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How Severe Market Crises Affect Nordic Hedge Funds' Excess Returns

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Abstract

Drawing from a unique dataset of 11 801 observations of Nordic hedge funds spanning 1991-2021, this paper provides evidence on how severe market crises affect hedge funds' ability to generate alpha. Employing ordinary least squares (OLS) and logistic regression analyses, this study analyses three distinct periods: the financial crisis (2007-2009) and the COVID-19 pandemic (2020), and normal periods (all other times).

The results show that during normal periods, Nordic hedge funds consistently generate alpha. In contrast, during the financial crisis, while alpha was not significant in the OLS models, the logistic models imply that hedge funds maintained a meaningful probability of achieving positive excess returns, suggesting strategic adaptability. Conversely, during COVID-19, neither of the models find alpha to be significant, reflecting the unprecedented challenges posed by the pandemic.

In addition, I provide evidence on how systematic factors, particularly the market risk premium (*Mkt-RF*), emerged as the primary drivers of hedge fund performance during crises. The results contribute to existing literature and are consistent with prior research, such as Ibbotson, Chen and Zhu (2011) and Frydenberg et al. (2017).

1. Introduction

Over the history of modern financial markets, few events have tested the resilience of different institutions and strategies as profoundly as the 2007-2009 financial crisis and the COVID-19 pandemic. The financial crisis, originally fueled by the collapse of the subprime mortgage market, triggered a global economic shock that wiped out trillions of dollars in wealth and shook the foundations of the whole financial system globally. A bit over a decade later, the COVID-19 pandemic took the world by surprise by bringing an entirely different kind of shock – on distinguished by unprecedented market volatility, rapid sell-offs, and equally swift recoveries driven by enormous liquidity injections from central banks. In the middle of this turbulence, hedge funds have stood in the epicenter with roles as amplifiers of systemic risk, but also as potential stabilizers. With their unmatched flexibility, capacity to take leverage and access to sophisticated tools, hedge funds have had a unique opportunity to either rise above the chaos or succumb to it.

While these events undoubtedly marked as some of the most challenging times of our generation, they provide a rare lens through which to study hedge fund returns. The financial crisis tested the limits of traditional investment strategies, whereas COVID-19 forced funds to adapt to a market environment characterized by extreme unpredictability. However extant literature does, to my knowledge, remain inconclusive on how effectively hedge funds navigated these crises and what does their performance reveal about their capacity to create independent value amidst extreme circumstances.

For example, Ibbotson, Chen and Zhu (2011) found that hedge funds were, in fact, able to generate alpha during the financial crisis, whereas Frydenberg et al. (2017)

claimed that none of the 13 strategies analyzed by the team generated alpha during bearish market conditions. Accordingly, Stafylas, Anderson and Uddin (2018) found that hedge funds' alpha generation is significantly higher in bullish market conditions, with only a few strategies, like Global Macro, implying consistent success during bearish seasons. This gap leaves ground for further research on the relationship between the two crises and hedge funds.

As a response, this paper provides evidence on how the financial crisis and COVID-10 affect hedge funds' ability to generate excess returns. I hypothesize that hedge funds' ability to generate alpha is negatively affected by both of the crises, although the negative effect is more significant for COVID-19 due to its unprecedented nature. Taking a novel approach by using a unique dataset on Nordic hedge fund returns over the years 1991-2021, this study examines alpha across three distinct periods: the financial crisis (July 2017 – June 2009), the COVID-19 pandemic (March 2020 – December 2020), and normal market conditions. By employing ordinary least squares (OLS) and logistic regression models, this paper also evaluates the role of systematic risk factors, such as the Fama-French five-factors, and fund-specific characteristics, such as age, in shaping hedge fund performance across different conditions.

It is essential to highlight that no official definition exists for hedge funds. However, hedge fund managers can be distinguished by their ability to employ a diverse range of investment strategies and tools, such as short selling, extensive leverage, or derivatives – approaches that are rarely used by mutual funds. This unique fund type is a particularly important and current field to study for a number of reasons. Firstly, hedge funds are incentivized and capable of holding very concentrated, illiquid positions in the market, strengthening their negotiation power. In contrast, mutual-and pension funds are required by law to maintain more diversified positions (Jiang, Li and Want, 2012).

Second, the hedge fund industry appears to be significantly larger than commonly thought and growing fast, as shown by Barth, Joenväärä, Kauppila and Wermers (2020). In short, the research shows that in 2016, net assets under management (AUM) for hedge funds globally were more than $5 trillion and the value of gross assets higher than $8.5 trillion. Putting these numbers into perspective, regulators estimate the net assets under management to range between $2.3-$3.7 trillion in 2016. The size difference is particularly significant, because hedge funds are closely interconnected to other financial market players, like prime brokers, making them important for the whole financial system. In addition, hedge funds could be claimed to have the most sophisticated investor base in the financial field, including foundations, pension funds and certain accredited individuals – further emphasizing their power in the market.

