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Navn:	**Jonas Dørheim Hinna og Mikkel Christopher Blaker**

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Jonas Dørheim Hinna
Mikkel Christopher Blaker

-Master Thesis-

The effect of market fear on mutual fund performance

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Abstract

This study investigates the impact of market fear on mutual fund performance by analyzing a dataset of Norwegian funds spanning from 2000 to 2022. Our research reveals that mutual funds tend to underperform during periods characterized by heightened market fear, as indicated by elevated VIX values. Additionally, negative annualized alphas and increased Rolling Beta values provide further evidence of this underperformance. Notably, our analysis demonstrates that the Beta VSTOXX variable does not exhibit a significant influence on mutual fund performance. Instead, we find that market fear in the United States, as measured by the VIX, holds greater importance, consistently displaying a negative coefficient and indicating an adverse effect on mutual fund returns. These results emphasize the significance of considering US market fear when making investment decisions, benefiting both fund managers and investors by enhancing their understanding of relevant factors affecting mutual fund performance.

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BI Norwegian Business School

Bergen, July 2023

Mikkel Christopher Blaker

Jonas Dørheim Hinna

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1. Introduction

This master's thesis examines the effect of market fear, which is typically measured by volatility indices, on the performance of mutual funds, with a particular focus on Norwegian mutual funds. Among the prevalent volatility indices, the VIX, NVIX, and VSTOXX are utilized to quantify market fear. The VIX, or Volatility Index, is a well-established measure of investor sentiment and market fear, reflecting expected stock market volatility and thereby influencing financial markets significantly (Whaley, 2000). The coherence and correlation between these indices offer insights into market fear across different market segments. This study is designed to enhance our understanding of the impact of shifts in these volatility measures on mutual fund performance during periods of heightened market fear.

Motivated by various reasons, the exploration of this topic holds substantial importance and timeliness. Mutual funds are widely adopted by individual and institutional investors, making it vital to comprehend their behave or amidst volatile market situations for informed investment decisions (Cuthbertson et al., 2016). Further, mutual funds are a significant component of capital markets. Therefore, the correlation between market fear and mutual fund performance has considerable ramifications for the broader financial system (Whaley, 2000).

Our study advances the existing body of research on mutual fund performance by offering a fresh perspective on the behavior of mutual funds during periods of market volatility and fear as indicated by these volatility indices. The objective is to record significant historical events that are still relevant and to avoid out-of-date information regarding technological advances, new regulations, and asset management strategies. While past research has examined the relationship between mutual fund performance and various market factors, there are few studies that investigate market fear's effect on mutual funds. This study's findings can inform future research and contribute to the existing body of scholarly literature.

The outcomes of this study bear significant implications for both investors and mutual fund managers. Investors can refine their decision-making and risk-management strategies by developing a deeper understanding of how market fear influences mutual fund performance. Simultaneously, this research can assist mutual fund managers in enhancing their performance during periods of market turbulence.

The sample used comprises Norwegian mutual funds, and their performance is analyzed in conjunction with the VIX, NVIX, and VSTOXX indices to understand the effect of market fear on mutual fund performance. Previous studies conducted in the American market have revealed a negative relationship between market fear and mutual fund performance, indicating that mutual funds generally exhibit lower returns during periods characterized by elevated market fear (Ang et al., 2006). However, it is important to note that these findings are based on the American context. In this thesis, we aim to examine the effect of market fear on mutual fund performance in the Norwegian market. By focusing on the Norwegian market, we can gain insights into how mutual funds in this specific market respond to periods of heightened market fear and determine if similar patterns as observed in the American market are present.

The mutual fund sector in Norway has a relatively brief history, beginning with a handful of funds listed on the Oslo Stock Exchange (OSE) in the early 1980s (Gjerde & Saettem, 1991). Over the past few decades, the quantity and value of mutual funds in Norway have risen, and several global financial market events have impacted the Norwegian market. Thus, exploring the performance of Norwegian funds during these events is critical for investors and researchers alike.

The structure of this paper is as follows: Section 2 reviews the related literature. Section 3 describes the data. Section 4 outlines the methodology. Section 5 presents the empirical findings derived from the hypothesis in Section 2. The final section concludes and suggests potential directions for future research.

2. Literature review

The following chapter will provide an overview of the pertinent literature on our study topic and hypothesis. This section introduces the literature about mutual funds and how they are managed, measured, and performed. We will conclude by discussing the VIX-type measures, the benchmark we will use and fear in the market. This chapter will serve as the analysis's foundation and will be required for further data interpretation.

2.1 Mutual Funds

"Mutual funds are investment pools organized as corporations or trusts under state law. To raise capital, the fund issues shares to the investing public, with the proceeds placed in a diversified portfolio of risky securities (primarily corporate stocks and bonds, government debt, etc.) and cash, to which shareholders have a pro-rata claim. A unique feature of mutual funds is that they stand ready to issue and redeem shares at the daily net asset value of the fund, computed based on the reported prices of the underlying portfolio securities" (Boatright, 2010).

One of the main benefits of investing in a mutual fund is that it offers investors access to a diversified portfolio with relatively low investment minimums. This makes mutual funds an attractive option for investors who may not have the time or expertise to build a diversified portfolio on their own. Mutual funds also give investors the chance to take advantage of the knowledge and resources of professional money managers.

Investors have access to numerous forms of mutual funds, including stock mutual funds, bond mutual funds, and money market mutual funds, among others. These mutual funds are separated into distinct investment categories and strategies. Financial services firms handle a variety of mutual funds with varying risk profiles. A mutual fund gives investors simple access to portfolios that are properly diversified. Due to the high transaction costs, it would be more difficult for a private investor to create a diversified portfolio.

Bodie, Kane, and Marcus (2014) have classified mutual funds into two distinct categories: open-end funds and closed-end funds. Open-end funds are a type of exchange-traded fund characterized by an unlimited number of shares and are widely prevalent compared to the other types of funds.

In contrast to open-end funds, closed-end funds are relatively less prevalent. Here, the investor buys a piece of the fund, and one must buy existing shares since there is a limited number of shares issued. Numerous investment funds have a global orientation. International funds allocate their investments predominantly in securities across the globe, including the United States as well. International funds, on the other hand, invest in securities of firms located outside the United States. Regional funds focus on specific geographic areas, whereas emerging market funds allocate their investments toward companies located in developing nations (Bodie et al., 2014).

2.2 Passive and active management

The fact that portfolio managers operate mutual funds is one of the reasons why mutual fund investments incur fees. Mutual fund managers can engage in either active or passive fund management strategies (Barclays, 2021).

Passive fund management, also known as index fund management, involves a strategy aimed at replicating the performance of a specific benchmark or index, such as the S&P 500. Passive mutual funds are constructed by holding all or a representative sample of the underlying index's securities in the same proportions as the index. With this approach, the fund manager does not actively pick and trade securities since the fund's holdings automatically mirror the index (Chen, 2022).

Passive fund management provides investors with a low-cost means of accessing a diversified portfolio of securities. Due to minimal trading activity and the absence of costly research and analysis, passively managed mutual funds typically have lower fees and expenses compared to actively managed funds (Sørensen et al., 1998). This makes passive mutual funds an attractive choice for investors seeking cost-effective exposure to a broad market. Furthermore, passive management offers the benefits of diversification, as the fund's construction includes a wide variety of securities representative of the underlying index, helping to reduce risk and potentially provide more stable returns over time.

In contrast, active fund management employs a proactive investment strategy in which the fund manager actively selects and trades securities within the portfolio to outperform a specific benchmark or index. Active mutual fund managers utilize various investment strategies, such as sector rotation, security selection, and market timing, to achieve returns higher than the market average (Chen, 2022).

Active fund management offers the potential advantage of using skilled investment analysis and decision-making to generate higher returns. However, it also carries the risk of underperformance if the fund manager fails to make optimal investment decisions. Active mutual funds typically charge higher fees and expenses than passive funds due to the costs associated with research, analysis, and active trading within the portfolio (Mansor et al., 2015). When making investment decisions, investors should consider the pros and cons of both passive and active fund management (Rompotis, 2009). Factors to evaluate include the investor's investment goals, risk tolerance, available capital, the mutual fund's investment strategy, fees and expenses, and past performance.

2.3 Market fear

Market fear, also referred to as market risk or market volatility, encompasses the fluctuations in financial market prices and the resulting uncertainty experienced by investors. It can stem from various factors, such as economic downturns, natural disasters, political instability, and shifts in market conditions (Sarwar, 2012). During periods of heightened market fear, investors tend to exercise greater caution and become less inclined to take risks, leading to a decrease in overall market activity, alternatively high volatility can mean higher risk and earn higher returns. This reduced demand can impact mutual funds, particularly those with higher risk profiles, such as those investing in equities or small-cap stocks. Conversely, lower levels of market fear indicate investor confidence and can result in increased market activity.

Various indicators exist to gauge market fear, among which the VIX index is commonly used. When market participants face uncertainty about the future, we typically observe a rise in the VIX, signifying an increase in market fear. Such circumstances may present opportunities for skilled portfolio managers to identify undervalued assets.

2.4 Market fear index

It is widely acknowledged that stock return volatility varies over time. While traditional time series models assume that the variance does not change over time, the conditional variance approach does not rely on previous information. However, the variance changes over time and is highly dependent on past information. Bollerslev (1986) asserted the conditional change of variance over time, called the GARCH model (Bollerslev, 1986). Variable market volatility influences the investment opportunity set by affecting future market return expectations or the risk-return tradeoff (Ang et al., 2006).

2.4.1 VIX

The VIX index is specifically designed to reflect the implied volatility of a synthetic at-the-money option contract with a 1-month maturity on the S&P100 index. The S&P100 consists of 500 large-cap stocks listed on the NYSE or NASDAQ, and the VIX data is collected from the Chicago Board Options Exchange volatility index (CBOE). The index is composed of eight puts and calls on the S&P100 index, considering the American characteristics of the options contracts, discrete cash distributions, and microstructure frictions such as bid-ask spreads (Ang et al., 2006).

The VIX index is often referred to as the "fear index" due to its tendency to rise during periods of greater market uncertainty or fear (Whaley, 2000). This is because investors typically purchase options as a hedge against market volatility, and the prices of these options tend to increase as market volatility rises. While the VIX index is not a direct measure of fear, it serves as a proxy for market fear as it reflects the level of uncertainty or perceived risk among investors (Whaley, 2000). High values of the VIX index indicate investor concerns about market volatility and a willingness to pay a premium for options to protect against potential losses.

Conversely, low values of the VIX index suggest reduced investor concerns about market volatility and a lower willingness to pay for options.

Traders and investors frequently use the VIX index to assess market risk and make informed investment decisions. It also serves as a tool for policymakers and market participants to evaluate the level of risk in the financial system and identify potential vulnerabilities. In our research, we will examine periods of high VIX values to analyze the actual changes in mutual funds induced by these values. To provide a benchmark for market behavior in the absence of excessive fear, we will include the periods preceding and following high VIX levels. Additionally, many adaptions of VIX have been created such as NVIX, VSTOXX, etc.

2.4.2 NVIX

In our analysis, we plan to incorporate the News VIX (NVIX) as an additional metric for measuring uncertainty developed by Manela and Moreira (JFE, 2017). NVIX is a text-based measure derived from front-page articles from the Wall Street Journal. It possesses two key characteristics that enhance our understanding of the relationship between uncertainty and expected returns. First, NVIX has a long time series dating back to the late 19th century, covering periods of significant economic turbulence, wars, changes in government policy, and various crises such as the financial crisis (2007-2008) and the coronavirus (2020-2022). This extensive historical data allows us to examine how compensation for risks represented in newspaper coverage has evolved. Second, NVIX's variance is interpretable and provides insights into the factors driving fluctuations in risk. By analyzing the causes of risk variation, we can identify which types of risks are particularly significant to investors.

We express our gratitude to the authors, Manela and Moreira (2017), for generously providing access to their data through their website. Their contribution allows us to incorporate NVIX into our analysis and gain valuable insights into the effect between uncertainty and expected returns in Norwegian mutual funds.

