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Relationship Between Risk Exposure, Volatility Forecasting, and Financial Performance of Hedge Funds

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This is to certify that the doctoral study by

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Walden University
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Abstract

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of Hedge Funds

by

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MS, George Washington University, 2011

BENG, University of East London, UK, 1997

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

Poor hedge fund performance can impede the financial performance of an organization. Despite the success of hedge funds, they incurred a loss of 33% during the global economic recession of 2007-2009. Understanding volatility and risk exposures are vital for investors and managers to increase hedge fund returns in various market conditions. Grounded in Markowitz's modern portfolio theory, the purpose of this quantitative correlational study was to examine the relationship between hedge fund risk exposure, volatility forecasting, and financial performance. Data were collected from archival data from the HedgeNews Africa database and financial databases in South Africa between 2007 and 2020. The results of the multiple linear regression analysis indicated the model was able to predict the financial performance of hedge funds significantly, $F(2, 149) = 238$, $p < 0.001$, $R^2 = .950$, with risk exposure (3 month-credit spread), ($\beta = -0.789$, $t = -9.417$, $p < 0.001$), accounting for the highest contribution to the model. Volatility forecasting did not explain any significant variance in the financial performance of hedge funds. A key recommendation for hedge fund managers is to include risk exposure to maximize financial performance. The implications for positive social change include the potential for maximum profits in turbulent market conditions for institutional and individual investors, which could be applied to provide social amenities for communities and improve the welfare of people.

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Dedication

I dedicate this study to my daughters, Sanele Lasana and Ayanda Lasana, for their patience, sacrifice, and support, and my sister, Ramona Nicolas, for her support. I would not have been motivated to pursue this study without them. Their support gave me the strength to complete this doctoral study despite its many challenges.

Acknowledgments

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Section 1: Foundation of the Study

The goal of a hedge fund manager is to consistently provide superior performance using dynamic strategies (Almeida et al., 2020). Cui and Kolokolova (2020) and Muteba Mwaba (2017) attributed superior performance to either manager timing skill, asset selection ability, or a combination of both. However, Limam et al. (2017), Stafylas and Andrikopoulos (2020), Cai et al. (2018), and Racicot and Théoret (2018) provided evidence that hedge fund performance is subject to structural breaks, discrete shifts, market volatility, and time-varying properties of hedge fund dynamics. Under severe market conditions, various hedge fund strategies are likely to have different exposures to changes in market risk factors based on varying volatility regimes (Agarwal et al., 2018a).

Investment decisions rely on each strategy's risk/reward ratio, which requires managers to use the appropriate style analyses in the hedge fund market (Stafylas & Andrikopoulos, 2020). Skilled timing managers deliver excess returns by timing market liquidity and predicting both market and volatility conditions (Cao et al., 2018a). On the other hand, selecting managers deliver consistently excessive returns due to their selecting abilities (Cui & Kolokolova, 2020). However, when managers fail to forecast sudden shocks, which results in unexpected trends in asset prices, they deliver low returns. The purpose of this study was not to evaluate the skills of hedge fund managers directly, but to examine the relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds.

Background of the Problem

In the last two decades, from 2000 to 2020, hedge funds became popular in producing absolute returns in varying market conditions. Despite the success of hedge funds, they remained susceptible to losses during the financial crisis of 2007-2009 (Metzger & Shenai, 2019; Zhang et al., 2021). During the global financial crisis of 2007-2009, the total number of assets managed by the hedge fund industry declined by approximately 33% (Billio et al., 2017; Page & Panariello, 2018). The authors attributed the problem to hedge funds' exposure to new types of market risk factors. Furthermore, evaluating hedge funds using conventional methodologies may be inadequate (Chevalier & Darolles, 2019).

Hedge funds use varying investment strategies to produce higher returns than traditional assets (Cai et al., 2018). Consequently, the returns of hedge funds show abnormal and dynamic risk characteristics. Some researchers have come up with models to capture the hedge fund return dynamics (Almeida et al., 2020; Balcilar et al., 2017; Shin et al., 2018). The authors identified the regime-switching model as the most efficient model to capture time-varying risk exposure for hedge funds that are conditional on various market situations. Forecasting volatility captures the asymmetry and changes in the hedge fund returns characteristics (Limam et al., 2017). Xaba et al. (2017) found that using Markov regime-switching modeling was more accurate to forecast nonlinear time series. This study was an attempt to evaluate hedge fund performance relationships with volatility dynamics and market risk factors to understand market behavior and drivers of return.

Problem Statement

Poor hedge fund performance can negatively impact the financial performance of a business organization (Metzger & Shenai, 2019; Zhang et al., 2021). During the global financial crisis of 2007-2009, the total number of assets managed by the hedge fund industry declined by approximately 33% (Billio et al., 2017; Page & Panariello, 2018; Stoforos et al., 2017).). The general business problem is that hedge funds have a negative effect on company profits in a downturned market. The specific business problem is that some managers do not understand the relationship between risk exposure, volatility forecasting, and financial performance of hedge funds.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds. The independent variables were volatility forecasting, and risk exposure. The dependent variable was the financial performance of hedge funds. The targeted population comprised archival data from hedge fund databases in South Africa. The implication for positive social change includes the potential to provide organizational leaders who partner with hedge funds the ability to maximize profit by diversifying risk in volatile market conditions. Using an investment tool to dispel uncertainty in various market conditions is a financial means to foster a positive change (Sosner & Steblea-Lora, 2022). Accordingly, through partnerships with foundations and nonprofit organizations, hedge funds may help organization leaders fund projects in local communities.

Nature of the Study

Researchers may use quantitative, qualitative or mixed method approaches to conduct a study (Morgan, 2018; Zoellner & Harris, 2017). A quantitative method of research was suitable for this study as it is used to identify solutions through statistical data analysis and provide explanations of predictions and causal relationships (Köhler et al., 2017). Further, the quantitative method was appropriate for this study because the purpose was to examine the relationship between variables. A qualitative method is applicable when a researcher intends to understand the experiences and attitudes of people in a business or social setting (Mohajan, 2018). A mixed methods approach includes both quantitative and qualitative methods (Brannen, 2017). Researchers employ the mixed methods approach to combine the qualitative and quantitative methodologies when analyzing both textual and numerical data (Brannen, 2017; Williamson et al., 2020). Therefore, the qualitative portion of a mixed methods approach was not appropriate for this study.

Researchers may use a correlation design to examine the ability of the variables to predict an outcome (Zyphur & Pierides, 2020). A correlation design was appropriate for this study because of its purpose in examining the efficacy of modern portfolio constructs predicting financial performance of hedge funds. Other designs such as experimental and quasi-experimental comparative designs are appropriate when researchers seek to examine how independent variables may influence a dependent variable (Cortina, 2020). I did not manipulate the variables, and I did not randomize the secondary data during the collection process. An experimental research design was, therefore, not appropriate for this study, and the correlation design was most appropriate.

Research Question

Is there a statistical significant relationship between risk exposure, volatility forecasting, and financial performance of hedge funds?

Hypotheses

H_0: There is no statistically significant relationship between risk exposure, volatility forecasting, and financial performance of hedge funds.

H_a: There is a statistically significant relationship between risk exposure, volatility forecasting, and financial performance of hedge funds.