The rest of this paper is organized as follows. Chapter 2 examines existing literature on hedge funds, their ability to generate excess returns and Fama-French five factors over different market conditions. Next, Chapter 3 describes the data and variable definitions, while Chapter 4 outlines the used research methodologies. Chapter 5 examines the empirical findings and addresses identified limitations. Finally, Chapter 6 presents conclusions and discusses avenues for future research.

2. Literature review

Back in 1970, Eugene F. Fama first introduced the article “Efficient Capital Markets: A Review of Theory and Empirical work”, outlining a definition and levels for market efficiency. In short, Fama claims the market to be perfectly efficient if there are no transaction costs to trading, all market parties can retrieve all available facts without a cost, and everyone agrees on the impact of information for the current and future prices of the securities. By contrast, Grossman and Stiglitz (1980) introduced *the Grossman Stiglitz Paradox*, stating that gaining information is costly for investors, compensated by potentially mispriced assets, yielding that not all information is reflected in the prices. While Fama’s 1970 article has served as the foundation for examining the efficiencies of capital markets globally. unsurprisingly, the consensus of the academic world is that the markets are, in fact, not fully efficient.

The empirical evidence on market inefficiencies indicates that the traditional Capital Asset Pircing Model (CAPM), introduced by Sharpe (1964) and Litner (1965), does not consistently explain asset returns. CAPM posits that the expected return of an asset is determined linearly by its sensitivity to market risk. To overcome the limitations of CAPM, Fama and French (1993) first introduced the Three-Factor model to address CAPM’s limitations by incorporating two additional factors: size (SMB), capturing the historical tendency of small-cap stocks to outperform large-cap stocks, and value (HML), reflecting the premium associated with value stocks in comparison to growth stocks. Later in 2015, Fama and French expanded their framework by two additional factors, profitability (RMW), reflecting that firms with higher profitability tend to deliver better returns, and investment (CMA), depicting that firms with more conservative investment policies usually outperform those with aggressive policies.

For instance, Hou, Xue and Zhang (2015) show that systematic market inefficiencies exist, making it possible to generate excess returns using specific strategies. Similarly, Stambaugh, Yu and Yuan (2012) show that negative investor sentiment can trigger specific market anomalies, that are not fully removed even when liquidity and trading activity is high, as presented by Chordia, Subrahmanyam and Tong (2014). These anomalies leave ground for investors to make excess returns. In particular, hedge funds often employ anomaly-based strategies to generate profits by exploiting inefficiencies and mispricing in the market. In fact, several studies show that hedge funds possess and information advantage over other institutional investors (Sias, Turtle and Zykaj, 2016; Cao et al., 2015). Similarly, a recent study by Paliienko et al. (2020) demonstrated that despite the five-factors' significant explanatory power, certain anomalies persist.

The first known hedge fund was not a product of an investment strategy developed by university business professionals but formed by the sociologist Alfred W. Jones in 1949. In practice, Jones raised $60,000 and invested a further $40,000 of his own savings to pursue a market neutral strategy based on long-short equity positions and leverage, allowing him to take large and risky positions with limited resources. He also innovated the incentive fee, being 20% of realized profits in his case. In 1966, Fortune published an article about Jones' substantially high returns, using the term "hedge fund" to describe his strategy. Hot on the heels of the article being published, numerous "Jones imitators" entered the market and the hedge fund industry, as we know it, was born. (Fung and Hsieh, 1999; Brown et al., 1999; Stulz, 2007)

Hedge funds quickly expanded over 1967 and 1968, until the bearish periods in 1968-1970 and 1973-1974 yielded substantial losses and capital withdrawals for many of the funds. It was not until 1986 when *the Institutional Investor* published an article on Julian Robertson's Tiger Fund, that hedge funds gained back their popularity. The article highlighted that during the first six years of its existence, the fund had yielded phenomenal annual returns of 43%, even net of incentive fee and other expenses. Since then, hedge funds have become a crucial part of the financial system (Fung and Hsieh, 1999). In fact, the hedge fund industry nowadays is even larger and more impactful than regulators and industry experts have thought. For instance, Barth, Joenväärä, Kauppila and Wermers (2020) show that in 2016, net assets under management (AUM) and gross assets under management for hedge funds globally were in fact more than double the regulators' estimate of $2.3-$3.7 trillion .

While no official definition exists to this day, hedge funds can be characterized by their flexible investment styles, sophisticated investors, special fee structures and lightly regulated organizational structures with managers in particularly strong roles (Ackermann, McEnally and Ravenscraft, 1999). Thus, in contrast to companies with complex organizational structures, hedge fund performance can be attributed to managerial abilities of specific teams (Agarwal, Jiang, Tang and Yang, 2013; Kosowski, Naik and Teo, 2007; Zingales, 2000), making their ability to create returns and survive different market conditions particularly interesting to study.