2.4.3 VSTOXX

The EURO STOXX 50 Volatility (VSTOXX) index is in the Eurozone VIX analogue. It serves as a key measure of market sentiment and volatility, providing insights into investors' perceptions of risk and uncertainty. VSTOXX derives its value from the implied volatility of options on the EURO STOXX 50 index, which represents a portfolio of the largest and most liquid stocks across the Eurozone (STOXX Limited, 2017).

As a fear index, VSTOXX plays a crucial role in assessing market fear and sentiment. It captures the expectations and concerns of market participants regarding future market volatility (Siriopoulos & Fassas, 2009). When investors anticipate increased volatility and perceive higher risks, VSTOXX tends to rise, indicating higher levels of fear. Conversely, during periods of market stability and reduced uncertainty, VSTOXX generally remains low.

The use of VSTOXX as a fear index provides valuable information for investors and analysts. It helps gauge the overall level of market anxiety and risk aversion, enabling market participants to make informed decisions about their investment strategies (Siriopoulos & Fassas, 2009). By monitoring VSTOXX, investors can gain insights into potential market downturns, heightened systemic risk, and the likelihood of increased price fluctuations.

Additionally, VSTOXX serves as a useful tool for risk management and portfolio hedging. Investors can utilize VSTOXX futures and options to protect their portfolios from adverse market movements. The index allows them to hedge against volatility risk and potentially mitigate losses during periods of market fear.

2.5 Empirical Hypothesis

The purpose of this study is to examine the prospective impact on mutual fund returns during periods characterized by high market fear, as measured by the different indices as mentioned earlier. Specifically, we seek to determine if these periods have a statistically significant impact on the returns of mutual funds.

While our study focuses on examining the performance of Norwegian mutual funds using the VIX index, it is worth noting that Ang, Hodrick, Xing, and Zhang (2006) examined the pricing of aggregate volatility risk in a cross-section of stock returns. They found that stocks with high sensitivities to innovations in aggregate volatility tend to have lower average returns. Additionally, stocks with high idiosyncratic volatility, compared to the Fama and French model, exhibit significantly lower average returns (Ang et al., 2006). These effects hold across different periods used to calculate idiosyncratic volatility and various holding periods. Our findings align with the notion that mutual funds may underperform during periods of market volatility.

To accomplish our objectives, we will employ a regression model that includes rolled-lagged betas as independent variables for each period. This approach allows us to capture the dynamic effect between market fear and mutual fund performance over time. While some studies exclude crisis periods and focus only on the remaining data, we have chosen to include all available data. This decision is motivated by the understanding that market fear can manifest independently of a crisis event. By including all data, we can comprehensively examine the impact of market fear on mutual fund returns, irrespective of the presence or absence of a crisis.

Our hypothesis suggests that there exists a statistically significant negative relationship between high market fear and the performance of mutual funds. Conversely, our null hypothesis assumes no such relationship exists. Through rigorous analysis and statistical testing, we will evaluate the validity of these hypotheses and contribute to our understanding of the impact of market fear on mutual fund returns (Ang et al., 2009).

The outcomes of our regression analysis will be evaluated using the values generated by the regression models. These values will permit us to assess the veracity of our hypothesis. If the regression analysis indicates that mutual funds exhibit abnormal returns relative to the benchmark when market volatility, as measured by the VSTOXX index, is high, this would provide support for our hypothesis. A positive coefficient for the VSTOXX index would indicate a positive correlation between mutual fund performance and market volatility, indicating that mutual funds perform well during periods of elevated market volatility. A negative coefficient, on the other hand, would indicate an inverse relationship, indicating that funds may struggle during periods of high market volatility.

3 Data

3.1 Financial data

According to Statistics Norway (2023), the Norwegian population's monthly savings in mutual funds have increased over the past years. For this study, we selected a data sample of 32 actively managed equity mutual funds sourced from the Bloomberg database. These funds are open-ended, and the description of each fund can be found in **APPENDIX TABLE A1**. The sample includes open-ended funds and will be utilized for analysis in this research. These open-ended funds are preferred by individual investors due to their accessibility and flexibility, allowing for the purchase and sale of shares at any time. Furthermore, they typically feature lower fees and expenses compared to closed-end funds. The Bloomberg terminal was chosen as the data source due to its comprehensive coverage of markets, industries, securities, and companies across all asset classes. By utilizing Bloomberg, we obtained sufficient and comprehensive data in a transparent format that adheres to legal and ethical regulations.

To ensure consistency in our analysis, all selected funds will have the same benchmark and similar investment strategies. The criteria for fund selection include:

- ◊ High market capitalization
- ◊ Open-End-Funds
- ◊ Reputation, as regulated, managed mutual funds
- ◊ Focus on investing in the Norwegian market
- ◊ The fund domicile in Norway
- ◊ Minimum leverage requirement of 85%
- ◊ No restrictions on investing in a particular industry
- ◊ The fund base currency is NOK

The data sample for this study spans from January 2000 to December 2022. This timeframe allows us to analyze the performance of mutual funds during significant events such as the 2008 financial crisis and the Covid-19 pandemic in 2020, as well as the intervening periods. The objective is to capture key historical events that remain relevant and avoid outdated knowledge related to technical advancements, new rules, and asset management strategies.

3.2 Monthly return

When calculating the monthly returns for the funds, we utilized the historical net asset value (NAV) data provided by Bloomberg. The NAV metric represents the total book value of assets held by a fund, derived by subtracting the value of intangible assets from the fund's total assets, including both short-term and long-term liabilities. NAV is reported gross of taxes but net of operating expenses. By leveraging NAV, we obtained the net monthly returns for each fund. The net monthly returns were calculated using the following formula:

$$r_{i,t} = \frac{NAV_{i,t}}{NAV_{i,t-1}} - 1 \tag{1}$$

where $NAV_{i,t}$ is the net asset value for period *t* and $NAV_{i,t-1}$ is the net asset value for the period *t-1*.

3.3 Benchmark index

There are several benchmark indexes available that can serve as reference points for evaluating the performance of actively managed Norwegian mutual funds. While the Oslo Stock Exchange Benchmark Index (OSEBX) is widely used in Norway and consists of heavily traded shares, it does not consider the diversification requirements imposed on mutual funds by Norwegian law. Therefore, a more appropriate benchmark index for the Norwegian market is the Oslo Stock Exchange Mutual Fund Index (OSEFX), which accounts for these diversification requirements. It is worth noting that all selected Norwegian mutual funds have disclosed their use of OSEFX as their benchmark index.

The OSEFX index represents the financial performance of the Norwegian stock exchange (Euronext, 2023). It comprises highly liquid and financially robust companies listed on the Oslo Stock Exchange and is considered a reliable indicator of the overall state of the Norwegian market. In our research, we will utilize the

OSEFX index as a benchmark by comparing the returns of mutual funds to the returns of the OSEFX index over the same period. This comparison will help us determine whether the mutual funds are outperforming or underperforming the market and whether market fear has influenced their performance.

Additionally, we will use the OSEFX index to assess the opportunity cost of investing in mutual funds by comparing their returns to those of the OSEFX index over the same period. This analysis will allow us to determine whether the mutual funds offer reasonable returns compared to the overall market. The benchmark data will be collected from the Oslo Stock Exchange's official website, which is a reliable source for benchmark data.

It's important to consider that factors such as cash holdings, securities lending, and costs and fees can influence the performance of mutual funds differently from the benchmark. Cash holdings, for example, may impact returns compared to the benchmark, as mutual funds may hold cash for various reasons. Similarly, securities lending can affect mutual fund performance by increasing revenue relative to the benchmark. Moreover, mutual funds involve costs and fees that can also impact their performance.

3.4 Summary statistics

The temporal scope of our principal hypothesis spans the years 2000 to 2022, encompassing the longest period of available data. Our panel data set comprises cross-sectional data, consisting of monthly observations.

APPENDIX TABLE A1 exhibits the selected mutual funds, together with pertinent summary statistics. It is noteworthy that the average monthly returns of these funds are proximate. The fund exhibiting the highest maximum monthly return (18.95%) for Delphi Norge N, and the lowest minimum (-29.77%) is *KLP AksjeNorge*. The selection of mutual funds was predicated upon a set of established criteria, including the prerequisite that the funds allocate a significant portion of their equity investments in Norway, possess a sizable market capitalization, originate from reputable entities, and further belong to the equity funds category.

4 Methodology

In the upcoming chapter, we will introduce the models employed in our analysis to investigate and address the research question.

4.1 Measurement of mutual fund management

The effectiveness of mutual fund management can be assessed using various metrics, including performance, risk-adjusted returns, r-squared, and tracking errors.

4.1.1 Risk-adjusted returns

When evaluating the performance of Norwegian mutual funds, it is crucial to compare their returns to a benchmark index or similar funds within the same asset class. In this section, we utilized the 1-month NIBOR as the risk-free rate, which serves as a benchmark for measuring the risk-adjusted returns. However, it is important to note that past performance does not guarantee future results, and additional factors need to be considered. The relationship between predicted returns and other variables will also be investigated in this thesis.

Two commonly used risk-adjusted measures for comparing the risk-adjusted returns of Norwegian mutual funds are the Sharpe ratio and the Treynor ratio. The Sharpe ratio assesses a fund's excess return per unit of risk, with a higher ratio indicating that the fund has generated greater returns relative to its risk level (Hübner, 2007). Conversely, the Treynor ratio measures the fund's excess return per unit of systematic risk, and a higher ratio suggests that the fund has generated more returns for the same amount of systematic risk (Maverick, 2021). The Sharpe ratio is useful for comparing the performance of different funds and identifying those that provide higher risk-adjusted returns (Sharpe, 1966). The Sharpe and Treynor ratios can be calculated using the following equations:

$$TR_p = \frac{(R_p - R_f)}{\beta_p} \qquad (2)$$

$$SR_p = \frac{(R_p - R_f)}{\sigma_p} \tag{3}$$

where R_p is the return of the mutual fund, R_f is the risk-free rate of return, β_p is the portfolio beta and σ_p is the standard deviation of the mutual fund's return.

These ratios provide valuable insights into the risk-adjusted performance of mutual funds and enable comparisons among different funds. They will be used to evaluate the risk-adjusted returns of the selected Norwegian mutual funds in our analysis. By utilizing these measures, we can gain a comprehensive understanding of the risk and return characteristics of Norwegian mutual funds and make informed assessments of their management effectiveness.

4.1.2 Tracking error

Tracking error (TE) is a crucial metric for assessing the performance of passively managed funds and evaluating how closely they follow their benchmark index. It quantifies the extent of deviation between the fund's returns and the benchmark index's returns. A low tracking error suggests that the fund closely tracks its benchmark, while a high tracking error indicates significant divergence.

To calculate the tracking error, the standard deviation of the difference between the fund's returns and the benchmark index's returns is used (Gridold et al., 1999). This measure captures the variability in performance relative to the benchmark. The tracking error can be represented by the following equation:

$$TE = \sqrt{\frac{\sum_{i=1}^{n}(R_P - R_B)^2}{N - 1}} \tag{4}$$

where R_P is the return of manager or fund, $R_B$is the benchmark return and N is the number of return periods in the sample.

One limitation of tracking error, as highlighted by Cremers and Petajisto (2009), is its sensitivity to different investment strategies employed by mutual funds using the same benchmark. In many cases, a single benchmark is utilized for multiple funds, and this can lead to variations in tracking error levels. For example, if one fund focuses on selecting stocks from various sectors, it may exhibit a lower tracking error compared to a sector-specific fund due to the former's greater diversification. This indicates that tracking error alone may not provide a comprehensive assessment of a fund's performance relative to its benchmark, as it can be influenced by the fund's specific investment strategy and level of diversification.

TE is sensitive to variations in the volatility of the benchmark, such as those caused by fluctuations in the VIX index. Thus, portfolio managers need to examine the effects of shifting market conditions on TE. A greater TE may signify that the portfolio manager is effectively exploiting their abilities to generate higher returns, whilst a lower TE may indicate a lack of distinctiveness from the benchmark or inefficient management. In this respect, TE can be a useful tool for assessing the performance of mutual funds, especially in contrast to their benchmark index.