Theoretical Framework

Markowitz (1952) developed the modern portfolio theory to explain how to reduce a portfolio's risk and increase the expected rate of return when combining uncorrelated asset classes. Markowitz demonstrated that researchers could use the variance of the rate of return to calculate a portfolio's risk. Furthermore, Markowitz derived the statistical formula for computing the covariance of a portfolio (Shadabfar & Cheng, 2020). With the covariance formula, Markowitz was able to demonstrate the importance of diversifying investments to reduce risks effectively.

Diversification is the core concept of the modern portfolio theory, and is also a concept used to calculate risk (Tan & Trinidad, 2018). Markowitz contended that, over time, a diversified portfolio reduces volatility more efficiently than one that isn't diversified. Based on the analysis, the most prominent tenets of the modern portfolio theory are (a) an assumption that markets are efficient, and markets use this information to determine security prices; (b) investors receive higher returns for using high-risk investments over time; (c) adding high-risk, low-correlation asset classes to a portfolio can increase the expected rate of return and decrease volatility; and (d) investors can diversify passive asset class fund portfolios over time to deliver the highest expected rate of return (Markowitz, 1952). Similarly, Markowitz identified the key constructs of the modern portfolio theory as (a) volatility forecasting and (b) risk exposure. As applied to this study, the independent variables (modern portfolio constructs) were measured using archived data collected from publicly and privately accessible databases to predict the financial performance of hedge funds. The MPT applies to this study because the goal is to examine variables that may relate to the financial performance of hedge funds.

Operational Definitions

Capital markets: Capital markets include regulated markets where all-size capitalized companies can acquire funding for their short and long-term investments, including core corporations and expansion (Cao et al., 2018a).

Financial bubble: Financial bubble refers to an economic phase characterized by a sudden rise in asset prices followed by their reduction. Unjustifiable investor behavior can create a surge in asset prices (Jang & Kang, 2019).

Funds of funds: Funds of funds refers to an investment strategy of owning a portfolio of other investment funds. A fund of fund invests in other hedge-funds instead of investing in particular securities (Getmansky et al., 2019).

Hedge fund management and incentive fees: The management fee is usually set at 2% of the total asset, and is paid to the hedge fund manager for asset management. The incentive or performance fee can be up to 20% of the fund's profit. The incentive fee is to reward the hedge fund manager for good performance, including taking higher risks (Ben-David et al., 2020).

Hedge funds: Hedge funds or alternative investments are a collective of private investment vehicles that allow different investors to combine their money (Getmansky et al., 2019). The funds are under the management of an investment manager according to terms and conditions set in the fund prospectus. Hedge funds use dynamic trading strategies to seek absolute returns, regardless of the market condition (Stafylas et al., 2018a).

Institutional investor: An institutional investor is an organization that trades securities in significant quantities or a large sum of money, such as banks, pension funds, investment advisers, insurance companies, and mutual funds. Institutional investors are often eligible for preferential treatment and lower commission (Kolokolova et al., 2020).

Regime-switches: Regime-switches are structural changes in the market. According to the risk environment, the regime represents good and bad or up/down equity market conditions (Stafylas et al., 2017).

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions, which are statements, issues, ideas, or positions the researcher accepts without verification during a study, are an accepted part of the research process

(AbuRaya & Gomaa, 2020; Foss & Hallberg, 2017). In this study, there were three assumptions. The first assumption was that the sample represents the population I inferred. The second assumption was that the data were accurate and performed the measurements. Finally, the third assumption is that the hedge fund return data included all the necessary elements before assigning value for the quality.

Limitations

Researchers confront some limitations when performing a research study. Limitations are potential weaknesses of a study out of the researcher's control (Harari & Lee, 2021). Limitations usually relate to the study's design and methodologies, such as bias or specific statistical models (Ross & Bibler Zaidi, 2019). The first limitation is associated with the generalizability of study findings due to a specific time sampling period (Greener, 2018). Because hedge funds report voluntarily to commercial databases, hedge fund data can have biases (Joenväärä et al., 2021b). The two biases that have significant impact on hedge fund data include survivorship bias and backfill bias (Hutchinson et al., 2021). The second limitation arises from the bias inherent in archival data. Some biases that may exist in databases can also influence hedge fund empirical research (Aragon & Nanda, 2017). The sample in this study was subject to the bias of missing time series data (Kiss et al., 2017). In addition, hedge fund returns are subject to delisting bias because managers can choose when and which funds to disclose to the data vendor (Aragon & Nanda, 2017). The final limitation is the generalization of the study findings to the hedge fund industry.

Delimitations

Delimitations are actions taken by the researcher to determine the study's scope or boundaries (Theofanidis & Fountouki, 2018). Unlike assumptions and limitations, delimitations are under the researcher's control. This doctoral study's first delimitation was the research problem's scope, which includes the theoretical perspectives and variables of interest. The second delimitation was the restriction of the specific study period, as the sample time frame puts restrictions on the examined study results. The third delimitation relates to the restriction to a geographical area in South Africa. Thus, the conclusion might infer only to hedge funds based in South Africa.

Significance of the Study

Contribution to Business Practice

Hedge fund managers and individual investors stand to benefit from this study. Hedge fund managers may benefit from a better understanding of effective methods to reduce portfolio risks by diversifying assets to maximize the expected rates of return (Stafylas et al., 2017). Also, individual investors such as retirees could have a better understanding of their invested funds (Stafylas et al., 2017). Furthermore, business owners could use volatility forecasting as a risk management tool to price derivatives and hedge risks (Gaetano, 2018). In addition, the results of the study might positively impact the financial professionals' ability to predict the market volatility (Xaba et al., 2017). Thus, a better assessment of the impact varying economic conditions or business phases have on the risk dynamics of the strategies.

Implications for Social Change

The implication for positive social change includes the potential to provide organizational leaders who partner with hedge funds the ability to maximize profit by diversifying risk in volatile market conditions. The ability to use an investment tool to dispel uncertainty in various market conditions is a financial means to foster positive change (Sosner & Steblea-Lora, 2022). Well-informed investors make profitable decisions that could generate advantages for the societies and organizations to which they contribute. Accordingly, through partnerships, hedge funds can help leaders of foundations and nonprofit organizational fund projects in local communities.

A Review of the Professional and Academic Literature

The purpose of this quantitative study was to investigate the relationship between risk exposure, volatility forecasting, and financial performance. The literature review was an essential component of the research study as it provides an extensive analysis of the subject area, defines the theoretical framework, and substantiates the research problem (Snyder, 2019). Investigating how hedge funds can be used as potential alternative investments for investors, as well as comprehension of hedge fund performance and fund-specific characteristics were part of the professional and academic literature review.

Search Strategy

I used the peer-reviewed articles and journals found in Walden University's library databases to conduct the academic literature search. The databases included Business Source Complete, Sage, ProQuest, ScienceDirect, ABI/INFORM, Dissertations, Directory of Open Access Journals, Google Scholar, and Emerald Management Journals.