Considering hedge funds' ability to generate alpha, Brown et al. (1999) studied hedge fund returns with data dating all the way back to 1989 until 1995 and demonstrated significant alpha over the period. Since the turn of the millennium, researchers have continued to show that hedge funds have mostly been able to generate relatively high excess returns with low correlation to other asset classes. That said, the results of the vast body of research on the field are not fully aligned, giving ground for further study on the phenomena.

For example, Frydenberg et al. (2011) claim that certain hedge fund strategies, like global macro and managed futures, can create positive alpha even in bearish market conditions. While other strategies were shown to be less effective in difficult market conditions, the lowered exposure to the stock market during these times seemed to protect returns from negative market shocks. Similarly, in their multi-factor model Frydenberg et al. (2017) demonstrate that over time, eight out of thirteen hedge fund strategies produce alpha. However, in contrast to Frydenberg et al. (2011), the results indicate that during bearish market conditions, none of the strategies create alpha. Although the authors suggest that hedge funds' alpha was more common during the 1990s than in later periods, Ibbotson, Chen and Zhu (2011), analyzing hedge fund returns between 2005 and 2009, show that hedge funds could create excess returns even during the financial crisis.

Supporting Frydenberg et al. (2011) and Ibbotson, Chen and Zhu (2011), also Stafylas, Anderson and Uddin (2018), examining 11 US hedge fund strategies over 1990 and 2014, show that in bullish conditions, nine out of eleven hedge fund strategies generate alpha, whilst global macro is the only strategy yielding significant alpha during bearish times, in addition to their "others" category. Overall, it seems evident that the number of strategies yielding alpha is significantly higher during bullish times, whereas only global macro seems to continuously yield excess returns during bearish times.

Speaking of bearish times, 2020 was an extraordinary year for everyone and not least for investors. From all-time highs during January and February, the break of the COVID-19 pandemic induced major sell-offs starting in March. This was followed by major quantitative easing practices and liquidity being brought back to the system, yielding a fast recovery of risky assets. This makes it particularly interesting to shed further light into how hedge fund performance was affected during the unique market shock. For example, Khelife et al. (2022) find that the pandemic significantly affected hedge fund performance, although managed futures and relative value strategies remained less impacted.

Studying hedge fund managers from a diversity perspective, Tommar et al. (2022) used the lockdown due to COVID-19 pandemic to study if inequalities in childcare affect highly skilled female hedge fund managers' productivity at work. The results suggest that female hedge fund managers' ability to create alpha was cut back by 9% during school closures, whilst male managers' remained the same. The researchers also compared these results to the financial crisis that did not include clearly increased need for childcare at home and found no difference between mothers and fathers' performance at work. While providing important insights on structural gender equality matters, this study provides one explanation for declining alpha during COVID-19.

In this paper, I make use of novel dataset on Nordic hedge fund returns from a long timespan from 1991 to 2021. I examine how the financial crisis and COVID-19 affected Nordic hedge funds' ability to generate excess returns. Based on extant literature, I hypothesize that hedge funds' ability to generate alpha is negatively affected by both of the crises, although the negative effect is more significant for COVID-19 due to its unprecedented nature.

3. Sample and Data

My research uses novel dataset from HedgeNordic. The dataset consists of Nordic hedge fund returns spanning the years 1991-2021 and includes 11 801 observations of 88 unique funds from Denmark, Finland, Norway and Sweden. Of these, 1 159 observations are from the financial crisis timeframe from July 2007 to June 2009. 1 298 observations are from the COVID-19 period, extending from March 2020 to December 2020. All other 9 344 observations are considered to fall under the "Normal time" category.

The Financial Crisis (2007–2009) is defined as the period from July 2007 to June 2009. This timeline is in line with the onset and acute phase of the global financial crisis. The starting point, July 2007, marks the beginning of heightened market volatility and financial instability, triggered by the collapse of the U.S. subprime mortgage market and subsequent credit crunch (Brunnermeier, 2009; Acharya et al., 2009). The endpoint, June 2009, reflects the period when global stock markets began to recover and major economies showed signs of stabilization, supported by large-scale government bailouts and monetary interventions (Taylor, 2009).

On the other hand, the COVID-19 Crisis (2020) is defined as the period from March 2020 to December 2020. This timeline captures the economic and financial shock caused by the onset of the pandemic. March 2020 was marked by the World Health Organization's declaration of COVID-19 as a pandemic and the subsequent global market sell-off, which saw equity markets experience their fastest declines in modern history (Baker et al., 2020). The endpoint, December 2020, reflects the partial stabilization of markets, aided by aggressive monetary and fiscal policy responses from central banks and governments worldwide (Chebbi et al., 2022).

Table 1 below shows descriptive statistics for the variables used in the analysis, including the number of observations (*N*), mean, median, standard deviation and the 1st and 3rd quartiles.