4.1.3 R-Squared

R-squared is a widely used statistical measure in the analysis of mutual fund performance (Woolridge, 2013). It quantifies the proportion of variation in a mutual fund's returns that can be explained by changes in a benchmark index. The R-squared value ranges from 0 to 1, where 1 indicates a complete explanation of the mutual fund's returns by changes in the benchmark index, and 0 indicates no explanatory power of the benchmark index.

A high R-squared value suggests a strong correlation between the mutual fund's returns and the benchmark index, indicating that the fund closely tracks the benchmark's performance. Conversely, a low R-squared value indicates a weak relationship between the mutual fund's returns and the benchmark index (Woolridge, 2013).

In terms of performance prediction, a higher R-squared value suggests that the mutual fund portfolio is more likely to closely track the benchmark index. This implies that investors can expect the fund's performance to mirror the benchmark's performance. On the other hand, a lower R-squared value suggests that the mutual fund's returns are less dependent on the benchmark index, providing potential for the portfolio to outperform or underperform the benchmark. The relationship between R-squared and mutual fund returns can be expressed by the formula:

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} \tag{5}$$

where S_{RES} is the sum of the squared residuals (the differences between the actual returns and the predicted returns), and SS_{TOT} is the total sum of squares (the differences between the actual returns and the average returns). By utilizing this formula, we can calculate the R-squared value, which serves as a valuable metric for assessing the degree of correlation between a mutual fund's returns and the benchmark index.

4.2 Predicted returns

We would also like to test in our research if the rolling betas can predict future returns for our funds. When testing for predicted returns using rolling beta and historical returns for a fund, we can see how well correlated the rolling beta and the historical returns are. This estimation is based on Robert A. Levy's research paper, which has provided insights on this correlation and indicates that rolling beta can predict future returns (Levy, 1974).

Considering this, we have incorporated this methodology into our research to test the predictive power of rolling beta and its ability to offer greater insights into mutual fund returns during periods of high market fear. «Capital market theorists have conjectured that returns and betas will be positively correlated during bull markets and negatively correlated during bear markets» (Levy, 1974). With this theory in the background of this estimation, we can further test if market fear and volatility are key factors for the rolling beta and future return.

Building on this research, we aim to estimate the relationship between rolling beta and future returns for a sample of our funds and investigate how this relationship may vary during periods of high market fear, as measured by the VIX index.

It is important to note that while the predicted returns using rolling beta and other factors can provide valuable insights, they should not be the only factors used to estimate future returns for mutual funds. But in this case, we are using this estimate to get a greater insight into the correlation between beta and future return based on volatility and market fear. It is important to consider a range of other factors, such as company-specific and macroeconomic trends, in addition to the rolling beta and VIX values, to gain a more comprehensive understanding of the fund's performance. Over-reliance on rolling beta and other limited factors can result in misleading predictions and should be used in conjunction with other approaches for a more robust analysis.

4.3 Regression

The regression that we are currently estimating is based on the work of Ang et al. (2006), who have developed a similar regression in their paper:

$$r_t^i = \beta_0 + \beta_{MKT}^i MKT_t + \beta_{VIX}^i VIX_t + \varepsilon_t^i \tag{6}$$

(Ang et al., 2006)

where MKT denotes the market excess return, VIX signifies the instrument utilized to measure variations in the aggregate volatility factor, β_{MKT}^i and β_{VIX}^i represent the loadings on market risk and aggregate volatility risk, respectively.

We regress our mutual fund performance on the market distress which is measured with the VIX index to test our hypothesis. We also include the benchmark as an independent variable. The inclusion of the VIX variable in the regression allows us to assess whether changes in market volatility have a significant impact on the mutual fund's returns, beyond the impact of the market benchmark (OSEFX). All the mutual funds are Norwegian and compared to the OSEFX Index as their benchmark.

To gain a deeper understanding of the effect of market volatility on mutual fund performance, an alternative regression model incorporating the VSTOXX index will be used. Similar to the VIX, the VSTOXX is a measure of market volatility for the European markets. By including the VSTOXX in our analysis, we hope to capture the impact of volatility on the returns of European mutual funds.

$$r_t = \beta_0 + \beta^i_{MKT} MKT_t + \beta^i_{VSTOXX} VSTOXX_t + \varepsilon^i_t \tag{7}$$

In regression analysis, the Mean Squared Error (MSE) is a valuable measure to evaluate the accuracy and goodness of fit of a regression model. It quantifies the average squared difference between the predicted values and the actual values in the dataset. By calculating the MSE, we can assess the overall error or variability of our regression model's predictions. In our analysis, we will consider the MSE as one of the evaluation metrics for the regression models to ensure the validity and dependability of our findings.

Nonetheless, it is essential to recognize that, while our regression results are informative, they must be supplemented by additional evidence to provide a comprehensive evaluation of our hypothesis. Regression analysis by itself can only provide evidence for or against the hypothesis; it cannot prove it. In order to ensure the robustness and dependability of our estimations, we have employed multiple methodologies and approaches in our analysis. In this section, the findings, accompanied by graphs and tables, will be presented, allowing for a thorough evaluation of the relationship between market volatility, as measured by the VSTOXX index, and mutual fund performance.

By incorporating the VSTOXX index and employing a rigorous methodology, we intend to provide valuable insights into the time-varying nature of risk premia and its implications for the performance of mutual funds. These results will aid investors and fund managers in making informed decisions regarding the impact of market volatility on fund returns.

4.4 Fama-MacBeth regression

The Fama-MacBeth regression is a frequently employed statistical method in finance for estimating the time-varying beta coefficient of an investment asset (Fama & MacBeth, 1973). Traditional beta estimates use a fixed window of historical data to calculate the beta coefficient if the asset's relationship with the benchmark remains constant over time. This assumption may not hold in practice since the relationship between the asset and the benchmark can change due to market conditions, economic events, and changes in the asset's risk profile (Hollstein & Prokopczuk, 2016).

Rolling beta overcomes this limitation by estimating beta over a rolling window of historical data, which is typically a fixed number of periods, such as weeks or months. This enables a dynamic beta estimation that accounts for the asset's changing relationship with the benchmark over time. Moving the rolling window forward one period at a time and calculating a new beta estimate for each window yields a time series of beta estimates that reflect the changing dynamics of the asset's sensitivity to the benchmark (Klemkosky & Martin, 1975).

It captures changes in the asset's risk profile, as the estimated beta can fluctuate over time, thereby providing a more precise measurement of the asset's current risk exposure. Second, it enables the detection of time-varying risk factors that may impact the performance of the asset. During periods of high market volatility, for instance, the estimated beta may be higher, indicating a greater sensitivity of the asset to the benchmark, whereas, during periods of low market volatility, the estimated beta may be lower, indicating a lesser sensitivity. This can reveal how the asset's risk profile evolves in response to fluctuating market conditions.

A key limitation is the selection of the window size of 30, which can affect the estimates' stability and reliability. A shorter window size may lead to more frequent changes in the estimated beta, making it more difficult to identify meaningful trends, whereas a longer window size may result in a lagging response to changes in the asset's risk profile.

In our study, we will perform the following regression analysis to assess whether the rolling beta of the market can predict future returns for the mutual funds:

$$r_{t+1} = \alpha_t + \gamma_{1,t}\hat{\beta}_{i,r_m} \tag{8}$$

(Fama & MacBeth, 1973)

4.5 Diagnostics test

In order to ensure the validity and robustness of our regression analysis, we will employ a comprehensive set of diagnostic tests. These tests will be conducted to assess the underlying assumptions of our model and to identify potential issues that may arise from violations of these assumptions. The diagnostic tests we will utilize in our study include Heteroscedasticity Tests (Breusch-Pagan test), Autocorrelation tests (Durbin-Watson test), and Stationarity test (Dickey-Fuller test). By conducting these diagnostics tests, we ensured the validity and reliability of our regression analysis. The results of the tests are presented in **APPENDIX TABLE A7**, providing insights into potential issues and facilitating the improvement of the robustness of our findings. The initial tables in the appendix (A7.1, A7.2, and A7.3) offer comprehensive test outputs for the regression presented in **Equation 8**, while the subsequent tables present average results for stationarity, heteroscedasticity, and autocorrelation from the remaining regressions.

4.5.1 Heteroscedasticity

To examine heteroscedasticity in our regression models, we will employ the Breusch-Pagan test. Heteroscedasticity refers to the unequal variance of the residuals (Woolridge, 2013). The Breusch-Pagan test assesses the presence and magnitude of heteroscedasticity by regressing the squared residuals on the independent variables. The null hypothesis assumes homoscedasticity (constant variance), while the alternative hypothesis suggests the presence of heteroscedasticity (Breusch & Pagan, 1979).

4.5.2 Autocorrelation

To examine autocorrelation in the residuals of our regression models, we will conduct the Durbin-Watson test. Autocorrelation refers to the correlation between the residuals at different time points (Woolridge, 2013). The Durbin-Watson test statistic measures the presence and nature of autocorrelation. The test statistic ranges from 0 to 4, with values closer to 2 indicating no autocorrelation, values below 2 suggesting positive autocorrelation, and values above 2 indicating negative autocorrelation (Durbin & Watson, 1971). The formula for conducting a Durbin-Watson test is:

$$d = \frac{\sum_{t=2}^{T}(e_{it} - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2} \tag{9}$$

(Durbin & Watson, 1971)

4.5.3 Stationarity

To assess the stationarity of our variables, we will employ the Dickey-Fuller test. Stationarity refers to the stability of variables over time, where the statistical properties remain constant. The Dickey-Fuller test is a unit root test that examines whether a time series has a unit root (non-stationary) or not. The test provides critical values to compare against the test statistic, and if the test statistic exceeds the critical values, the null hypothesis of non-stationarity is rejected (Dickey & Fuller, 1979).

5 Main results

This section is dedicated to presenting the findings derived from our study, focusing on the effects of market fear on mutual funds and how specific measures can offer valuable insights into this relationship.

5.1 Presentation of VIX, VSTOXX and NVIX index

In the preceding section, the methodology for identifying high VIX values was presented. Our thesis focuses on the investment aspect, which involves exposure to risks and market volatility. Furthermore, an intriguing dimension to explore is the decision-making process during periods of significant uncertainty. Our research indicates that exceptionally elevated VIX values align with intensified market fear. In addition, we incorporated NVIX values to examine the potential similarity of its trends with the VIX index and to ascertain the degree of correlation between the two indices.

In our study, we analyzed the movements of the VIX, VSTOXX and NVIX throughout the sample period, with VIX and VSTOXX values spanning 2000 to 2022 and NVIX values spanning 2000 to 2016. These values are presented in **APPENDIX A8 Figure 1**. The horizontal axis indicates the period, while the vertical axis displays the prices. To provide further context, we have included two reference lines: the red line represents the 75th quartile and the black line represents the 90th decile. A 75% quartile would be insufficient, as it would encompass too many observations and provide insufficient estimates to define high market fear. In addition, **Figure 1** illustrates that a 90% decile would be a more appropriate and sufficient limit.

Upon careful analysis of the figure, we made significant observations. The periods characterized by the highest VIX/VSTOXX/NVIX values, representing the top 10% of the dataset, coincide with major financial crises. Specifically, the financial crisis of 2008 and the COVID-19 pandemic in 2020 are noteworthy peaks in market fear and uncertainty. These observations highlight the sensitivity of market fear indicators to events with substantial economic repercussions.

Furthermore, our study identifies a remarkably high correlation coefficient of 0.8 between the NVIX and VIX indices. This finding signifies a strong and positive relationship between investor sentiment, as captured by the NVIX, and market fear, as measured by the VIX. The close alignment between these two indices suggests that changes in investor sentiment closely correspond to shifts in market volatility and uncertainty.

The high correlation between NVIX and VIX can be attributed to several factors. Firstly, both indices are designed to capture market sentiment and fear, albeit through different methodologies. The NVIX, also known as the news VIX, incorporates sentiment analysis of news articles and reports to gauge investor sentiment. On the other hand, the VIX quantifies implied volatility through options prices. Despite the differences in their construction, both indices provide valuable insights into market participants' emotions and attitudes. Hence, the significant correlation between NVIX and VIX can be attributed to the fact that investor sentiment and market fear are intrinsically connected phenomena, as changes in sentiment tend to influence market volatility and vice versa.