The keywords used included industry-specific terms such as *hedge funds*, *mutual funds forecasting volatility, volatility, equity markets, modern portfolio management, efficient market hypothesis, risk exposure in the market, regime-switching models, hedge funds risk management, performance persistence, liquidity, hedge funds characteristics, hedge fund managers, behavioral finance, value investing, beta, time-varying risk, Hedge funds in South Africa*, and *performance evaluation.*

Table 1

Summary of Literature Review Resources

Reference type	> 5 Years	< 5 Years	Total
Peer-reviewed Journals	191	37	228
Nonpeer-reviewed Journals	5		5
Dissertations	0	0	0
Books	2	3	5
Government or Corporate Sites	5		5
Total	203	40	243

The literature review content included 243 sources, one website, three books, and one dissertation. Out of the total cited sources, 228 (94%) journals were peer-reviewed, and 203 (84%) of the sources were current within 5 years of my expected graduation date. The literature review structure begins with the background discussion of the theoretical framework grounding the study, including the models describing the theoretical link between risk and return. The seminal literature is grounded on modern portfolio theory (MPT) by Markowitz (1952) as the theoretical framework to investigate the relationship between risk exposure, volatility forecasting, and financial performance of hedge funds. During the research, I identified additional models to extend the MPT and to discuss the key themes (Bedoui et al., 2020).

The second part of the section covers the following supporting and contrasting theories: (a) value investing theory (Graham et al., 1934) and (b) behavioral finance theory (Tversky & Kahneman, 1974). The central part of the literature review covers the critical analysis and synthesis of the sources on each study variable: (a) volatility forecasting, (b) risk exposure, and (c) the financial performance of hedge funds. The literature review chapter will conclude with a summary of critical contents and an overview of primary objectives.

Modern Portfolio Theory

This study is grounded in the modern portfolio theory (MPT). I used the MPT for this purpose because it supports the principle of diversification, which is a risk management technique for investors and fund managers (Arize et al., 2019). Harry Markowitz is the founder of the modern portfolio theory, which is an influential economic theory to engage in finance and investment practices (Markowitz, 1952). Markowitz proposed two principles for portfolio construction and optimization via MPT: (a) the mean-variance model or risk-return model, and (b) the efficient frontier. The mean-variance model focuses on an asset's risk and return elements (Moulya et al., 2019). In this model, the investors allot weights to each asset or risky securities to create a portfolio in a vector format. Oliinyk and Kozmenko (2019) recommended that investors construct portfolios by allotting optimal weights on the risky assets to minimize the risk of the expected return. Bender et al. (2019) compared alternative weighting schemes for constructing portfolios. The authors recommended constructing portfolios of factors based on average variance values because they describe details comprehensively due to the explicit use of input factors.

Investors gain the expected return of an asset by accepting the variance of an asset's returns or risk (Schadler & Steurer, 2019). Simultaneously, by diversifying securities in a portfolio, an investor can reduce the expected return variance. Thus, an investor who aspires to reduce the volatility of portfolios' total returns may seek funds with lower returns and, therefore, lower risk. Xin Rui et al. (2018) examined the relationship between risk in financial investment and the expected return. The research findings correspond to those found by Zhu et al., (2020), noting a significant positive relationship between risk and return during up markets.

According to MPT, an investor can use each asset's mean return and the mean-variance of that asset to determine both (a) the expected return and (b) the expected variance of a portfolio, respectively. Also, the investor can determine the covariance between assets by using the correlating coefficient between the returns of the assets in the portfolio (Markowitz, 1952). The mean-variance model postulates that the assets' historical returns influence future returns (Sui et al., 2020). The variables are obtainable from archival data in the market. The investor can calculate the proportion of each asset to allocate in the portfolio using weights. The expected return of the portfolio as follows:

$E(R_{port}) = w_a ER_a + w_b ER_b + \ldots$, where table 2 describes all terms.

Table 2

Term Description for Expected Return for Portfolio using MPT

Term	Description
$E(R_{port})$	Expected return on the portfolio
w_a	Individually weighted of asset a in the portfolio
ER_a	Expected return on the asset a
w_b	Individually weighted of asset b in the portfolio
ER_b	Expected return on the asset b

Note. From "Portfolio Selection" by H. Markowitz, 1952, *Journal of Finance, 7*(1), p. 77. (https://doi.org/10.1111/j.1540-6261.1952.tb01525.x)

The MPT postulates that investors are risk-averse or risk-neutral, and thus try to maximize the trade-off between risk and expected return in investment decisions (Guo et al., 2019). Thus, investors and fund managers can create an investment portfolio representing the investor's perceptions and requirements, ultimately leading to a collection of efficient portfolios known as the efficient frontier (Siswanah, 2020). Furthermore, each level of expected return on the efficient frontier has minimum volatility, and each volatility level has the maximum expected return. The MPT showed that the return rate variance is an appropriate measure of portfolio risk under certain assumptions (Gruszka & Szwabinski, 2020). The variance formula indicates the importance of diversifying investments to reduce the total risk of a portfolio. Thus, MPT allows investors to minimize risk and maximize their wealth.

Managers aim to select an optimal portfolio along the efficient frontier to meet the investor's profile and utility function (Zavera, 2017). In this case, Zavera applied the MPT to evaluate the performance and risk of portfolios in the Romanian stock market, using historical data from 2010 to 2015 of the gas sectors, energy sector, and food sector to create three securities. From these, Zavera (2017) determined the efficient frontier and the portfolio's minimum variance. The study findings were negative returns because of the inadequate sample size for the study. Also, this lack of information makes it difficult to make decisions for the investor. Besides the diversification component, the MPT has an inherent strategy of low asset classes' low correlation (Arize et al., 2019). Assets can lower volatility when in an uncorrelated combination. Bessler et al. (2017) found that a broader diversification by adding government bonds enhances portfolio optimization benefits. Also, Oliinyk and Kozmenko (2019) showed that portfolio diversification grants higher returns for a given risk for the minimum-variance portfolio; the variability in returns is due to variability in allocation in estimating weights.

Investors and fund managers desire better downside risk protection. Lin and Wu (2018) found that risk-adjusted returns, volatility, diversification, correlation, and downside protection allow investors to search for tools to customize portfolios and improve performance. Wu et al. (2020) recommended a differential evolution algorithm to dissipate financial and portfolio risks under certain conditions. However, Bessler et al. (2017) suggested incorporating alternative asset classes, such as commodities and hedge funds, to improve the risk-free rate. Simonian and Wu (2019) applied the regression method to replicate hedge fund strategies to build portfolios for hedging risks and increase returns. The term hedge fund is an alternative investment that aims to increase risk-adjusted performance or absolute returns (Getmansky et al., 2019).

Markowitz (1952) found that risk could not be diversified entirely away from an investment. Each investment has two main types of risk: (a) s*ystematic risks, beta β, and* *(b) unsystematic risks. Systematic risks are* part of a security's risk that originate from external factors affecting the whole market; systematic risks cannot be diversified away (Xin Rui et al., 2018). Examples of such factors are interest rates, inflation, liquidity, equity, credit, wars, fiscal, monetary policies, and pandemics. Avkiran (2018) found the systematic risk to be related to macroeconomic shifts associated with the market conditions.

Unsystematic risks refer to specific risks part of a security risk caused by factors unique to a firm (Xin Rui et al., 2018). According to Puspitaningtyas (2017), this risk can diversify away because it originates from internal factors (microeconomic). Sources of specific risks include company management, credit rating, lawsuits, marketing strategies, strikes, and other related issues unique to the company. In summary, a portfolio's systematic risk of assets is correlated to market factors, while unsystematic risks are not correlated.