Table 1: Descriptive statistics

This table presents descriptive statistics for the dataset of Nordic hedge funds spanning over the years 1991-2021. The dataset includes observations from normal periods as well as two significant crises: the financial crisis (July 2007 – June 2009) and the COVID-19 pandemic (Match 2020 – December 2020). The data is divided into two panels: Panel A provides statistics for hedge fund characteristics, while Panel B focuses on return components. Panel A reports the number of observations (*N*), mean, median, first quartile (25%) and third quartile (75%), and standard deviation for key hedge fund characteristics. Fund size is measures as assets under management (AUM) in millions of euros and fund age is calculates the number of years since the fund's inception. Excess return serves as the main dependent variable in this study, while the Fama-French five-factors serve as the main independent variables.

	N	Mean	Median	25%	75%	Std. Deviation
Panel A: Hedge Fund characteristics						
Annual management fee (%)	88	1.14%	1.00%	1.00%	1.50%	0.40%
Performance fee (%)	88	15.97%	20%	10.00%	20.00%	5.98%
Size (AUM in USD mil)	88	354	119	39	314	831
Age (months)	88	120	117	60	170	71
Panel B: Return components						
Excess return	11801	0.005	0.004	-0.006	0.018	0.032
Mkt-RF	11801	0.010	0.014	-0.014	0.034	0.046
SMB	11801	0.000	0.002	-0.018	0.017	0.027
HML	11801	-0.005	-0.005	-0.020	0.011	0.030
RMW	11801	0.002	0.002	-0.009	0.011	0.017
CMA	11801	-0.001	-0.001	-0.013	0.009	0.016
RF	11801	0.001	0.000	0.000	0.002	0.001

In the OLS analysis, the dependent variable is *excess return*, calculated as the difference between the fund's total return and the risk-free rate. For the logistic models, on the other hand, the dependent variable is *positive return*, which refers to a binary variable that gets the value of 1 if the fund achieved a positive excess return and otherwise 0. In both models, the independent variables include the Fama-French five factors and additional fund-specific characteristics:

Market risk premium (*Mkt-RF*) is defined as the excess return of the market portfolio over the risk-free rate, measuring the fund's exposure to overall market risk.

Size (*SMB*) is calculated as the return difference between portfolios of small-cap and large-cap stocks, capturing the fund's leniency towards smaller firms.

Value (*HML*) shows the return difference between value stocks (high book-to-market ratio) and growth stocks (low book-to-market ratio), measuring the fund's preference for value-oriented strategies.

Profitability (*RMW*) is calculated as the return difference between highly profitable firms and less profitable firms, indicating the fund's possible exposure to profitability anomalies.

Investment (*CMA*) shows the return difference between firms with conservative and aggressive investment policies, calculating the fund's sensitivity to firms' investment strategies.

In addition to the Fama-French five-factors described above, fund age fixed effects (*Age_Group*) are used to account for variability related to fund age. The value is calculated based on the difference between the observation year and the fund's inception year the dummy variables are created for three age groups: funds younger than 5 years (*Age_Group1*), funds aged between 5 and 10 years (*Age_Group2*) and funds older than 10 years, representing the reference group.

Lastly, year fixed effects are included in the normal period model to control for time-specific shocks and trends that may affect performance.

4. Research methodology

I examine how market crises, namely the financial crisis and COVID-19, affect hedge fund excess returns using two different regression models. More specifically, I use ordinary least squares (OLS) regression analysis and logistic regression analysis to obtain a robust overall conclusion of the phenomena. First, the OLS is particularly effective for calculating the average effect of each factor on excess returns, making it useful for evaluating how hedge funds adapt their strategies to navigate different time periods.

Second, the logistic analysis complements OLS by estimating the probability of hedge funds achieving positive excess returns, rather than focusing on average returns. The binary outcome approach is useful for analyzing performance under crisis conditions, where the likelihood of generating alpha may vary significantly across funds and periods.

I also employ several methods to control for possible bias in the sample. First, I use the White-test to examine whether there is heteroskedasticity for each time period of my dataset. As the White-test indicates the possibility for heteroskedasticity, I adjust my analyses using heteroskedasticity robust standard errors. Second, in both models, I control for year fixed effects to account for covariation caused by unusual characteristics in a particular year during the "normal period" timeframe.

Finally, I test for potential multicollinearity of the variables. The pairwise correlations between the variables are adequately low, as presented in Table 2 below. In addition, I completed the VIF-test for multicollinearity. The test showed values below 5, more specifically between the range 1.1 and 1.7, for all variables, indicating no significant multicollinearity.