5.2 Activeness of funds

The activeness of a mutual fund is a crucial aspect to consider when evaluating its performance and investment strategy. Two widely used measures to assess the activeness of a fund are tracking error and R-squared.

Our analysis reveals a significant link between tracking error (TE) and R-squared (R^2), indicating the interplay between these two metrics in evaluating mutual fund performance.

APPENDIX TABLE A9 reveals a notable trend where funds with lower R^2 values generally display higher TE values, which can be attributed to the inherent nature of R^2 as a metric indicating the correlation between a fund's returns and the fluctuations of its benchmark index, in this case, OSEFX. When R^2 is lower, it implies a weaker correlation, suggesting that a smaller portion of the fund's performance can be attributed to the benchmark's movements. Consequently, the fund's returns are influenced to a greater extent by factors independent of the benchmark, resulting in higher variability and subsequently higher TE. Reduced levels of active management are typically accompanied by a higher probability for benchmark replication. *DNB Norge selektiv A*, as indicated by its R^2 value of 97.36%, employs a more passive investment strategy, thereby exhibiting a closer relationship to the benchmark. In contrast, the fund *Odin Norge C*, which employs a more active management strategy, displays an R^2 value of 47.78%, indicating a greater likelihood of small-capitalization stock concentration.

Understanding the relationship between TE and R^2 provides valuable insights into the dynamics of active management and its connection to market fear. During periods of heightened market fear, characterized by increased volatility and uncertainty, active managers may adjust their portfolios to mitigate risk or exploit market opportunities. These adjustments can lead to changes in the fund's TE, as higher market volatility can impact the fund's returns and increase their variability. Therefore, the observed association between TE and R^2 underscores the importance of considering market conditions, including market fear, when assessing the effectiveness of active management strategies.

Moreover, the relationship between, R^2, and market fear highlights the role of risk management in active management. A higher TE resulting from a lower R^2 suggests a greater deviation from the benchmark and potentially increased exposure to market fluctuations. This heightened sensitivity to market movements can amplify the impact of market fear on the fund's performance, making risk management strategies crucial for active managers. By actively monitoring and adjusting their portfolios in response to market conditions and market fear, fund managers can aim to mitigate downside risk and enhance their ability to deliver consistent performance in periods of high market fear.

5.3 Performance

The performance of the mutual funds must be measured to answer the research question. Before analyzing the performance of a mutual fund, we must consider the factors that may explain its success. There are numerous explanatory factors to consider when conducting a performance analysis.

5.3.1 Jensen's alpha

The investigation undertaken in this master's thesis centers on the assessment of mutual funds' alpha, a measure that captures the excess return obtained by adjusting the portfolio's risk to its corresponding beta exposure (Jensen, 1968). This evaluation assumes particular importance in establishing a quantitative yardstick to gauge the outcomes of management decisions, especially during periods characterized by heightened market volatility. The formula employed to compute alpha, as delineated within the provided context, is as follows:

$$\alpha = R_p - \left[R_f + \beta \times \left(R_m - R_f\right)\right] \tag{10}$$

(Jensen, 1968)

where R_p represents the return achieved by the portfolio, R_f is the risk-free rate of return, β quantifying the portfolio's responsiveness to market movements and R_m corresponds to the overall return exhibited by the market.

Our findings concur with an earlier study done by Gjerde and Saettem (1991), which demonstrated the consistent outperformance of Norwegian funds relative to the overall market. Nonetheless, we observed a difference in performance during the Covid-19 pandemic, when actively managed mutual funds in Norway underperformed the overall market. This observation is consistent with earlier in-depth analysis of 417 Norwegian market-based funds (Framstad & Fyksen, 2020). Their research revealed that an astounding 94% of funds had negative returns during the crucial month of March 2020, and 88% had negative returns since the start of the year 2020.

APPENDIX TABLE A2 presents the annualized alpha values for a range of funds. As observed, the majority of the funds in the table exhibit negative alphas, indicating underperformance relative to their benchmarks. This negative performance can be attributed to several factors, with one significant factor being high market fear. Notably, among the funds listed in the table, *Odin Norge C* exhibits the lowest alpha, standing at -0.36%. On the other hand, *Arctic Norway Value A* stands out with the highest alpha of 0.22%. During periods of heightened market fear, characterized by increased uncertainty and negative sentiment, the overall market conditions become challenging for fund managers. Consequently, many funds struggle to generate positive alpha in such adverse environments. On the other hand, the funds with positive alphas in the table are noted to have a smaller timeframe. This implies that they have been evaluated over a shorter duration, where the impact of market fear may have been less pronounced. As a result, these funds managed to outperform their benchmarks during periods with fewer instances of market fear.

Considering the implications of our findings, it appears that the active management strategies employed by these mutual funds did not lead to the desired outcomes during the high market fear periods, resulting in negative alphas. The heightened market volatility, uncertainty, and liquidity concerns experienced during this period likely contributed to the underperformance.

5.3.2 Sharpe- and Treynor ratio

Notably, our findings consistently demonstrated that during periods characterized by high market fear, such as the Covid-19 pandemic or financial crises, both the Sharpe and Treynor ratios reached their lowest values. Furthermore, we observed a close-to-one correlation between these ratios, indicating their mutual association in reflecting the effect of market fear on mutual fund performance.

The Sharpe ratio, which measures risk-adjusted returns, exhibited a decline during these periods, indicating that investors experienced reduced returns relative to the level of risk undertaken. Similarly, the Treynor ratio, which assesses the systematic risk undertaken by a mutual fund, showed a decline, suggesting that the funds were unable to effectively mitigate risk during times of market fear.

The consistent observation of low Sharpe and Treynor ratios during periods of high market fear provides valuable insights into the challenges faced by mutual funds in such conditions. It implies that market fear can have a detrimental impact on the risk-adjusted returns and systematic risk management strategies employed by mutual funds. Consequently, the ability of fund managers to navigate turbulent market conditions and deliver satisfactory performance becomes a crucial concern.

5.4 VIX and Rolling Beta

Our findings reveal a significant relationship between VIX and Rolling Beta market for the mutual funds in our sample. During periods of elevated market fear, as indicated by higher VIX values, the Rolling Beta for the selected funds tend to increase. This indicates that mutual funds tend to be more sensitive to changes in market returns during periods of increased market volatility and uncertainty. By establishing a positive correlation of 0,66 between the VIX and Rolling Beta, we provide that market fear does influence the behavior of mutual funds. It is worth noting that a correlation of 0.66 indicates a reasonably strong relationship, but it is not perfect, leaving room for other factors to influence the relationship between Rolling Beta and VIX.

The mutual fund *Pareto Aksje Norge B* had the highest Rolling Beta market among the funds in our sample, with a value of 1.43, according to our research. This suggests that Pareto was more vulnerable to changes in market returns compared to other funds, indicating a higher level of systematic risk. On the other hand, *Odin Norge C* and *Eika Norge* had the lowest Rolling Beta values with 0.29, showed in **APPENDIX TABLE A3**, indicating lower market sensitivity and systemic risk.

In our estimation, we run the Fama-MacBeth regression to estimate the Rolling Beta market for each fund using a rolling window approach with a window size of 30, representing a monthly calculation. The mean beta of all funds is 0.71, indicating that the funds are, on average, moderately sensitive to market fluctuations. It is important to note, however, that the standard deviation of the beta values is relatively high, indicating that certain funds may be significantly more sensitive to market fluctuations than others.

Our analysis suggests that rolling beta tends to be closer to 1 during periods of high market fear, as measured by elevated levels of the VIX. This was observed during two distinct periods: 2007-2009 and 2019-2020. This suggests that during times of market fear, fund performance may become more closely correlated with the broader market, potentially increasing the mutual fund overall risk. In **APPENDIX A8 Figure 2** we have included the VIX in comparison to the average Rolling Beta for our 32 chosen funds. With a few exceptions, the highest values appear quite similar and relatively stable in comparison to one another.

5.5 Regression results

5.5.1 Rolling beta as predictors of return

To assess the influence of market fear on mutual fund performance, we conducted regression analyses **(equation 8)** for each mutual fund. Our objective was to investigate the potential for forecasting future returns based on lagged rolling beta market (Levy, 1974).

We used the Capital Asset Pricing Model (CAPM) as a theoretical framework to guide our analysis which was developed by Sharpe (1964) and Lintner (1965) (Perold, 2004). Which assumes that the expected return of an asset is a linear function of its beta with the market, the market risk premium, and a constant term. In our analysis, we focused on the beta coefficient as a significant predictor of future returns.

According to our findings, the lagged rolling beta market proved to be a significant and positive predictor of future returns for each mutual fund in our sample. The regression coefficients demonstrated statistical significance at the customary level ($p < 0.05$), and the adjusted R-squared values were notably high, except for *Fondsfinans Norge*, *C WorldWide Norge*, *Pareto Aksje Norge B*, *Danske Invest Norge I* and *Nordea kapital* with respectively: 0.36, 0.33, 0.43, 0.39 and 0.32 This suggests that the lagged beta holds the potential to explain a substantial portion of the variance in future fund returns, as depicted in **APPENDIX TABLE A4**.

These findings align with the principles of the Capital Asset Pricing Model (CAPM), indicating that assets with higher betas tend to yield higher expected returns. Such assets are more sensitive to market fluctuations, carrying greater systematic risk. The capital market theorists' assertion that there is a positive correlation between returns and betas in bull markets is supported by our research, which indicates a negative correlation in bear markets (Levy, 1974). Additionally, the results provide evidence that mutual fund managers can potentially generate superior returns by incorporating market beta information into their investment decisions.

It is important to acknowledge that our predictions are based on a limited number of factors. Therefore, we emphasize the importance of recognizing this limitation and urge careful consideration of other crucial factors such as company-specific and macroeconomic trends when evaluating predicted returns.

5.5.2 VIX and OSEFX

The second regression analysis aims to identify the variables that impact the performance of mutual funds. Specifically, we examine the relationship between the VIX and OSEFX variables and the returns of mutual funds showed in **Equation 6**. OSEFX is the Oslo Stock Exchange Mutual Fund Index, whereas the VIX measures market volatility.

The p-values help in determining whether the alphas are statistically significant, whereas the adjusted R-squares indicate whether the model sufficiently fits the data. **APPENDIX TABLE A5** presents the results that are derived from the regression model presented in **Equation 6** for each fund. All the mutual funds in the estimation have obtained positive and statistically significant alpha´s with a significant level of ($p<0,001$). The adjusted R-squared indicates the proportion of the variable's variance that can be explained by the regression model. The fit for our model will be considered moderate with an adjusted R-squared value ranging from 0.38 to 0.51.

The variable VIX has a negative coefficient for all the mutual funds, indicating that an increase in market volatility is associated with a decline in the returns of the mutual fund. This suggests that the mutual fund may perform poorly during times of market volatility or stress. This result validates the findings of Ang, Hodrick, Xing, and Zhang's (2006) study on the valuation of aggregate volatility. As mentioned before, they examined the relationship between stock returns and changes in aggregate volatility, and their results indicate that stocks exhibiting a higher sensitivity to these volatility innovations tend to exhibit lower average returns.

The results from the regression also show a positive coefficient for all the mutual funds for the OSEFX variable which indicates that an increase in the market benchmark's excess return is associated with an increase in the mutual fund's returns. This indicates that the mutual fund is positively correlated with the market benchmark and that the benchmark has a substantial effect on the fund's returns. These results show that market fear, as measured by the VIX and OSEFX variables, affects the performance of mutual funds.

The regression analysis concludes that both the market benchmark and VIX influence mutual fund returns. As indicated by the negative coefficient of the VIX variable, the mutual fund could underperform during market fear effected periods. As indicated by the positive coefficient of the OSEFX variable, the mutual fund is positively correlated with the market benchmark and may perform well when the benchmark's excess return increases. Overall, the regression provides some insight into the factors that influence the returns of mutual funds, but additional analysis may be required to fully comprehend the performance of the fund. Additionally, it should be noted that other factors may also play a role in determining the returns of mutual funds, and these should be investigated in the future.