Assumptions and Limitations of MPT

Markowitz (1952) based the model on the following assumptions (a) Investors are rational and risk-averse, which may not apply to all investors. Stork et al. (2020) found evidence contrasting the theories that assume rational expectations and support the bounded rationality theory of behavioral heterogeneity. Alternatively, Taffler et al. (2017) found that the prospect theory asserts that investment decisions stem from various behavioral biases that encourage the investors from rationality (b) Markets are efficient. All information is available to all investors. However, behavioral theories attest that the market is inefficient because of frequent anomalies (Filbeck et al., 2017). Also, Senarathne (2019) pointed out that bounded rational theory explains that not all market participants have access to all information to make possible decisions, (c) Identifies an asset's return with a normal distribution. However, the real world's correlation between asset returns is not constant (Xin Rui et al., 2018). (d) The mean-variance model presumes that the assets' expected return stems from the mean of the assets' historical returns. Jones (2017) argues that the archival method ignores risk factors that impact assets' returns.

Capital Asset Pricing Model (CAPM)

The CAPM is a continuation of the MPT that attempts to assess the price of risk of assets. Sharpe (1964) and Lintner (1965) introduced the CAPM to model the relationship between risk and expected return for equities. The CAPM is a simplified and more practical extension of Markowitz's MPT and is applicable to assess the relationship between risk and return rate. The model bases its theory on the two aspects of risk, systematic and unsystematic (Fernando, 2018). As discussed, the MPT shows that diversification cannot eliminate systematic risk. The model also allows an investor to evaluate a portfolio's expected return, given the risk β. (Puspitaningtyas, 2017). Hence, the CAPM evolved to determine the systematic risks in a portfolio.

Sharpe (1992) built the CAPM on the basis of fundamental assumptions about the capital market and investors' operation: First, all investors have identical expectations, and all information is freely available to all market participants simultaneously. Secondly, investors are rational and seek to maximize their utility, and high expected returns at a lower risk. Third, all investors can borrow or lend any money at a risk-free rate of return. Fourth, there is a linear relationship between the expected return rate of an asset and its risk. The fifth assumption is that transactions are exempt from any fees or tax costs. The sixth assumption is that markets are efficient; investors do not affect prices and have the same odds for the expected return. Most of these assumptions have a drawback for unrealistic reflection of the actual market. Sharpe (1992) formulated the CAPM based on the principle that an asset's return rate equals risk plus the risk-free rate. The following formula represents the CAPM is as follows:

$E(R_a) = R_f + \beta_a\ (ER_m - R_f)$, where table 3 describes all terms

Table 3

Term Description for CAPM Equation

Term	Description
$E(R_a)$	Expected return on asset a
R_f	Risk-free rate return of an asset (10-year government bond-yield)
$E(R_m)$	Expected return of market, m or Index
β_a	Systematic risk (beta) of asset a

Note. From "Capital asset prices: A theory of market equilibrium under conditions of risk" by W. F. Sharpe, 1964, *Journal of Finance*, *19*(3), p. 432. (https://doi.org/10.2307/2977928)

The beta (β) coefficient measures an asset's relative sensitivity to market movements: the asset's risk exposure. Black and Scholes (1973) studied price movements in stock portfolios relative to the Stock Exchange between 1931 and 1965. From these Black and Scholes (1973) confirmed the linear relationship between the returns of their stock portfolios and their betas. However, Fama and French (1993) found that the difference in betas over time did not justify stocks' performance in the portfolio. The equation for expected returns represents the relationship between an asset's risk and return, named the Security Market Line (SML). The efficient frontier graph rearranges to illustrate the performance of individual assets. In the SML equation, the coefficient of beta, βa, is as follows:

$\beta_a = cov_{(a^* m)} / \rho^2{}_m$, where table 4 describes all terms

Table 4

Term Description for Beta in the SML Equation

Term	Description
β_a	Systematic risk (beta) for asset a
$cov_{(a^* m)}$	Covariance between asset *a*, and market *m* or index.
$\rho^2{}_m$	Variance on returns on the market m or index

Note. From "Capital asset prices: A theory of market equilibrium under conditions of risk" by W. F. Sharpe, 1964, *Journal of Finance, 19*(3), p. 439. (https://doi.org/10.2307/2977928)

For the average asset, beta is equal to or greater than 1; then, it contributes higher than average risk to the portfolio (Bolander et al., 2017). If the beta is less than zero, the securities will perform well when the market does poorly and vice versa (Puspitaningtyas, 2017). Thus, the CAPM model can help investors determine the sources of common equity risk factors in a portfolio. Unlike traditional funds, hedge funds evaluate relative and absolute returns performance. The relative return requires the fund manager to compare performance to other investment instruments such as other funds, hedge funds, and indexes (Zhang et al., 2021). Also, performance comparison requires a time frame.

On the other hand, absolute returns or risk-adjusted returns require a performance comparison to the other hedge fund strategies (Hwang et al., 2017). Hentati-Kaffel and de Peretti (2015) conducted a nonparametric study to examine the randomness and persistence of hedge funds' relative returns. In this case, Hentati-Kaffel and de Peretti used Hedge Fund Research (HFR) data, from January 2000 to December 2012, and the

S&P500 as a benchmark. The study concluded that about 80% of the absolute returns were random, and the event-driven and relative value strategies present clustering in relative return. The study confirms that hedge funds' relative returns vary with a benchmark.

Beta β represents a fund's systematic risks, α, alpha represents the non-systematic return generated by an asset (Puspitaningtyas, 2017). Furthermore, the unsystematic risk does not relate to market factors. However, the alpha coefficient is related to the hedge fund manager's skills and critical quantitative skills when allocating assets to hedge fund managers (Frydenberg et al., 2017). Consequently, the most efficient hedge fund strategy will yield a risk-adjusted return with systematic risk factors. Jensen (1968) highlighted the importance of a better understanding portfolio risks when analyzing alpha. The Jensen equation is as follows:

$E(R_a) = \alpha_a + R_f + \beta_a\ (ER_m - R_f) - \mathcal{E}_a$ where table 5 describes all terms

Table 5

Term Description for Jensen Equation

Term	Description
$E(R_a)$	Expected return of asset a
α_a	Risk adjusted return of an asset *a*, or performance measure
R_f	Risk-free rate return of an asset (3-month government bond-yield)
β_a	Systematic risk (beta) of asset a
$\mathcal{E}_a$	Error term. For asset a, idiosyncratic term will be zero

Note. From "The performance of mutual funds in the period." by M. C. Jensen, 1968, *Journal of Finance, 23*(2), p. 393. (https://doi.org/10.1111/j.1540-6261.1968.tb00815.x)

Jensen's equation above shows a method to evaluate the risk-adjusted return of a portfolio. Jiang et al. (2022) confirmed by remarking that a manager's alpha is a testament to time the market effectively. Still, it is more complex to evaluate hedge fund returns than for classical funds. Unlike mutual funds, a hedge fund manager emphasizes evaluating absolute returns (Swartz & Emami-Langroodi, 2018). According to Almeida et al. (2020), managers generate relative returns required by comparing returns to a benchmark over a set time. On the other hand, to generate absolute returns, the manager compares them to other strategies. A hedge fund strategy's primary goal is to perform a risk-adjusted return uncorrelated with systematic risk factors (Puspitaningtyas, 2017). The CAPM model assumes that the variance in asset returns is linear, depending on the market's risk factors. However, the drawback of using the CAPM to assess hedge fund returns relative to risk is that hedge fund returns do not have a normal distribution.

Arbitrage Pricing Theory (APT).