Table 2: Pairwise correlation matrix

This table presents pairwise correlations of the variables used in the OLS and logistic regression analyses, based on Nordic hedge fund returns from 1991 to 2021. The dependent variables are excess return and positive return (binary) for the OLS and logistic models, respectively. Independent variables include the Fama-French five-factors (*Mkt-RF, SMB, HML, RMW, CMA*) and fund-specific characteristics such as fund age fixed effects. All variables are described in Section 3 of this paper.

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
(1) Excess return								
(2) Positive_Return	0.615							
(3) Mkt-RF	0.368	0.283						
(4) SMB	0.172	0.103	0.433					
(5) HML	0.088	0.047	0.248	0.366				
(6) RMW	-0.050	-0.052	-0.143	-0.310	0.017			
(7) CMA	-0.060	-0.043	-0.125	0.029	0.482	0.054		
(8) Age_years	-0.001	-0.030	-0.041	0.040	0.122	0.036	0.092	

4.1. OLS regression model

In the first model, I employ the ordinary least squares (OLS) regression models to analyze excess returns controlling for systematic risk factors (Fama-French five factors) during market crisis and normal times. The main hypothesis studied is that **hedge funds' ability to generate alpha is negatively affected by both of the crises**, although the negative effect is more significant for COVID-19 due to its unprecedented nature.

The dependent variable is hedge fund excess returns, and the explanatory variables consist of the Fama-French five factors, as described in Section 3 of this paper. In addition, I include year fixed effects in the normal period to account for possible unobserved time-specific effects. I also used fund age fixed effects to account for potential performance differences across funds of different maturity. That is, younger funds may exhibit higher risk-taking behavior, whilst older funds may benefit from established processes and experience. Also, robust standard errors are used to address heteroskedasticity in the sample. I estimate a separate OLS model for crisis conditions as follows:

$$Excess_t = \beta_0 + \beta_1 Mkt - RF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \sum_{j=1}^{J} \gamma_j \,\mathrm{Age}_j + \varepsilon_t$$

For the normal periods, the model can be presented as:

$$Excess_t = \beta_0 + \beta_1 Mkt - RF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \sum_{i=1}^{T} \gamma t \,\mathrm{Year}_t + \sum_{j=1}^{J} \gamma_j \,\mathrm{Age}_j + \varepsilon_t$$

Where,

$Excess_t$ = The dependent variable: excess return of hedge funds in the sample at time t

$Mkt - RF_t$ = Market risk premium showing the excess return of the market portfolio above the risk-free rate at time t

SMB_t = Size factor (small minus big) showing the difference in returns between small-cap and large-cap stocks at time t

HML_t = Value factor (high minus low), showing the difference in returns between value stocks and growth stocks at time t

RMW_t = Profitability factor (robust minus weak), showing the difference in returns between companies with high and low profitability at time t

CMA_t = Investment factor (conservative minus aggressive), showing the difference in returns between firms with conservative and aggressive investment strategies at time t

β_0 = Intercept parameter

β_1 = Slope parameter for market risk premium

β_2 = Slope parameter for size factor

β_3 = Slope parameter for value factor

β_4 = Slope parameter for profitability factor

β_5 = Slope parameter for investment factor

$\sum_{j=1}^{J} \gamma_j \, \mathrm{Age}_j$ = Fund age fixed effects; dummies Age1 and Age2 refer to funds younger than 5 years and between 5-10 years, respectively. Funds older than 10 years are part of the reference group

$\sum_{i=1}^{T} \gamma t \, \mathrm{Year}_t$ = Year fixed effects, including a set of dummy variables controlling for time-specific effects during the Normal period

ε = Error term

4.2. Logistic regression model

Second, the logistic regression model studies the probability that hedge funds achieve positive excess returns (alpha) during market crises in comparison to "normal periods". In this case, I study the hypothesis that **market crises reduce the probability at which hedge funds achieve positive excess returns.**

I create three separate logistic models for each condition, the Financial crisis, COVID-19 and normal period. To employ a logistic model, I create a binary dependent variable, *Positive_Return* -dummy, that gets the value of 1 if a hedge fund achieves a positive excess return and 0 if the excess return is negative or zero.

Again, I employ Fama-French five factors specified above to control for systemic factors. To account for heteroscedasticity, I use robust standard errors. I also add fund age fixed effects as additional control. For the normal period, I add year fixed effects to control for economic cycles, changes in monetary policies and other changes in market conditions. Year fixed effects are not needed for crisis models, because the timespan of those is very short. More formally for the crisis periods the model can be presented as:

$$logit\big(P(Positive\_return = 1)\big) = \beta_0 + \sum_{i=1}^{5} \beta_{i+2}\,\mathrm{FF}_i + \sum_{j=1}^{J} \gamma_j\,\mathrm{Age}_j + \varepsilon$$

For the normal periods, the model can be presented as:

$$logit\big(P(Positive\_return = 1)\big) = \beta_0 + \sum_{i=1}^{5} \beta_i\,\mathrm{FF}_i + \sum_{j=1}^{J} \gamma_j\,\mathrm{Age}_j + \sum_{t=1}^{T} \delta_t\,\mathrm{Year}_t + \varepsilon$$