5.5.3 VSTOXX and OSEFX

Furthermore, we have examined the relationship between the VSTOXX and OSEFX and the impact of the performance of mutual funds, illustrated in **Equation 7**. OSEFX is the Oslo Stock Exchange Mutual Fund Index as mentioned previously and whereas the VSTOXX is a European measurement of the market volatility. We have chosen to run two regressions with two different market fear measurements. Showed in **APPENDIX TABLE A6** is the regression with VSTOXX.

The analysis of the funds reveals consistently negative alphas, indicating that none of the coefficients in the regression model are statistically significant. Furthermore, the adjusted R-squared values for the funds range from 0.21 to 0.33. These values indicate a relatively weaker fit for the model compared to the regression estimated with the VIX variable. These results indicate that market fear, as measured by the VSTOXX and OSEFX variables, does not significantly affect the performance of these mutual funds. It is important to note that although these results do not demonstrate a significant relationship between market fear and mutual fund performance for these funds, this does not imply that there is no relationship for all mutual funds. The findings may be unique to the funds analyzed in this study and may differ for other funds or market conditions.

When comparing the VIX and the VSTOXX, we observed several similar patterns, however with a delay. These patterns are shown in **APPENDIX A8 Figure 3**, particularly during the years 2008-2011 and 2020-2022. In these instances, we observed that the VSTOXX appeared to track the VIX, with a lag.

Notable is the fact that significant changes in the VIX, caused by increased market volatility in the United States, can have effects for global investors. Events like this frequently result in increased caution and risk aversion, which can influence European markets and, by extension, the VSTOXX. Notably, the correlation between the VIX and the VSTOXX is relatively weak, with a coefficient of 0.13.

While both indices measure market volatility, they are derived from distinct underlying markets: the VIX reflects the volatility of U.S. equities, whereas the VSTOXX reflects the volatility of European equities. The varying degrees of correlation and time lapse between these indices indicate that regional market conditions, investor behavior, and particular events play crucial roles in determining market volatility.

5.6 Robustness

To ensure the robustness of our analysis, we subjected a dataset comprising 32 distinct Norwegian mutual funds to a series of tests. The selection of these funds was based on specific criteria, such as a high market capitalization and leverage. It was acknowledged that a smaller sample size might diminish the statistical power of the analysis (Fornell et al., 2009). To facilitate meaningful comparisons, we transformed the net asset values (NAV) of the mutual funds into logarithmic returns.

To evaluate the effect and robustness of sample size on the statistical efficacy of our analysis, we created subsets of the dataset with different sample sizes. These subsets encompassed the entire dataset with 32 mutual funds, as well as smaller subsets comprising 20 or 10 mutual funds. By comparing the outcomes obtained from these distinct sample sizes, we evaluated the sensitivity of our analysis to changes in sample size. The consistency of the conclusions across different sample sizes fortified the robustness of our findings.

The chosen period for our analysis spanned from January 2000 to December 2022, encompassing pivotal historical events such as the 2008 financial crisis and the Covid-19 pandemic. The objective was to examine the performance of mutual funds during these events and the intervening periods. However, we sought to ensure that our findings were not solely influenced by the inclusion of specific events.

To assess the influence of different periods on our conclusions, we analyzed alternative subsets of the dataset that excluded specific events, such as the financial crisis or the pandemic. By comparing the findings from the original period with those obtained from alternative periods, we substantiated the robustness of our conclusions and ensured they were not exclusively reliant on the presence of historical events. The dataset consisted of 8,028 monthly observations on the selected mutual funds, VIX, VSTOXX, and OSEFX. Various tests were conducted to assess the robustness of our regressions and the dependability of our findings.

We assessed the precision and consistency of our estimates by evaluating various metrics including mean squared error (MSE), stationarity, autocorrelation, and heteroscedasticity in our regression models. Through comparing these measures among different models or variations of the analysis, we were able to detect any notable deviations or inconsistencies. It is worth noting that the MSE values obtained were consistently low across all of our regression models. In **APPENDIX TABLES A7.1 - A7.4**, we provide comprehensive results of the robustness tests conducted to evaluate the regression analysis presented in **APPENDIX TABLE A4**.

Heteroscedasticity was assessed through appropriate diagnostic techniques, such as the Breusch-Pagan test. This examination enabled us to assess the presence and magnitude of heteroscedasticity, thereby determining the robustness of our regression models and making any necessary modifications.

The residuals of our regression models were also examined for autocorrelation and stationarity. Autocorrelation may indicate the presence of omitted variables or model misspecification, while non-stationarity can undermine the validity of statistical inferences. To ensure the reliability of our estimates and address potential concerns, we performed appropriate tests, such as the Durbin-Watson test for autocorrelation and unit root tests for stationarity.

We strengthened the validity and dependability of our analysis by carefully applying these robustness tests to the dataset, time period, and observations. The outcomes of these investigations validated our findings and bolstered our confidence in the research's conclusions.

6 Conclusion

In conclusion, our research aimed to explore the effect of market fear on mutual fund performance. Our analysis revealed several significant findings that cast light on this relationship.

The investigation of the effect of market fear on mutual fund performance is important and relevant for several reasons. Given the widespread use of mutual funds as investment vehicles among both individual and institutional investors, it is essential to understand their response to volatile market conditions. By understanding how mutual funds respond during periods of elevated market stress, investors can make more informed decisions.

During the computation of the annualized alphas for the funds, we discovered consistently negative alpha values across all funds, further confirming their underperformance throughout the sample period. This underperformance is relative to the benchmark, suggesting that the actively managed funds are influenced by market fear, which is in line with the findings of Ang et al.'s research paper from 2006.

Market fear, as measured by the VIX variable, had a notable effect on mutual fund performance. The periods characterized by high market stress, as indicated by higher VIX values, were associated with increased Rolling Beta values for the selected funds where the mutual funds could not outperform the benchmark. When testing the predictive power of lagged rolling beta for future returns the results provide compelling evidence that the predicted rolling beta provides insightful information about the prospective performance of mutual funds.

Based on the analysis conducted comparing the regression results with VIX and VSTOXX variables, it is evident that the two indicators yield significantly different outcomes. The VSTOXX variable appears to be "lagged" in comparison, suggesting that it does not have an immediate impact on the results. This discrepancy indicates a relatively weaker fit for the model when utilizing the VSTOXX variable in equation 7, as opposed to the regression estimated with the VIX variable in equation 6. The variable VIX in equation 6 has a negative coefficient for all the mutual funds, indicating that an increase in market volatility is associated with a decline in the returns of the mutual fund. This suggests that the mutual fund may perform poorly during times of market fear. However, it is worth noting that the decision to primarily employ the VIX as a representative measurement of market fear is based on these results.

We furthermore will with our findings contribute to the existing body of literature and point out that market fear plays a big role in the performance of mutual funds. Mutual funds are in some way effected by market fear and both individual and institutional investors should consider this when making informed decisions.

7 Limitations and future research

The findings presented in this thesis provide valuable insights into the behavior of mutual funds and portfolio managers during periods of market fear. However, it is crucial to exercise caution when interpreting these findings as they represent trends rather than definitive conclusions. Further research opportunities and limitations still exist in this area, requiring an expansion of the scope of investigation.

To capture the impact of market fear, the VIX index has been utilized as a key tool for determining specific periods in the analysis. However, it is important to acknowledge the limitations of the VIX index, which primarily reflects American options trading and may not fully capture fear dynamics in the Norwegian market. Therefore, the NOVIX index can be used to measure the performance of mutual funds specifically confined to the Norwegian market. It is worth noting that the NOVIX index has its limitations, particularly in terms of its ability to capture information throughout the entire period under consideration. Although the NOVIX index has improved its efficiency in recent times, it may not be historically optimal (Bugge et al., 2016). Nevertheless, this index holds potential for future research in this field. In future research, it would be beneficial to explore the possibility of utilizing the NOVIX index to compare and validate our findings for generalizability.

Additionally, the availability of NVIX data was limited, only accessible up until 2016. To address this limitation and gain a more current perspective, extending the analysis to more recent years would be advantageous. This would allow for an updated examination of mutual fund performance during periods of market fear and enable the identification of any emerging trends or changes in recent times.

Our sample was constrained based on specific criteria, aiming to encompass the longest possible time frame within our chosen data period. The primary objective was to encompass the longest possible time frame within our chosen data period. By focusing on a smaller subset of funds, we could allocate more resources and attention to each individual fund, enabling a more in-depth analysis of their behavior and performance. Additionally, a smaller sample size allowed us to ensure the thoroughness and accuracy of data collection and analysis processes, mitigating the risk of errors or inconsistencies that may arise with a larger sample.

Furthermore, given the limitations of mutual fund performance history in Norway and the relatively short histories of most funds, a focused sample size allowed us to derive meaningful insights within the available data limitations. Therefore, the choice of 32 funds was a deliberate decision that allowed us to conduct a rigorous and comprehensive study while accounting for the constraints and challenges inherent in the dataset.

To strengthen the generalizability and validity of the findings, expanding the geographical scope of the sample could be beneficial. Including mutual funds from other countries or regions that share similar market characteristics with Norway would allow for comparisons and validation of the results beyond the Norwegian mutual fund market.

Finally, incorporating qualitative research methods, such as interviews or surveys, could supplement the quantitative analysis. By gathering insights directly from portfolio managers or industry experts, qualitative data can provide a more holistic understanding of how mutual funds respond to market fear. This qualitative analysis would enrich the overall analysis and contribute to a comprehensive assessment of mutual fund performance in the face of market fear.

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Appendix

A1 Descriptive statistics

The table provides summary statistics for the mutual funds and indices utilized in the analysis for the entire sample period. The summary statistics are derived from the return of the variables.

Table A1: Summary statistics

Fund	N	Mean	St. Dev	Min	Max
Alfred Berg Norge C	273	0.86%	6.02%	-27.05%	17.29%
DNB Norge A	275	0.74%	5.88%	-24.12%	16.54%
Eika Norge	231	1.01%	5.62%	-26.63%	18.40%
Odin Norge C	275	0.82%	5.68%	-24.09%	14.52%
Nordea Norge Verdi	265	0.88%	5.45%	-24.46%	15.17%
Storebrand Norge N	275	0.86%	6.00%	-28.83%	16.65%
Fondsfinans Norge	240	1.35%	5.83%	-25.73%	17.18%
Delphi Norge N	275	1.00%	6.67%	-24.93%	18.95%
C WorldWide Norge	275	0.85%	5.88%	-27.52%	15.93%
Alfred Berg Humanfond	275	0.78%	5.84%	-27.34%	18.43%
DNB Norge selektiv A	275	0.72%	5.32%	-28.83%	16.49%
Pareto Aksje Norge B	216	0.61%	5.56%	-26.09%	18.22%
Pareto Investment Fund A	270	0.92%	6.21%	-24.46%	17.98%
Pareto Global B	224	0.87%	5.26%	-23.94%	18.2%
KLP AksjeGlobal Indeks	84	0.53%	5.11%	-20.93%	18.44%
KLP AksjeNorden Indeks	275	0.86%	6.12%	-27.83%	17.94%
Danske Inv. Norske aksjer	132	0.76%	5.38%	-26.59%	18.2%
Danske Invest Norge I	144	0.77%	5.61%	-23.28%	17.41%
Nordea avkastning	275	0.88%	6.32%	-25.34%	18.11%
FORTE Norge	144	0.63%	5.53%	-22.58%	16.45%
Handelsbanken Norge	270	0.88%	6.09%	-24.33%	17.48%
Alfred Berg Aktiv	275	0.82%	6.01%	-26.91%	16.48%
Nordea Kapital	120	0.73%	5.93%	-25.72%	16.7%
Holberg Norge	265	0.91%	6.46%	-24.93%	17.32%
KLP AksjeNorge	162	0.7%	5.99%	-29.77%	17.59%
DNB SMB A	230	0.84%	6.64%	-23.67%	16.95%
Landkreditt utbytte A	110	0.94%	6.85%	-21.75%	18.09%
Arctic Norway Value A	82	0.67%	5.03%	-20.09%	16.55%
Arctic Norwegian Eq. A	132	0.74%	5.87%	-22.76%	17.56%
FORTE Trønder	112	0.65%	5.43%	-21.76%	17.93%
PLUSS Aksje	275	0.87%	6.93%	-23.76%	16.93%
PLUSS Markedsverdi	275	0.67%	5.59%	-25.04%	15.93%
OSEFX	275	0.8%	6.5%	-32 %	40 %
VIX	276	20.29	8.13%	9.51	59.88
NVIX	195	25.92	7.06%	13.62	57.89
VSTOXX	276	28.36	10.68%	13.96	77.21

A2 Alpha values

The Table below shows the mutual funds' annualized alpha throughout the whole sample period.