The APT is a different approach to the CAPM to evaluate asset prices. Ross (1976) adapted a multifactor model to mitigate the limitations presented by the CAPM. The APT is based on a linear process like the CAPM but with fewer assumptions. The main difference is that although the CAPM is not a complicated model, it is not easy to verify empirically. The underlying assumption essential for the CAPM on the natural economic conditions makes it challenging to study the impact of the capital market on an investor's decision or performance (Yildiz & Erzurumlu, 2018). The APT specifies several risk factors and expands the definition of systematic investment risk (Frydenberg et al., 2017). The authors found that some of the factors could be statistical or fundamental. Roll and Ross (1980) identified the three underlying assumptions of the APT as follows: (a) prices of securities, governed by multiple factors, which have categories such as macroeconomic or specific risk factors, (b) diversification erases the unsystematic risk (specific risk) in a portfolio. Lastly, if a portfolio is well-diversified, investors will have no arbitrage opportunity. The APT incorporates all the assumptions in the following equation:

$E(R_a) = R_f + \beta_1 F_1 + \beta_2 F_2 + . \beta_n F_n + \mathcal{E}_a$, where table 6 describes all terms

Table 6

Term Description for Expected Return of an Asset using the APT

Term	Description
$E(R_a)$	Expected return of asset a
R_f	Risk-free rate return of an asset (3-month government bond-yield)
$\beta_n F_n$	Price relationship between risk premium and (n beta factors)
F_n	Risk premium related to the nth risk factor
$\mathcal{E}_a$	Error term. For asset a, idiosyncratic term will be zero

Note. From “The performance of mutual funds in the period.” by M. C. Jensen, 1968, *Journal of Finance, 23*(2), p. 393. (https://doi.org/10.1111/j.1540-6261.1968.tb00815.x)

The APT extends the CAPM, and identifies the risk factors (Fernando, 2018). Thus, the APT users apply the model to determine the relevant factors that might affect the asset's returns. Roll and Ross (1980) concluded that the important factors would include: (a) the variation in inflation, (b) variation in risk premiums and market risk, (c) change in the amount of industrial production, and (d) change in interest rates. Ultimately, the CAPM and APT are similar, as they aim to estimate the expected returns of assets or portfolios.

Several studies investigated methods to derive risk exposures from hedge fund return data (Hespeler & Loiacono, 2017; Mestre, 2021; Stafylas et al., 2017). Frei and Hughes (2013) adapted the Posterior Cramer-Rao Bound (PCRB) concept from Sharpe's

(1992) earlier study when analyzing hedge fund portfolios of varying securities within an asset class. The authors applied the PCRB to several hedge fund models to demonstrate its efficiency in assessing the achievable accuracy of return-based hedge fund exposure. The authors claimed that the model is appropriate when a researcher lacks access to hedge fund data. Also, the authors demonstrated that for a manager to achieve an accurate exposure estimate, they need to consider the following variables (a) covariance of asset factor, (b) variance of the idiosyncratic error, and (c) value of fund's exposure.

Frydenberg et al. (2017) used the multifactor quantile regression model to determine which risk factors affect an asset's various hedge fund strategies. The authors collected data from the Hedge Fund Research (HFR) database containing statistics for more than 7,000 funds ranging from April 1, 2003, to March 6, 2009. The authors modeled nine indexes in the study to determine any differences in estimated risk exposures using quantiles regression compared to the ordinary least squares (OLS) approach. The analysis revealed that the OLS approach only revealed the risk factors that contribute to the average return of a hedge fund strategy but failed to account for how the different risk factors affect tail risk. However, the quantile regression approach determined the difference in investment styles in each hedge-fund category.

Efficient Market Hypothesis (EMH)

The Efficient Market Hypothesis (EMH) connects to the MPT and is also relevant to this study. Karp and Van Vuuren (2019) observed that MPT and its precepts evolved from the EMH. Academic researchers and practitioners use the EMH to study price movement in the market (Cao et al., 2018b). Fama (1970) described the EMH as a measure of how the financial markets rapidly process publicly available new information. Also, Karki (2018) defined the EMH as the Random Walk Theory, demonstrating that stock price changes fully reflect available information about the firm's value. Furthermore, the firms are cannot make excess profits from exploiting this information. Thus, the EMH is a concept of information efficiency and the market's ability to analyze the data into prices.

Fama (1970) conducted an empirical analysis of the EMH using the fair game model based on the following assumptions: (a) When market prices fully reflect all available information, the market is informationally efficient (Cao et al., 2018b), (b) When market conditions are efficient, only new information creates volatility. However, stock prices vary with the news, which affects macroeconomic factors (Okonkwo, 2019). EMH has another assumption, which asserts that investors' reactions, on average, are appropriately in a normal distribution pattern (Kristoufek & Vosvrda, 2018). On the contrary, investors, and financial markets are characterized by nonlinear dynamic systems of interacting agents who rapidly process new information (Mallikariuna & Rao, 2019; Rehman, 2020). Tiwari et al. (2017) argued that fractals provide a realistic market risk framework for prices.

In his empirical work, Fama (1970) introduced three market efficiency versions strong-form, semi-strong, and weak form efficiency. A weak-form efficient market if the current prices indicate all historical or past information. Prices follow the random walk, and investors cannot use technical analysis to earn an excess return. Thus, the stock return is serially uncorrelated, and has a constant mean and normal distribution

(Kristoufek & Vosvrda, 2018). When public and future expectations fully reflect an efficient market in a semi-strong form, neither technical nor fundamental analysis can trace a stock's behavior pattern. A condition necessary for abnormal returns is for market participants to access private information because all publicly available information shows current prices. The strong-form efficient markets include all information in the public and private market and reflects in current prices. Thus, all investors can earn abnormal profits in this form of efficiency. Fama (1970) proposed these three conditions to attain strong-form market efficiency: (a) no transaction fees, (b) free access to relevant information, and (c) a similar way of assessing stocks by all investors. However, Fama (1970) also noted that these conditions do not represent fundamental financial markets. Furthermore, infringing on these conditions does not necessarily infer inefficiency, but it is potential aid.

Cao et al. (2018b) and Cao et al. (2018a) studied hedge fund literature and found that hedge fund trading enhances market efficiency. In comparing the impact of trading by mutual funds and hedge funds on the stock prices, the studies found that the aggregate flows to hedge funds correct the market pricing, while mutual funds worsen it. Hwang et al. (2017) confirmed the positive impact of hedge fund trading on financial markets. The authors showed that hedge fund returns negatively correlate with market flow changes, suggesting hedge funds increase market efficiency. Also, Guptha and Rao (2018) report a positive relationship between hedge fund return shocks and subsequent returns, suggesting that hedge fund investors have more information than other investors.

Related and Contrasting Theories

To incorporate enough literature into the modern portfolio theory section, I will discuss two other theories related to and contrasting with the MPT. The two theories include the behavioral finance theory and the value investment theory. Academic researchers and practitioners use the value investing theory to evaluate the current investment price, and the firm’s profit relative to market performance (Zhang, 2019). Behavioral financial theory can replace the mean-variance portfolio theory, CAPM, asset CAPM, and other risk models related to expected returns (Mei & Nogales, 2018).