Where,

$P(ExcessPositive = 1)$ = Probability for positive excess return

β_0 = Intercept parameter representing baseline probability of achieving positive excess returns, ceteris paribus

FF_i = Fama-French factors used as control variables (Mkt-RF, SMB, HML. RMW, CMA)

β_i = Slope parameter for Fama-French factors

$\sum_{j=1}^{J} \gamma_j$ Age_j= Fund age fixed effects; dummies Age1 and Age2 refer to funds younger than 5 years and between 5-10 years, respectively. Funds older than 10 years are part of the reference group

$\sum_{t=1}^{T} \delta_t$ Year_t = Year fixed effects, including a set of dummy variables controlling for time-specific effects during the Normal period

ε = Error term

5. Empirical Results

5.1. Ordinary Least Squares- and Logistic regression results

Overall, the results of the OLS and logistic regression analyses imply that there are significant differences in alpha generation under different market conditions in the Nordics. First, the ordinary least squares regression results presented below in Table 3 analyze hedge funds' alpha generation across three different time periods; The financial crisis (July 2007 - June 2009), COVID-19 (March 2020 – December 2020) and normal periods (all other times). In the OLS models, the constant term, representing alpha, is significant only during normal times (0.045, $p < 0.01$), suggesting that hedge funds generated consistent excess returns in stable market conditions. However, during the financial crisis and COVID-19, alpha is not statistically significant, indicating that hedge funds had to rely more on systematic factors to achieve returns during those times. This pattern underlines the challenge hedge funds face in maintaining high independent performance under volatile market conditions with high systemic risk.

These findings are rather consistent with extant literature. For example, according to Frydenberg et al. (2017), as presented in Section 2 of this paper, most hedge funds lower their exposure to the stock market during bearish conditions, protecting them from negative market shocks, but making alpha generation more difficult. Similarly, Ibbotson, Chen and Zhu (2011) showed that while hedge funds were able to generate alpha on average, their performance during the financial crisis was more dependent on systematic risk factors rather than independent skill. This is also in line with Fung and Hsieh's (1997) framework, highlighting that hedge funds' ability to generate alpha is clearly constrained during times of extreme market stress, caused by their reliance on dynamic risk exposures.

Table 3: Ordinary Lest Squares (OLS) analysis on Nordic hedge fund excess returns across market crises

This table presents the results of the ordinary least squares (OLS) regression analysis of hedge fund excess returns, focusing on the effects of systematic risk factors, fund characteristics, and time-specific dynamics across different periods. The analysis employs a dataset of Nordic hedge funds spanning 1991-2021, capturing both, normal market conditions and two major crises: the financial crisis (July 2007 – June 2009) and the COVID-19 pandemic (March 2020 – December 2020). The dependent variable in all regressions is excess return, calculated as the difference between the fund's total return and the risk-free rate. The independent variables include the Fama-French five factors, and fund-specific characteristics captured through fund age fixed effects, accounting for performance differences across funds of varying maturity. Specifications 1,2 and 3 present the results for the financial crisis, COVID-19 and normal times, respectively. Year fixed effects are included in the normal period model (Specification 3) to control for macroeconomic changes during stable periods. Symbols ***, ** and * present statistical significance at the 1%, 5% and 10% levels, respectively. Heteroskedasticity robust standard errors are presented in the parentheses.

	Financial Crisis	COVID-19	Normal Times
	(1)	(2)	(3)
Market Risk (Mkt-RF)	0.408***	0.337***	0.203***
	(0.050)	(0.021)	(0.011)
Size (SMB)	-0.024	-0.052	0.001
	(0.046)	(0.043)	(0.016)
Value (HML)	-0.259***	0.061	-0.030*
	(0.065)	(0.052)	(0.016)
Profitability (RMW)	-0.032	-0.192***	-0.034
	(0.085)	(0.064)	(0.022)
Investment (CMA)	0.296***	-0.295***	-0.010
	(0.110)	(0.087)	(0.025)
Constant (Alpha)	-0.0005	0.002	0.045***
	(0.006)	(0.002)	(0.010)
Year Fixed Effects	No	No	Yes
Robust Standard Errors	Yes	Yes	Yes
Fund Age Fixed Effects	Yes	Yes	Yes
Observations	1,159	1,298	9,344
R^2	0.160	0.303	0.096

The logistic regression models presented in Table 4 below estimate the probability of achieving positive excess returns. As shown on Table 4, the constant term, representing the baseline likelihood of generating alpha, is significant both during financial crisis (0.502, $p < 0.01$) and normal times (12.301, $p < 0.01$), but is not statistically significant during COVID-19. The findings suggest that during the financial crisis, hedge funds were able to maintain a baseline probability of achieving alpha, perhaps through strategic adjustments or superior risk management. On the other hand, the absence of a significant constant term during COVID-19 suggests tat hedge funds struggled to generate independent alpha – likely due to the unique nature of the market volatility induced by the pandemic. These findings are in line with Tommar et al. (2022), as described in Section 2 of this paper, who propose that the heavy childcare burden during COVID-19 decreased women hedge fund managers' ability to concentrate on work and possibly hindered their ability generate significant alpha.