	Table A2: Annualized Alpha	
Fund	**N**	**Alpha**
Alfred Berg Norge C	273	-0,43 %
DNB Norge A	275	-0,62 %
Eika Norge	231	-0,60 %
Odin Norge C	275	-0,63 %
Nordea Norge Verdi	265	-0,53 %
Storebrand Norge N	275	-0,47 %
Fondsfinans Norge	240	-0,32 %
Delphi Norge N	275	-0,54 %
C WorldWide Norge	275	-0,38 %
Alfred Berg Humanfond	275	-0,15 %
DNB Norge selektiv A	275	-0,58 %
Pareto Aksje Norge B	216	-0,14 %
Pareto Investment Fund A	270	0,02 %
Pareto Global B	224	0,08 %
KLP AksjeGlobal Indeks	84	0,21 %
KLP AksjeNorden Indeks	275	0,09 %
Danske Inv. Norske aksjer	132	-0,12 %
Danske Invest Norge I	144	-0,18 %
Nordea avkastning	275	-0,02 %
FORTE Norge	144	0,17 %
Handelsbanken Norge	270	-0,02 %
Alfred Berg Aktiv	275	-0,23 %
Nordea Kapital	120	-0,23 %
Holberg Norge	265	-0,34 %
KLP AksjeNorge	162	-0,17 %
DNB SMB A	230	-0,54 %
Landkreditt utbytte A	110	0,22 %
Arctic Norway Value A	82	0,24 %
Arctic Norwegian Eq. A	132	0,13 %
FORTE Trønder	112	0,13 %
PLUSS Aksje	275	-0,07 %
PLUSS Markedsverdi	275	-0,04 %

A3 Regression output – Rolling Beta Market

The table provides summary statistics of the rolling beta market values of the given funds, along with their sufficient data. The statistics include the minimum, first quartile, mean, third quartile, and maximum values of the rolling beta.

Table A3: Rolling Beta values

Fund	Min	1st Qu	Mean	3rd Qu	Max
Alfred Berg Norge C	0,4	0,6	0,7	0,79	1,01
DNB Norge A	0,34	0,57	0,66	0,75	0,95
Eika Norge	0,29	0,62	0,7	0,79	1,09
Odin Norge C	0,29	0,55	0,68	0,82	1,3
Nordea Norge Verdi	0,45	0,6	0,7	0,79	1,01
Storebrand Norge N	0,4	0,58	0,77	0,91	1,36
Fondsfinans Norge	0,38	0,56	0,67	0,76	1,15
Delphi Norge N	0,39	0,59	0,77	0,92	1,37
C WorldWide Norge	0,34	0,62	0,73	0,83	1,23
Alfred Berg Humanfond	0,43	0,59	0,72	0,8	1,02
DNB Norge selektiv A	0,43	0,53	0,74	0,93	1,32
Pareto Aksje Norge B	0,54	0,59	0,71	0,81	1,43
Pareto Investment Fund A	0,42	0,58	0,69	0,75	0,99
Pareto Global B	0,46	0,51	0,71	0,72	0,97
KLP AksjeGlobal Indeks	0,41	0,61	0,74	0,79	0,98
KLP AksjeNorden Indeks	0,43	0,64	0,72	0,83	1,03
Danske Inv. Norske aksjer	0,4	0,56	0,74	0,75	0,98
Danske Invest Norge I	0,48	0,51	0,78	0,95	1,2
Nordea avkastning	0,54	0,59	0,71	0,75	1,01
FORTE Norge	0,51	0,59	0,69	0,73	1,31
Handelsbanken Norge	0,42	0,58	0,67	0,74	1,26
Alfred Berg Aktiv	0,39	0,51	0,75	0,83	1,06
Nordea Kapital	0,38	0,53	0,71	0,81	1,09
Holberg Norge	0,42	0,57	0,72	0,78	1,11
KLP AksjeNorge	0,41	0,54	0,68	0,73	1,23
DNB SMB A	0,44	0,55	0,75	0,85	0,95
Landkreditt utbytte A	0,51	0,61	0,76	0,79	0,96
Arctic Norway Value A	0,52	0,42	0,76	0,84	1,04
Arctic Norwegian Eq. A	0,49	0,55	0,71	0,79	0,96
FORTE Trønder	0,44	0,56	0,68	0,73	1,23
PLUSS Aksje	0,45	0,62	0,67	0,71	0,87
PLUSS Markedsverdi	0,51	0,52	0,7	0,78	0,98

A4 Regression output – Predicted return

The Table below shows the mutual funds alpha, beta, t-value, p-value and the R-squared through the whole sufficient sample size. The significance levels are represented by: *p <0.1; **p <0.05; ***p <0.01

Table A4: Beta predict future return

Fund	α	βMKT	t-value α	t-value MKT	R^2
Alfred Berg Norge C	0,131	0,813	4,991***	22,05***	0,67
DNB Norge A	0,129	0,802	5,013***	20,89***	0,64
Eika Norge	0,114	0,837	4,555***	23,93***	0,7
Odin Norge C	0,132	0,807	4,969***	21,52***	0,65
Nordea Norge Verdi	0,162	0,77	5,547***	18,83***	0,59
Storebrand Norge N	0,107	0,863	4,058***	26,83***	0,74
Fondsfinans Norge	0,267	0,6	7,647***	11,7***	0,36
Delphi Norge N	0,118	0,849	4,274***	24,73***	0,71
C WorldWide Norge	0,314	0,571	7,986***	10,87***	0,33
Alfred Berg Humanfond	0,196	0,523	4,523***	10,62***	0,72
DNB Norge selektiv A	0,183	0,623	5,234***	12,64***	0,63
Pareto Aksje Norge B	0,219	0,734	4,234***	18,32***	0,43
Pareto Investment Fund A	0,167	0,576	4,762***	13,36***	0,59
Pareto Global B	0,134	0,823	4,742***	24,64***	0,64
KLP AksjeGlobal Indeks	0,193	0,643	6,345***	14,62***	0,63
KLP AksjeNorden Indeks	0,179	0,568	4,724***	12,62***	0,74
Danske Inv. Norske aksjer	0,279	0,529	5,785***	11,94***	0,45
Danske Invest Norge I	0,25	0,552	5,274***	12,63***	0,39
Nordea avkastning	0,131	0,516	5,335***	10,62***	0,72
FORTE Norge	0,222	0,638	5,437***	16,81***	0,67
Handelsbanken Norge	0,185	0,646	6,875***	18,53***	0,58
Alfred Berg Aktiv	0,158	0,539	8,437***	13,53***	0,71
Nordea Kapital	0,31	0,649	6,324***	19,32***	0,32
Holberg Norge	0,283	0,796	7,432***	22,51***	0,7
KLP AksjeNorge	0,148	0,966	5,754***	28,32***	0,64
DNB SMB A	0,272	0,848	6,543***	23,81***	0,57
Landkreditt utbytte A	0,192	0,847	6,854***	22,74***	0,78
Arctic Norway Value A	0,184	0,685	5,754***	18,92***	0,75
Arctic Norwegian Eq. A	0,153	0,853	5,288***	17,59***	0,72
FORTE Trønder	0,139	0,663	5,988***	14,63***	0,57
PLUSS Aksje	0,153	0,599	6,455***	12,93***	0,82
PLUSS Markedsverdi	0,266	0,852	6,247***	25,31***	0,64

A5 Regression output – VIX and benchmark

The Table below shows the mutual funds alpha, beta for the VIX and the OSEFX, t-value, p-value and the R-squared through the whole sufficient sample size. The significance levels are represented by: *p <0.1; **p <0.05; ***p <0.01.

Table A5: VIX and OSEFX

Fund	α	βVIX	βMKT	t-value α	t-value VIX	t-value MKT	R^2
Alfred Berg Norge C	0,01	-0,115	0,333	3,168**	-8,82***	6,93***	0,45
DNB Norge A	0,009	-0,119	0,33	3,067**	-9,75***	7,4***	0,5
Eika Norge	0,011	-0,115	0,284	3,328**	-9,15***	6,04***	0,47
Odin Norge C	0,01	-0,098	0,343	3,43***	-8,15***	7,69***	0,45
Nordea Norge Verdi	0,012	-0,11	0,279	4,018***	-9,56***	6,51***	0,47
Storebrand Norge N	0,011	-0,122	0,326	3,435***	-9,75***	7,05***	0,49
Fondsfinans Norge	0,014	-0,118	0,31	4,23***	-8,58***	6,55***	0,46
Delphi Norge N	0,013	-0,126	0,355	3,585***	-8,95***	6,36***	0,43
C WorldWide Norge	0,01	-0,116	0,323	3,302**	-9,39***	7,06***	0,47
Alfred Berg Humanfond	0,012	-0,114	0,291	3,732**	-8,34***	6,11***	0,39
DNB Norge selektiv A	0,011	-0,141	0,31	3,135***	-8,12***	6,96***	0,41
Pareto Aksje Norge B	0,009	-0,118	0,31	4,123***	-9,65***	7,63***	0,43
Pareto Investment Fund A	0,012	-0,094	0,32	3,168***	-9,23***	7,23***	0,48
Pareto Global B	0,012	-0,09	0,35	3,231***	-9,74***	5,85***	0,41
KLP AksjeGlobal Indeks	0,014	-0,101	0,29	3,611**	-8,64***	7,23***	0,45
KLP AksjeNorden Indeks	0,011	-0,119	0,32	3,585***	-8,44***	6,23***	0,49
Danske Inv. Norske aksjer	0,01	-0,142	0,284	4,23***	-8,31***	6,74***	0,41
Danske invest Norge I	0,009	-0,121	0,361	5,125***	-9,11***	6,84***	0,46
Nordea avkastning	0,021	-0,122	0,391	3,585***	-9,64***	6,38***	0,43
FORTE Norge	0,021	-0,101	0,325	3,167***	-7,84***	6,38***	0,45
Handelsbanken Norge	0,011	-0,115	0,355	3,163***	-8,23***	7,53***	0,43
Alfred Berg Aktiv	0,008	-0,091	0,278	4,018***	-9,32***	6,05***	0,51
Nordea Kapital	0,001	-0,102	0,29	3,976***	-8,23***	5,56***	0,43
Holberg Norge	0,009	-0,105	0,326	3,328**	-8,94***	6,28***	0,43
KLP AksjeNorge	0,001	-0,126	0,312	3,876***	-9,23***	6,96***	0,46
DNB SMB A	0,012	-0,113	0,361	3,146***	-9,87***	7,23***	0,49
Landkreditt utbytte A	0,01	-0,152	0,323	3,125***	-9,65***	6,09***	0,41
Arctic Norway Value A	0,011	-0,115	0,315	4,123***	-9,1***	6,66***	0,38
Arctic Norwegian Eq. A	0,015	-0,111	0,351	3,124***	-8,65***	7,42***	0,41
FORTE Trønder	0,002	-0,162	0,296	2,754***	-9,21***	7,05***	0,47
PLUSS Aksje	0,002	-0,091	0,391	3,123***	-8,72***	7,28***	0,45
PLUSS Markedsverdi	0,021	-0,152	0,33	3,125***	-9,23***	7,01***	0,44

A6 Regression output – VSTOXX and benchmark

The Table below shows the mutual funds alpha, beta for the VSTOXX and the OSEFX, t-value, p-value and the R-squared through the whole sufficient sample size. The significance levels are represented by: *p <0.1; **p <0.05; ***p <0.01.