Behavioral Finance Theory

Behavioral finance theory is a contrasting theory to the modern portfolio theory in this study. Traditional finance theories like the EMH, MPT, or CAPM assume that investors are rational and maximize utility. However, behavioral economists argue that emotional and psychological factors shape investors' decision-making processes (Ahmad et al., 2017). There are two branches of behavioral finance: (a) micro and (b) macro (Statman, 2017). Micro behavioral finance studies focus on individual investors' behavior, and macro studies focus on anomalies in the market that behavioral models may account for (Statman, 2017). Investment decision-making incorporates micro and macro factors (Ahmad et al., 2017). This review will focus on both branches of behavioral finance to study investor behavior using the prospect theory components.

The current theories in behavioral finance are the bounded rational theory of Simon (1955), the prospect theory by Tversky and Kahneman (1974), and the adaptive theory by Tinbergen (1939). Behavioral finance originates from philosophical and psychological views, which assumes investor irrationality and inefficient financial markets (Ahmad et al., 2017). The prospect theory is used to understand the decision behavior of investors in financial markets (Abdin et al., 2019; Madaan & Singh, 2019). The primary presumption of the prospect theory is that investors are more risk-averse than have a desire for potential gains (Abdin et al., 2019). Ahmad et al. (2017) documented that investor decision-making has two thinking systems, the cognitive and the biased systems. The cognitive system leads to errors known as cognitive heuristics.

On the other hand, biases in decision-making arise from investor sentiment, emotion, and mood. Strömbaäck et al. (2017) defined *cognitive heuristics decisions* as a simple rule of thumb that explains how investors make decisions and solve problems. Abdin et al. (2017) divided the cognitive heuristics include the following three factors of investor behavior:

1. Availability, the tendency for investors to use available information
2. Hindsight, which refers to the investor's behavior to use past events or experiences to predict future events
3. Representativeness explains how investors use stereotypes when making decisions
4. Mental accounting, procedure investors, use to direct and measure financial activities

Abdin et al. (2019) showed that mental accounting has a significant positive effect on all anomalies. Areiqat et al. (2019) used four behavior biases to study investor emotional decision-making behavior; overconfidence bias, regret aversion, herd behavior, and loss aversion.

Herd behavior occurs when investors observe and imitate others' behavior during market distress (Yu et al., 2018). Also, it occurs when investors herd and ignore their decisions and follow others. Mertzanis and Allam (2018) found that herding is high during market anomalies and price bubbles. Chhapra et al. (2018) concluded that herd bias does not impact investors’ decision-making. However, Madaan and Singh (2019) found that herd bias strongly influences investors' investment decisions.

Overconfidence is a psychological bias that steers an investor to overestimate skill, knowledge or perceive the probability of a result occurring (Joo & Durri, 2017). In behavioral finance, overconfidence leads to excessive trading volume, higher price volatility, and return variability. Mushinada and Veluri (2018) showed that overconfidence about comprehending and processing information could make investors overreact. Abdin et al. (2017) revealed that overconfidence is a negative predictor that forecasts the performance of investors during market anomalies. However, Chu et al. (2017) attested that financial literacy makes confidence in investors suitable for financial management decisions. Regret aversion bias occurs when investors fear their decisions will not reward gains (Golman et al., 2017). For example, regret aversion bias may cause the investor to hold on to losing positions for a long time because of fear of making wrong decisions. Abdin et al. (2019) showed that regret eversion bias positively affects fundamental market anomalies. Loss aversion bias occurs when investor perceives avoiding losses as more critical than gains (Areiqat et al., 2019).

According to Ahmad et al. (2017), individual investors react to behavioral biases such as herding, overconfidence, and hindsight compared to institutional investors. The researchers found that mental accounting bias affects institutional investors. Shantha (2019) suggested that most market participants make emotional reactions and heuristic decisions. Furthermore, there are two types of market participants: Emotional crowds and behavioral data investors (BDIs). Emotional crowds react to unfolding events, and BDIs make decisions based on the analysis of available data. Some studies support heuristics in rewarding decision-making, and some are against it (Chhapra et al., 2018; Rehan & Umer, 2017). When an investor must make an investment decision, the investor has to invest without prior knowledge of the outcome.

The MPT posits that rational investors arbitrage away price distortions caused by irrational investors (Swartz & Emami-Langroodi, 2018). Hence, rational investors are more influential in the financial pricing process. However, Economou et al. (2018); Hudson et al. (2018) argued that emotional crowds control markets' pricing and volatility. The events that cause crowd reactions may be short-lived, but their effects tend to last longer (Madaan & Singh, 2019). The price distortions are significant and persistent enough that the BDIs can use them as an opportunity to build portfolios (Wang et al., 2018). Subsequently, the behavioral finance theory posits that BDIs have higher returns than emotional crowds. Hedge fund managers receive management and incentive fees for excess returns they generate (Mitchell et al., 2019). The fees lead to hedge fund managers' return-chasing behavior due to fund return volatility and investor behavior.

Also, fewer regulatory restraints increase hedge fund managers' risk-taking behavior and the perception of skilled investors (Chhapra et al., 2018).

Value Investment Theory

Graham et al. (1934) presented in the seminal book publication on value investing and security analysis. Value investing involves identifying and purchasing underpriced securities in the market through fundamental analysis to profit (Kok et al., 2017). An example includes public stocks that trade at discounted prices, with low price-to-earnings (P/E) or price-to-book (P/B) ratios. Graham et al.'s (1934) seminal work classified investing into two distinct categories: (a) growth investing and (b) value investing. Growth investing refers to a company's value, including estimating the stock value (Graham et al., 1934).

By re-examining the modern portfolio theory from the value investing perspective, investor behavior is not rational decision-makers (Graham et al., 1934). Also, value investors prefer avoiding risk and not trading risk for return. However, this practice contrasts with one of the modern portfolio theory tenets: risk relates to return (Xin Rui et al., 2018). The value investing theory is suitable for the long term, whereas the MPT tends to be short-term oriented (Gimeno et al., 2020). For example, using variance or standard deviation as risk is a short-term strategy. Also, the MPT aligns with the tenets of efficient market hypotheses and asset pricing models. In value investing, publicly available information from value investors generates consistent long-term returns. Cao et al. (2018a) documented that using the information to construct portfolios resulted in higher than market returns without high risks. Thus, making the efficient market hypotheses obsolete.

Furthermore, value investors do not follow the MPT strategy of diversifying to reduce risk (Gimeno et al., 2020). The authors documented that diversification in value investing is not widespread because of the stock screening process. The stocks with low price-to-earnings ratios yield high dividends and are subject to high tax rate fees (Ghaeli, 2017). Again, this goes against the MPT, which assumes no tax charges. To evaluate the performance using value investing, Sondakh (2019) used listed financial service firms on the Indonesia stock exchange from 2015 to 2018. Sondakh (2019) analyzed the effect of dividend policies, liquidity, profitability, and firm size on firm value. The study results show that liquidity and firm size have a significantly positive effect on firm value, dividend policies have significantly negative effect, while profitability has no effect. Sondakh (2019) suggested that investors consider the ratio of dividend, liquidity, profitability, and firm size policies when investing in a firm they pick.

Sahoo (2017) showed that value stocks outperform when markets are down or up, good or bad, and when the news is good or bad, without high risk. An explanation could be investor bias of irrational behavior by overestimating, optimistic, and overreacting (Chhapra et al., 2018). Another issue the authors found is that the undervalued securities prices in a downturned market could be inaccurate as the market continues to drop.