These results mirror the fragility of hedge fund alpha generation when it comes to market conditions at hand. While some funds demonstrated resilience during the financial crisis, the inability to generate significant alpha during COVID-19 indicates that the pandemic indeed disrupted traditional strategies, forcing funds to rely more heavily on systematic factors like market risk. This is in line with Ibbotson, Chen and Zhu (2011), who implied that alpha generation becomes more constrained under extreme market conditions, especially when systemic risks dominate.

The OLS and logistic models seem to provide contrasting views on alpha generation during the financial crisis, as the logistic models reveal a significant constant term for the period, whereas OLS finds no statistical significance in the financial crisis constant. The contradiction could imply that while average alpha during the financial crisis was not substantial, certain hedge funds likely achieved positive excess returns through strategic adaptability. In terms of COVID-19, however, both of the models highlight the unique challenges of the pandemic, limiting the role individual managers' skills played in comparison to systemic risk.

Additionally, the systematic factors in both models further illustrate the dynamics of hedge fund performance. In both models, the market risk premium (*MKT-RF*) remains positive and significant across all periods, highlighting the reliance on market dynamics in order to achieve high performance, especially during crisis. The value factor (*HML*), on the other hand, remains negative and significant during financial crisis in both, OLS and logistic models, underline the presumed underperformance of value stocks during this time. Accordingly, the contrasting effects of the investment factor (*CMA*), which is positive during the financial crisis and negative during COVID-19, can imply strategic shifts as a response to changing market conditions.

All in all, the logistic models described in Table 4 elaborate on the OLS findings shown in Table 3 by showing that while average alpha may not have been significant during the financial crisis, hedge funds still had a meaningful probability of achieving positive excess returns. This could, for instance, been interpreted as a reflection of the adaptability of some strategies. On the other hand, both models were aligned in that COVID-19 caused a unique shock to the Nordic market, yielding insignificant average alpha and the likelihood of generating alpha.

Table 4: Logistic regression analysis on Nordic hedge funds' probability of achieving positive excess returns during market crisis

This table presents the results of logistic regression analyses evaluating the probability of hedge funds achieving positive excess returns across three periods: the financial crisis (July 2007 – June 2009), the COVID-19 pandemic (March 2020 – December 2020) and normal times (all other periods). The analysis employs a dataset of Nordic hedge funds spanning 1991-2021, focusing on systematic risk factors, fund characteristics, and time-specific dynamics. Specifications 1,2 and 3 present the results for the financial crisis, COVID-19 and normal times, respectively. The dependent variable *Positive_Return* is binary, and gets the value of 1 if the fund achieved positive excess return, and otherwise 0. The independent variables include the Fama-French five factors, and fund-specific characteristics captured through fund age fixed effects, accounting for performance differences across funds of varying maturity. Year fixed effects are included in the normal period model (Specification 3) to control for macroeconomic changes during stable periods. Symbols ***, ** and * present statistical significance at the 1%, 5% and 10% levels, respectively. Heteroskedasticity robust standard errors are presented in the parentheses.

	Financial Crisis	**COVID-19**	**Normal Times**
	(1)	**(2)**	**(3)**
Market Risk (Mkt-RF)	15.227***	19.852***	13.594***
	(1.692)	(1.616)	(0.798)
Size (SMB)	0.886	-8.722**	-1.187
	(2.700)	(3.813)	(1.188)
Value (HML)	-9.757***	-4.791	1.028
	(2.407)	(3.068)	(1.280)
Profitability (RMW)	-0.341	-6.635	-3.645**
	(4.228)	(6.050)	(1.794)
Investment (CMA)	23.092***	0.524	-5.456***
	(5.376)	(4.634)	(2.042)
Constant (Alpha)	0.502***	0.177	12.301***
	(0.071)	(0.151)	(0.500)
Fund Age Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes
Robust Standard Errors	Yes	Yes	Yes
Observations	1,159	1,298	9,344
Log Likelihood	-710.436	-659.859	-5,765.606

5.2. Limitations and discussion

Like all academic papers, this study contains several limitations related to data constraints, methodological assumptions and inherent complexity of hedge fund strategies. First, hedge fund return data may be affected by survivorship bias. That is, when a fund collapses, it is sometimes omitted from databases and the performance history is removed. In addition, backfill bias may be present in the data as some funds only start reporting their performance after a good run in returns. (Ibbotson, Chen and Zhu, 2011) Moreover, the models in this paper do not account for different hedge fund strategies, giving ground for additional research on the field.