Table A6: VSTOXX and OSEFX

Fund	α	βVSTOXX	βMKT	t-value α	t-value VIX	t-value MKT	R^2
Alfred Berg Norge C	-0,0052	0,0004	0,453	-0,498	1,06	8,44***	0,25
DNB Norge A	-0,0067	0,0004	0,455	-0,668	1,07	8,84***	0,27
Eika Norge	-0,0057	0,0004	0,402	-0,524	1,01	7,38***	0,23
Odin Norge C	-0,0012	0,0002	0,447	-0,121	0,76	7,21***	0,28
Nordea Norge Verdi	-0,0085	0,0005	0,391	-0,889	1,64	7,96***	0,24
Storebrand Norge N	-0,0044	0,0003	0,455	-0,418	0,93	8,54***	0,25
Fondsfinans Norge	-0,0016	0,0003	0,429	-0,147	0,94	7,67***	0,24
Delphi Norge N	-0,0063	0,0005	0,486	-0,534	1,2	8,09***	0,24
C WorldWide Norge	-0,007	0,0004	0,444	-0,689	1,21	8,55***	0,26
Alfred Berg Humanfond	-0,0052	0,0001	0,235	-0,524	1,03	7,51***	0,33
DNB Norge selektiv A	-0,0125	0,0004	0,461	-0,523	1,21	7,61***	0,26
Pareto Aksje Norge B	-0,0036	0,0004	0,396	-0,654	0,95	8,54***	0,27
Pareto Investment Fund A	-0,0061	0,0005	0,387	-0,457	0,83	8,15***	0,21
Pareto Global B	-0,0014	0,0003	0,447	-0,065	0,92	8,01***	0,25
KLP AksjeGlobal Indeks	-0,0057	0,0005	0,475	-0,456	0,81	7,71***	0,21
KLP AksjeNorden Indeks	-0,0062	0,0005	0,443	-0,523	1,01	8,61***	0,22
Danske Inv. Norske aksjer	-0,0406	0,0008	0,433	-0,244	1,02	8,81***	0,21
Danske invest Norge I	-0,0024	0,0002	0,41	-0,124	0,89	8,34***	0,26
Nordea avkastning	-0,0765	0,0001	0,429	-0,147	0,96	7,17***	0,25
FORTE Norge	-0,0235	0,0003	0,398	-0,543	0,97	6,99***	0,24
Handelsbanken Norge	-0,007	0,0001	0,399	-0,542	0,93	7,76***	0,24
Alfred Berg Aktiv	-0,0016	0,0002	0,491	-0,124	1,04	9,71***	0,29
Nordea Kapital	-0,0065	0,0001	0,461	-0,653	0,86	8,23***	0,28
Holberg Norge	-0,0071	0,0002	0,451	-0,453	0,92	8,92***	0,27
KLP AksjeNorge	-0,0012	0,0005	0,446	-0,534	0,96	8,27***	0,24
DNB SMB A	-0,0081	0,0004	0,444	-0,124	0,99	8,59***	0,23
Landkreditt utbytte A	-0,0463	0,0003	0,412	-0,643	1,06	7,81***	0,31
Arctic Norway Value A	-0,0046	0,0003	0,464	-0,356	1,2	8,63***	0,21
Arctic Norwegian Eq. A	-0,0001	0,0002	0,497	-0,732	1,05	9,13***	0,26
FORTE Trønder	-0,0012	0,0004	0,356	-0,452	0,98	8,61***	0,26
PLUSS Aksje	-0,0073	0,0002	0,377	-0,235	0,83	8,53***	0,25
PLUSS Markedsverdi	-0,0012	0,0005	0,488	-0,689	0,61	8,15***	0,31

A7 Tables for robustness test

The subsequent tables provide diagnostic tests for heteroscedasticity (Breusch-Pagan test), autocorrelation tests (Durbin-Watson test), and stationarity test (Dickey-Fuller test) corresponding to the regression analysis presented in Table A4.

As for the Breusch-Pagan test, the p-value exceeds the conventional significance level of 0.05 in all instances, indicating a lack of significant evidence for heteroscedasticity in the dataset. We do not have sufficient evidence to reject the null hypothesis of homoscedasticity.

	Table A7.1: Breusch-Pagan test	
Fund	**BP**	**p-value**
Alfred Berg Norge C	0,751	0,366
DNB Norge A	0,003	0,960
Eika Norge	1,365	0,243
Odin Norge C	0,789	0,780
Nordea Norge Verdi	0,899	0,340
Storebrand Norge N	0,107	0,863
Fondsfinans Norge	0,045	0,834
Delphi Norge N	0,235	0,753
C WorldWide Norge	1,245	0,160
Alfred Berg Humanfond	0,752	0,548
DNB Norge selektiv A	1,020	0,861
Pareto Aksje Norge B	0,569	0,628
Pareto Investment Fund A	0,034	0,560
Pareto Global B	0,453	0,395
KLP AksjeGlobal Indeks P	0,665	0,107
KLP AksjeNorden Indeks P	0,698	0,458
Danske Invest Norske aksjer	0,348	0,670
Danske Invest Norge I	0,567	0,412
Nordea avkastning	1,075	0,553
FORTE Norge	0,487	0,431
Handelsbanken Norge	0,976	0,880
Alfred Berg Aktiv	0,155	0,749
Nordea Kapital	0,013	0,975
Holberg Norge	0,658	0,237
KLP AksjeNorge	0,981	0,395
DNB SMB A	1,012	0,765
Landkreditt utbytte A	0,661	0,225
Arctic Norway Value A	0,386	0,713
Arctic Norwegian Equities A	1,277	0,566
FORTE Trønder	0,654	0,889
PLUSS Aksje	1,193	0,360
PLUSS Markedsverdi	0,386	0,679

The Durbin-Watson (DW) test results show that the DW values for all cases are close to 2. This indicates that the residuals do not display significant systematic patterns or serial autocorrelation. Moreover, the high p-values, above the significance level of 0.05, provide further evidence to support the conclusion that there is no significant autocorrelation in the residuals. As a result, we fail to reject the null hypothesis of no autocorrelation in all cases.

	Table A7.2: Durbin-Watson test	
Fund	**DW**	**p-value**
Alfred Berg Norge C	2,306	0,991
DNB Norge A	2,420	0,995
Eika Norge	2,282	0,984
Odin Norge C	2,212	0,403
Nordea Norge Verdi	2,550	0,808
Storebrand Norge N	2,545	0,762
Fondsfinans Norge	2,505	0,946
Delphi Norge N	2,136	0,937
C WorldWide Norge	2,261	0,503
Alfred Berg Humanfond	2,420	0,521
DNB Norge selektiv A	2,016	0,523
Pareto Aksje Norge B	2,102	0,673
Pareto Investment Fund A	2,075	0,524
Pareto Global B	2,318	0,519
KLP AksjeGlobal Indeks P	2,466	0,746
KLP AksjeNorden Indeks P	2,313	0,453
Danske Invest Norske aksjer	2,287	0,942
Danske Invest Norge I	2,116	0,819
Nordea avkastning	2,349	0,880
FORTE Norge	2,008	0,801
Handelsbanken Norge	2,062	0,653
Alfred Berg Aktiv	2,438	0,566
Nordea Kapital	2,053	0,726
Holberg Norge	2,026	0,762
KLP AksjeNorge	2,447	0,957
DNB SMB A	2,620	0,996
Landkreditt utbytte A	2,257	0,781
Arctic Norway Value A	2,446	0,749
Arctic Norwegian Equities A	2,149	0,864
FORTE Trønder	2,441	0,988
PLUSS Aksje	2,268	0,430
PLUSS Markedsverdi	2,301	0,917

The p-values below 0.05 indicate strong evidence to reject the null hypothesis of non-stationarity for all funds, suggesting they exhibit stationary behavior. This is desirable for financial analysis as it allows for more reliable modeling and forecasting. The negative Dickey-Fuller values further support the conclusion of stationarity, indicating a tendency for the data to revert to a long-term average.

Table A7.3: Dickey-Fuller test

Fund	Dickey-Fuller	p-value
Alfred Berg Norge C	-2,067	0,048
DNB Norge A	-1,976	0,026
Eika Norge	-3,539	0,005
Odin Norge C	-3,865	0,026
Nordea Norge Verdi	-1,976	0,045
Storebrand Norge N	-3,776	0,036
Fondsfinans Norge	-2,372	0,024
Delphi Norge N	-3,705	0,004
C WorldWide Norge	-1,765	0,041
Alfred Berg Humanfond	-3,517	0,045
DNB Norge selektiv A	-3,401	0,017
Pareto Aksje Norge B	-3,666	0,040
Pareto Investment Fund A	-3,758	0,030
Pareto Global B	-3,934	0,016
KLP AksjeGlobal Indeks P	-1,820	0,037
KLP AksjeNorden Indeks P	-3,704	0,040
Danske Invest Norske aksjer	-3,445	0,020
Danske Invest Norge I	-2,335	0,008
Nordea avkastning	-3,846	0,030
FORTE Norge	-2,678	0,023
Handelsbanken Norge	-1,598	0,025
Alfred Berg Aktiv	-2,934	0,036
Nordea Kapital	-3,308	0,008
Holberg Norge	-3,660	0,025
KLP AksjeNorge	-3,726	0,006
DNB SMB A	-3,922	0,018
Landkreditt utbytte A	-1,334	0,019
Arctic Norway Value A	-4,110	0,001
Arctic Norwegian Equities A	-3,832	0,049
FORTE Trønder	-3,709	0,014
PLUSS Aksje	-3,647	0,041
PLUSS Markedsverdi	-3,520	0,001

The following table displays the averaged results for stationarity, heteroscedasticity, and autocorrelation obtained from our regression analyses. These results provide evidence of no autocorrelation, no heteroscedasticity, and stationary regressions.

Table A7.4: Average result on diagnostics tests

	BP	p-value	DW	p-value	Dickey-Fuller	p-value
Regression A4	0,639	0,574	2,287	0,748	-3,139	0,025
Regression A5	0,531	0,633	2,467	0,562	-3,961	0,011
Regression A6	0,511	0,461	2,399	0,379	-2,863	0,032

A8 Figures

Figure 1: *VIX, VSTOXX and NVIX prices with quartile and decile*

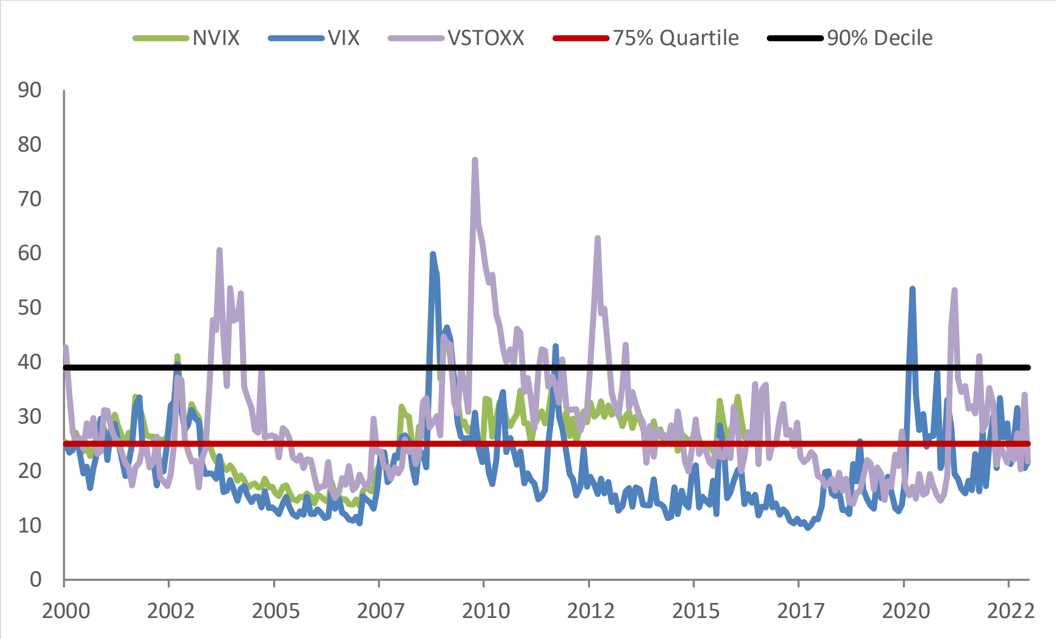


Figure 1 in displays the prices of VIX, VSTOXX, and NVIX over a specific time period. The vertical axis represents the prices of these indices, while the horizontal axis represents the corresponding time period. Additionally, the figure includes two reference lines: a red line indicating the 75th quartile and a black line representing the 90th decile. These lines provide further context and help assess the levels of market fear during the observed time period.