Risk Exposure Variable

Hedge funds are a component of the financial system and the hedge fund industry. The hedge fund strategies include using derivatives, non-traditional assets, and engaging in long/short positions in any financial instrument (Agarwal et al., 2017a; Gao et al., 2018a). However, such flexible practices expose hedge fund strategies to risk factors, including complex risk exposures that vary according to style and market environment (Stafylas et al., 2017). It is helpful for managers and investors to know current risk exposures to estimate a portfolio, gain insight into a manager's skill, and replicate strategies. Hedge fund managers vary the exposure of assets to changes in macroeconomic conditions and fluctuating market conditions (Agarwal et al., 2018a). The researchers suggest that hedge fund managers vary the portfolio exposure timely by predicting the fluctuating macroeconomic variables.

Statistical Characteristics of Hedge Funds Return

The principal purpose of hedge funds is to make absolute returns at lower risk levels unaffected by varying financial markets (Shin et al., 2018). Unlike traditional investment funds, hedge funds are subject to few regulatory requirements, which allows for flexible investment strategies (Metzger & Shenai, 2019). For example, hedge fund managers can combine long/short positions and invest in non-traditional asset classes. Swartz and Emami-Langroodi (2018) documented that researchers and investors can classify hedge funds into alternative strategies with specific characteristics, such as style, asset uses, returns, risk profile, and liquidity. Also, their strategies are grouped into two key components, to assess hedge fund returns, beta and alpha (Joenväärä et al., 2021b; Stafylas et al., 2018a). Beta (β) measures the volatility of the returns generated from the exposure to various asset classes (Frydenberg et al., 2017). In contrast, alpha (γ) shows the return generated by the manager's skill. Kapil and Gupta (2019) used this concept to classify the investment strategies of hedge funds to determine performance.

Market Neutrality

Market-neutral hedge funds aim to generate uncorrelated returns to market returns and return volatility (Joenväärä et al., 2021b). Also, the study's findings concluded that hedge funds correlate less with traditional assets than mutual funds with market indices. Joenväärä et al. (2021b) documented two types of hedge fund strategies; (a) Strategies that have a low correlation to the market and (b) Strategies that correlate with the market or specific index movement. Patton (2009) proposed to classify market neutrality into four concepts to create a method to measure non-neutrality:

Mean Neutrality. Establishes that a fund's expected return is neutral or negatively related to the downturned market. This neutral environment ignores the relationship between the fund and the market when it generates positive returns (Patton, 2009). This test can apply to test market neutrality controlling for hedge fund exposure to other sources of risk.

Variance Neutrality. Variance neutrality is another form of neutrality, where the risk of funds is neutral to market risk. The test is applicable where the variance is the measurement of risk. Agarwal et al. (2017a) applied the variance neutrality test to examine the influence of uncertainty on hedge fund returns by aggregate volatility.

Value-at-Risk Neutrality. The (VaR) provides an environment where the market return does not affect a portfolio. Crego and Galvez (2018) applied the value-at-risk (VaR) neutrality test to investigate the dependence of hedge funds' returns on the market portfolio. The study results concluded that the VaR for market-neutral hedge funds increases when market returns are more negative than positive. Also, the correlation between market-neutral funds and the stock market varies with the economic state.

Tail Neutrality. Tail risk is the possibility of significant losses in portfolio returns (Agarwal et al., 2017b). Therefore, investors are tail risk-averse, and there is a positive relationship between expected return and tail risk (Mhalla et al., 2020). Shin et al. (2017) conducted a bootstrap analysis to determine that the tail risk timing ability was because of managerial skill. The authors used a sample of 6147 equity-oriented hedge funds from 1996-2012 to investigate managers' time market tail risk by adjusting their portfolios' market exposure to changes to market tail risk. The study's analysis showed that a manager's tail risk timing skill persists over time, indicating managerial skill.

Non-Linearity

The dynamic use of long and short hedge fund positions produces a nonlinear relationship between the returns and market returns (Fung & Hsieh, 1997a, 2001, & 2004). The studies' results confirmed other studies that hedge funds have nonlinear returns (Cai et al., 2018; Huang et al., 2018). Also, the nonlinear exposures vary over time, according to market conditions. Several studies recommend incorporating a nonlinear relationship between hedge funds and market returns when analyzing the risk-return characteristics of hedge funds (Hambuckers et al., 2018; Stafylas et al., 2018a).

Agarwal and Naik (2004) used buy-and-hold and option-based risk factors to identify various hedge fund strategies' linear and nonlinear risks. The authors performed an analysis at the index level and individual level. The characterization of nonlinear risk-return relationships found that hedge funds show significant exposure to Fama and French's (1993) three-factor model and Cahart's (1997) momentum factor. Fung and Hsieh (2001), Mitchell and Pulvino (2001) tested neutrality on individual hedge fund strategies and extracted systematic risk factors. The authors used the Asset Based Style (ABS) approach, where the market index time can hold a more extended position to allow trend-following strategies.

A comparable study by Fung et al. (2002) used the ABS method to extract the well-known sources of risk associated with fixed-income hedge funds. The authors identified the ABS factors and could associate them with most fixed-income hedge funds. The findings had enormous implications for asset allocation and identifying the significant risks. Thus, in selecting the best variation of strategies that can increase alpha. Baker et al. (2017) applied multivariate regression to identify the factors of high-moment risks. Evidence from the study factors relating to leverage, incentives, and strategy is statistically significant in explaining all moments.

Skewness and Kurtosis

Skewness and kurtosis are characteristics of hedge fund returns, known as high-moment risks (Amin & Kat, 2003). Skewness measures the deviation symmetry of the hedge fund return distribution, and kurtosis measures the amount of extreme hedge fund performance (Knif et al., 2020). Also, a positive skewness implies higher expected returns and more minor losses. The Sharpe ratio assumes that hedge fund returns have a normal distribution (Sharpe, 1992). However, hedge fund returns mostly have negative skewness and high kurtosis because of the dynamic nature and nonlinear distribution

(Stoforos et al., 2017). Therefore, the Sharpe ratio is unsuitable as a performance measure for hedge funds. Kapil and Gupta (2019) examined monthly hedge funds' returns to account for the performance of various strategies. The author found that return distribution mostly deviates from the mean and is skewed negatively with excess positive kurtosis. The author could infer that the skewness and kurtosis occur because of the strategies' dynamic nature and the bias from data collection from hedge fund indexes.

Fang and Almeida (2018) recommend including higher moments when modeling hedge fund returns. The arguments for incorporating higher moments are that hedge fund returns do not have a normal distribution and investors' choice for high positive skewness and low kurtosis. The study’s evidence shows that most hedge funds outperform the market index during the study period, based on the Sharpe ratio performance method. However, the results were different by underperforming the market index with the inclusion of skewness and kurtosis funds. Thus, the author suggests the inclusion of skewness and kurtosis when analyzing hedge fund returns.

Hedge Funds Classification

When analyzing hedge funds, a broader system of classifying them is to group them into a two-step process (Stafylas et al., 2018b): (1) Assessing the fund's exposure to fluctuating market conditions and (2) Evaluating an aspect of exposure on the funds' risk/return characteristics. The technique leads to the emergence of three broad hedge fund categories: (a) event-driven funds, (b) non-directional funds, and (c) directional funds.

