, BE/ME for the value of the book-to-market ratio, INV for investments and OP for operating profitability. The portfolio return data was retrieved from the database published on Kenneth R. French's website (French, n.d.). The ACARs are expressed as a percentage.

	Pre-crisis		**Post-crisis**	
Portfolio	**Avg. Return**	**SD**	**Avg. Return**	**SD**
Small ME, low BE/ME	0.080	1.001	0.040	1.259
Small ME, high BE/ME	0.136	0.615	0.075	0.845
Large ME, low BE/ME	0.046	1.095	0.065	0.968
Large ME, high BE/ME	0.032	1.266	0.054	1.347
Small ME, low OP	0.123	0.844	0.059	1.04
Small ME, high OP	0.097	0.751	0.046	1.234
Large ME, low OP	0.036	1.321	0.057	1.269
Large ME, high OP	0.052	0.926	0.061	0.919
Small ME, low INV	0.141	0.837	0.071	1.082
Small ME, high INV	0.086	0.810	0.036	1.111
Large ME, low INV	0.058	1.149	0.066	1.037
Large ME, high INV	0.051	1.186	0.056	1.108
Low BE/ME, low OP	0.068	1.246	0.050	1.438
Low BE/ME, high OP	0.062	0.939	0.064	1.039
High BE/ME, low OP	0.140	0.745	0.067	0.953
High BE/ME, high OP	0.101	1.080	0.060	2.045
Low BE/ME, low INV	0.081	1.113	0.051	1.249
Low BE/ME, high INV	0.052	1.212	0.052	1.310
High BE/ME, low INV	0.153	0.777	0.083	1.078
High BE/ME, high INV	0.109	0.815	0.045	1.059

(Appendix 6 continues)

(Appendix 6 continued)

Low OP, low INV	0.132	0.967	0.071	1.115
Low OP, high INV	0.074	1.103	0.040	1.292
High OP, low INV	0.087	0.886	0.074	1.209
High OP, high INV	0.081	1.034	0.054	1.181

Source: own work.