Second, the separation of time periods into distinct regressions in both analyses could limit the direct comparability of the crisis impacts on alpha. That is, the method fails to account for possible cross-period dependencies and structural changes in market behavior. In addition, the logistic regression models rely on binary outcomes, whether the excess return is positive or not, that may oversimplify the multifaceted nature of hedge fund performance.

The Fama-French Five-Factor Model provides a common and comprehensive framework for analyzing equity returns and has become a standard tool for evaluating hedge fund performance. However, its limitations in capturing anomalies like momentum and its equity-focused nature mean that hedge fund managers frequently operate beyond the model's scope, leveraging strategies to generate alpha in ways the model cannot fully capture.

For example, Foye (2018) evaluates the applicability of Fama-French five factor model in emerging markets across 18 countries. Results indicate that in Asian markets, the profitability and investemtn factors are less distinguishable, indicating regional variations in the model’s effectiveness. As the sample used in this research paper is

Nordic, issues related to the model's effectiveness across different countries may bias the results.

As such, this research excludes the momentum factor, that has been shown to play a role in explaining asset returns of hedge funds (Jegadeesh and Titman, 1993). This possible omitted variable bias may lead to an incomplete understanding of the performance divers and affect the interpretation of the alpha. In addition, fundg leverage and liquidity constraints could be useful additional datapoints for future models studying the topic, but have been excluded from this paper due to data constraints.

Moreover, the relatively small sample size (*N*) during the crisis periods poses another limitation to the study. That is, while the normal period has some 9 344 observations, the financial crisis and COVID-19 periods only have 1 159 and 1 298 observations, respectively. This may reduce the statistical power of the models and limit the generalizability of the findings. A larger sample size across numerous crises could enhance the robustness of the analysis.

6. Conclusions

Overall, using several ordinary least squares and logistic regression models, this research shows that Nordic hedge funds' ability to generate alpha was significantly influenced by market shocks caused by the financial crisis and COVID-19. More specifically, the results show that during normal times, hedge funds consistently achieve positive excess returns, as demonstrated in the OLS models in Table 3 (0.045, $p < 0.01$). Accordingly, the logistic models in Table 4 show a strong baseline probability of generating alpha (12.301, $p < 0.01$).

In contrast, during the financial crisis (July 2007 – June 2009), Nordic hedge funds show a significant baseline likelihood for generating alpha (0.502, $p < 0.01$) in the logistic models, suggesting strategic adaptability among some of the funds. Yet, alpha was not significant in the OLS models, suggesting that average excess returns were more reliant on systematic risk factors during the time of the crisis. On the other hand, during COVID-19 (March 2020 – December 2020), alpha was not statistically significant in either of the models, underlining the unique challenges posed by the pandemic.

The findings from the two different regression models show that systematic risk factors, in fact, played a dominant role in hedge fund performance during the crises. The market risk premium (*Mkt-RF*) was consistently positive and highly significant across all periods researched, with the strongest impact during COVID-19 (19.852, $p < 0.01$). This implies that hedge funds heavily relied on market-wide movements to achieve returns during the crisis. Other Fama-French factors demonstrate varying effects, with the value factor (*HML*) significantly negative during the financial crisis, reflecting the underperformance of value stocks. Also, the investment factor (*CMA*) seems to shift from positive during the financial crisis to negative during COVID-19, implying strategic adjustments to changing market dynamics.

These results add to and align with extant literature in the field of hedge funds. For example, Frydenberg et al. (2017) show that hedge funds' alpha generation diminishes during bearish conditions, consistent with the findings of this study, especially during COVID-19. Accordingly, Ibbotson, Chen and Zhu (2011) found that hedge funds generated alpha during the financial crisis, albeit with increased sensitivity to market dynamics. Finally, the findings also corroborate with Khelife et al. (2022), who showed the pandemic's disruptive effects on hedge fund performance and the challenges of navigating unprecedented liquidity and policy interventions.

As for future research, it may be fruitful to consider repeating this study with a larger, more geographically varying strategy-specific dataset, including additional explanatory factors such as momentum, fund leverage and liquidity risk. Incorporating these variables could provide a more comprehensive view of hedge fund performance under different market conditions, while revealing nuanced dynamics in alpha generation across different strategies.

As an additional idea, future studies could explore the interaction between hedge fund performance and investor behavior during market crises. For example, factors such as redemption patterns and flows could be examined, as they can either exacerbate or mitigate market pressures. Lastly, given the increasing role of machine learning and AI in creating hedge fund strategies, future papers could assess whether technological advancements have affected alpha generation. As an ending note, the insights of this paper to hedge funds and investors could be summarized in Nassim Nicholas Taleb's quote: "*Black Swan events are unpredictable, but their impacts can be mitigated through robust and resilient strategies*".

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