Figure 2: *VIX and Average rolling beta values*

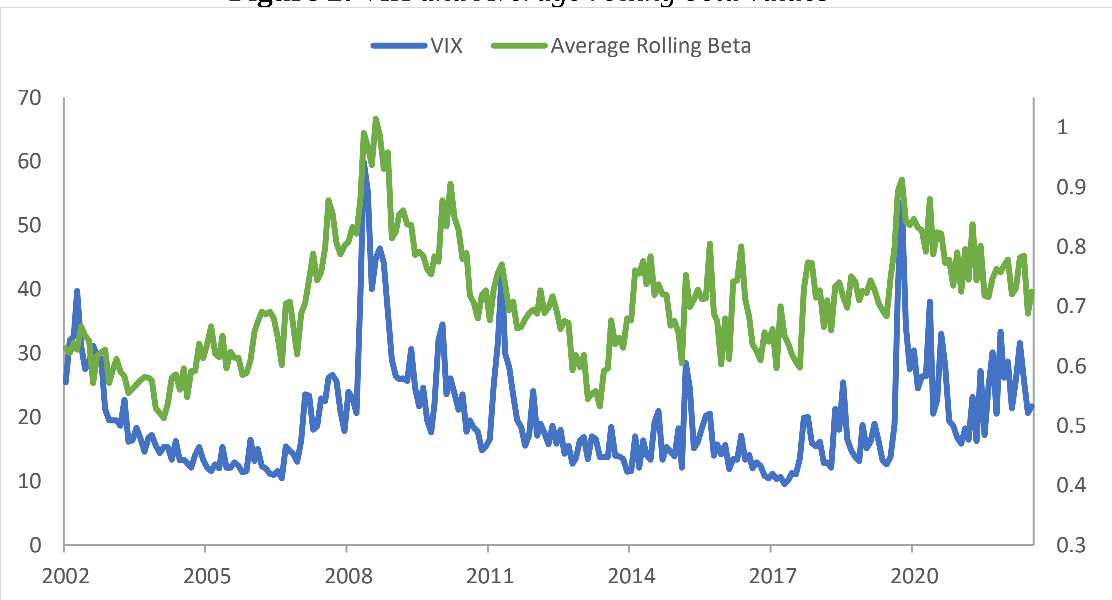
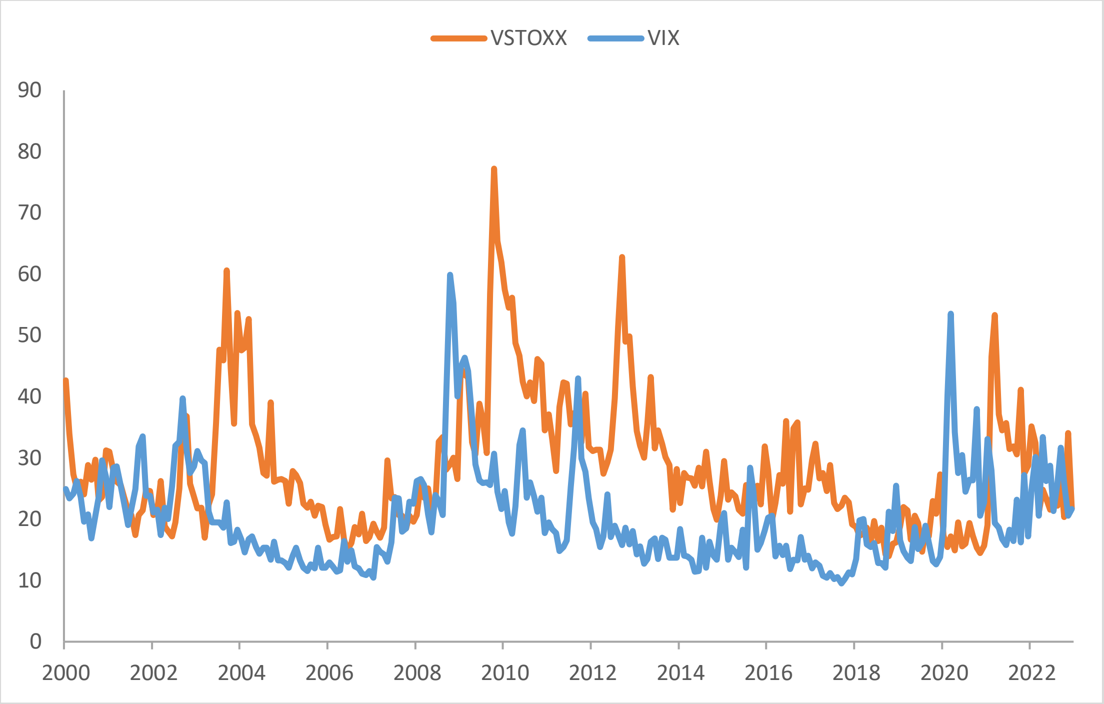


Figure 2 compares the Beta VIX (Volatility Index) to the average Rolling Beta of 32 selected funds in our chosen time period. Generally, the highest values of both indicators exhibit similarities and relative stability, although there are a few exceptions. This suggests a consistent relationship between the Beta VIX and the average Rolling Beta for most of the chosen funds, indicating similar levels of volatility and market risk across those funds.

Figure 3: *VSTOXX and VIX*



In Figure 3, we compared Beta VIX and Beta VSTOXX prices and observed similar patterns with a noticeable delay. This pattern was particularly evident during the years 2008-2011 and 2020-2022. During these periods, the VSTOXX appeared to follow the movements of the VIX, but with a time lag, suggesting that changes in volatility in one index were reflected in the other index with a delay.

A9 Fund activeness

The Table below shows the mutual funds' activeness throughout the whole sample period measured by adjusted R and Tracking Error.

	Most Active			
Ranking	**Fund**	R^2	**Fund**	**TE**
1	Odin Norge C	47.78 %	Fondsfinans Norge	12.43 %
2	Alfred Berg Aktiv	52.36 %	Odin Norge C	11.98 %
3	Fondsfinans Norge	64.07 %	Arctic Norway Value A	10.04 %
4	Arctic Norwegian Equities A	67.09 %	Alfred Berg Aktiv	9.49 %
5	Nordea Kapital	75.88 %	Arctic Norwegian Equities A	9.36 %
6	Arctic Norway Value A	76.97 %	Nordea Kapital	9.34 %
7	Alfred Berg Norge C	79.52 %	Alfred Berg Norge C	8.30 %
8	Eika Norge	82.11 %	Eika Norge	7.98 %
9	C WorldWide Norge	85.68 %	KLP AksjeNorge	6.93 %
10	KLP AksjeNorge	88.93 %	C WorldWide Norge	6.38 %
	Least Active			
Ranking	**Fund**	R^2	**Fund**	**TE**
23	Pareto Global B	96.69 %	Pareto Global B	4.12 %
24	KLP AksjeNorden Indeks P	96.98 %	Delphi Norge N	3.98 %
25	Pareto Investment Fund A	97.02 %	Pareto Investment Fund A	3.78 %
26	Alfred Berg Humanfond	97.13 %	Alfred Berg Humanfond	3.76 %
27	Storebrand Norge N	97.37 %	KLP AksjeNorden Indeks P	3.68 %
28	Delphi Norge N	97.42 %	Landkreditt utbytte A	3.35 %
29	KLP AksjeGlobal Indeks P	97.45 %	KLP AksjeGlobal Indeks P	3.09 %
30	Landkreditt utbytte A	97.66 %	Storebrand Norge N	3.02 %
31	DNB SMB A	97.87 %	DNB SMB A	2.98 %
32	DNB Norge selektiv A	98.36 %	DNB Norge selektiv A	2.67 %

A10 Regression output – NVIX and benchmark

The Table below shows the mutual funds alpha, beta for the NVIX and the OSEFX, t-value, p-value and the R-squared through the whole sufficient sample size. The significance levels are represented by: *p <0.1; **p <0.05; ***p <0.01.

Table A10: NVIX and OSEFX

Fund	α	βNVIX	βMKT	t-value α	t-value NVIX	t-value MKT	R^2
Alfred Berg Norge C	0,011	-0,112	0,31	3,61**	-8,02***	6,82***	0,41
DNB Norge A	0,009	-0,118	0,38	3,87**	-8,72***	7,39***	0,53
Eika Norge	0,014	-0,111	0,24	3,28**	-8,25***	6,02***	0,39
Odin Norge C	0,024	-0,099	0,24	4,43***	-8,85***	7,95***	0,46
Nordea Norge Verdi	0,011	-0,113	0,27	4,18***	-9,96***	6,61***	0,41
Storebrand Norge N	0,015	-0,125	0,36	4,35***	-9,25***	7,11***	0,40
Fondsfinans Norge	0,012	-0,114	0,32	4,53***	-8,92***	6,95***	0,43
Delphi Norge N	0,012	-0,128	0,36	3,55***	-8,63***	6,34***	0,44
C WorldWide Norge	0,01	-0,112	0,31	3,02**	-9,11***	7,51***	0,47
Alfred Berg Humanfond	0,017	-0,111	0,29	3,72**	-8,53***	6,16***	0,35
DNB Norge selektiv A	0,011	-0,149	0,31	3,35***	-8,16***	6,92***	0,42
Pareto Aksje Norge B	0,01	-0,113	0,34	4,93***	-9,73***	7,09***	0,49
Pareto Investment Fund A	0,009	-0,098	0,32	3,88***	-9,29***	7,03***	0,41
Pareto Global B	0,015	-0,041	0,35	3,21***	-9,14***	5,17***	0,47
KLP AksjeGlobal Indeks	0,012	-0,153	0,24	3,11**	-8,66***	7,73***	0,48
KLP AksjeNorden Indeks	0,011	-0,111	0,37	3,85***	-8,42***	6,82***	0,58
Danske Inv. Norske aksjer	0,01	-0,163	0,28	4,83***	-8,65***	7,23***	0,43
Danske invest Norge I	0,015	-0,163	0,36	4,25***	-9,93***	7,84***	0,47
Nordea avkastning	0,009	-0,116	0,35	3,85***	-9,13***	6,32***	0,48
FORTE Norge	0,021	-0,134	0,35	4,67***	-7,83***	6,27***	0,44
Handelsbanken Norge	0,01	-0,175	0,37	3,13***	-8,12***	7,82***	0,43
Alfred Berg Aktiv	0,009	-0,022	0,21	4,18***	-9,53***	6,85***	0,51
Nordea Kapital	0,001	-0,105	0,24	3,76***	-7,95***	5,28***	0,44
Holberg Norge	0,015	-0,102	0,32	3,28**	-8,94***	6,49***	0,44
KLP AksjeNorge	0,001	-0,121	0,31	4,76***	-9,29***	6,24***	0,48
DNB SMB A	0,012	-0,153	0,31	4,46***	-9,02***	7,83***	0,41
Landkreditt utbytte A	0,01	-0,192	0,33	3,25***	-9,05***	6,85***	0,45
Arctic Norway Value A	0,012	-0,112	0,35	4,23***	-9,12***	6,23***	0,39
Arctic Norwegian Eq. A	0,011	-0,115	0,31	3,24***	-7,93***	7,86***	0,40
FORTE Trønder	0,002	-0,169	0,26	2,74***	-9,01***	6,35***	0,43
PLUSS Aksje	0,009	-0,094	0,31	3,13***	-8,35***	6,23***	0,46
PLUSS Markedsverdi	0,021	-0,159	0,31	4,15***	-9,35***	7,76***	0,44