Event-Driven Funds

Strategies in the event-driven or arbitrage funds category aim to profit by focusing on investing in opportunities occurring in exceptional situations or events (Falkowski et al., 2020). The uncertainty of an event provides an opportunity to benefit by allocating funds to the issue's asset at the moment. The strategies in this category include distressed securities, merger arbitrage, risk arbitrage, and event-driven. Gao et al. (2018b) prove that hedge fund managers with more skills at exploiting rare disaster events can deliver superior expected fund performance with limited risk. Also, the funds are less exposed to disaster risk, and the managers possess skills in managing leverage and timing extreme market conditions.

Non-Directional Funds

Non-directional or equity funds strategies aim to eliminate risk exposures to the financial market movements by low correlation with the market (Fang & Almeida, 2018; Joenväärä et al., 2021b). Also, non-directional strategies are independent of any market trends and increase returns by exploiting market inefficiencies and arbitrage opportunities. The category strategies include fixed-income, market-neutral, convertible arbitrage, and multi-strategy (Frydenberg et al., 2017).

Directional Funds

The market-directional hedge funds display a high correlation with the market and seek high returns. Also, they use high leverage and adopt strategies that represent bets on the direction of markets (Frydenberg et al., 2017). Examples of market directional category strategies include global/macro, long-short equity, emerging markets, short bias, and managed futures (Frydenberg et al., 2017). Hong et al. (2018) used the multifactor model to examine hedge fund strategies during varying market conditions. From the study Hong et al. (2018) discovered that the multi-strategy, global macro and managed futures were the few strategies that could generate considerable alpha in a downturned market.

Data Evaluation

It is common for researchers to classify hedge funds in terms of their investment styles. Some researchers, such as Kapil and Gupta (2019); Gerhard and Rupert (2017), used a classification scheme created by database vendors. Other authors like Almeida et al. (2020) and Newton et al. (2021) used hedge fund indices provided by the database providers, ignoring the indices' representation's limitations. Most researchers use more than one database to mitigate bias because of hedge fund managers' voluntary inclusion, such as Metzger and Shenai (2019); Hespeler and Loiacono (2017).

The Hedge Fund Industry in South Africa (SA)

South Africa’s hedge fund sector is still in its infancy compared to its global counterpart. The first hedge fund began in 1995 and grew to 1.4 billion Rands by 2002 (HedgeNews Africa, 2021). Also, the lending market facilitated short selling in the 1990s, and by 2013, assets under management were part of the strategies. Muteba Mwamba (2017) identified the causes of growth in the hedge fund industry in South Africa as individuals seeking high investment returns in alternative investments and academics pursuing research on hedge funds' performance workings. Before 2012, hedge funds in SA were subject to few regulatory requirements until the National Treasury and

Financial Services Board (FSB) proposed a regulatory framework for hedge funds (CISCA, 2015). In 2015, the Collective Investment Scheme Control Act (CISCA) effectively published new hedge fund regulations (CISCA, 2015). Hedge fund managers had to register their management companies and portfolios within twelve months. Also, managers had to comply with investor protection per the regulations. South Africa is one of the few countries that enacted a comprehensive regulation for hedge fund instruments. The regulation aims to protect investors better, manage systemic risk spillovers, improve transparency, and oversee the financial market's progress (Bouamara et al., 2017). However, this contrasts with the sentiment that light regulations give hedge funds the advantage of engaging in flexible investments relative to traditional funds.

Macroeconomic Factors in SA

The economic and productivity growth has been declining in South Africa since 2015 (Kreuser & Newman, 2018). However, this study focuses on the economic factors that may impact the stock market return, volatility, inflation rate, and the short-term interest rate. Ten sectors make up the JSE. The sectors include basic materials, industrials, consumer goods, health care, consumer services, oil and gas, telecommunications, financials, technology, and utilities (Szczygielski et al., 2020). According to Szczygielski et al. (2020), the performance of each sector varies according to the macroeconomic factor that impacts it. The macroeconomic conditions affecting stock market factors include the Gross Domestic Product (GDP), inflation, and interest rates (Szczygielski et al., 2020). Interest rates are part of external and part of domestic microeconomic factors (Madaree, 2018). Mitra (2017) used dynamic cointegration to investigate the relationship between the effective exchange rate and the total stock transactions in South Africa between 1979 and 2014. The results revealed a significant positive correlation between the exchange rate and the total value of stock transactions in South Africa.

Jeelani et al. (2019) used the ordinary least squares technique to examine the structural changes in microeconomic variables such as GDP, interest rate, and exchange rates. The findings revealed that major economic events impacted the microeconomic variables. A low GDP harms investors, businesses, productivity, and uncertainty (Ceruttia et al., 2017). Understanding the macroeconomic factors of South Africa's market is necessary to proxy systematic influences for performing studies that model macroeconomic factors (French, 2017).

Hedge Fund Style Analysis

Style analysis is a component in hedge fund literature that focuses on risk exposure. The analysis examines dynamic hedge fund strategies' exposure to various systemic risk factors (Hespeler & Loiacono, 2017). Also, the risks vary since they can engage in short/long positions in any financial instrument and use high leverage. Fung and Hsieh (2004) found that investing flexibility and the ability to leverage positions are salient features that enhance hedge fund returns but potentially add to market volatility. In hedge fund literature, the risk exposure analysis is in three phases. The first is the classical linear model, which assumes a constant variance, such as the CAPM (Sharpe, 1964) and the APT (Ross, 1976) derived from modern portfolio theory. The CAPM only accounts for the market risk. Fama and French (1993) extend the CAPM by introducing the three-factor model by adding two factors based on size (SMB) and value (HML-high minus low bond value ratio).

Carhart (1997) extends the 3-factor model by introducing momentum (MOM) to a four-factor model. The momentum of a stock is the tendency for its trend. The beta represents the exposure to the risk factor (systematic risk). However, the focus of the study is more on the economic association of the exposure. The second phase adapts to the Asset-Based Style Factors (ABS-Factors). It incorporates location factors that proxies for buy-and-hold strategies on equity, bond, and commodity markets to control nonlinear risk exposures of hedge funds (Agarwal & Naik, 2004; Bali et al., 2014). However, the ABC factor model does not account for hedge funds' dynamic property or the market risk factor's regime volatility.

The next phase is the addition of models that account for dynamic economic risk factors. Fung et al. (2008) employed the breakpoint analysis to examine the structural breaks in hedge fund risk exposures from September 1998 to March 2000. The study's findings revealed significant structural breaks in hedge fund risk during the study period. The authors confirmed that the structural breaks were associated with the long-term capital crisis in 1998 and the internet bubble in 2000. Bollen and Whaley (2009) introduced the changepoint regression models to examine the time-varying risk exposures of hedge funds. The study results showed that excluding time-varying risk exposures of hedge funds leads to inaccurate risk and return estimates. Siegmann and Stefanova (2017) discovered optimal change-points in the relationship between beta and liquidity during market turmoil or structural change.

Racicot and Théoret (2019) used the regime-switching model to study hedge funds' risk exposures to traditional asset class factors in different regimes. The study findings confirmed that hedge funds face nonlinear, option-like risks. Racicot and Théoret (2019) used the regime-switching process to show that higher moment risk is conditional to volatility. Another study by Zheng and Osmer (2018) employed the Markov regime-switching model to investigate the dynamic effect of aggregate stock market sentiment on various hedge fund strategies' performance. The researchers examined the effect of investor sentiment on the relationship between investor sentiment during pessimistic periods. The study analysis found that investor sentiment affects hedge fund performance during optimistic periods. Furthermore, the relative-event hedge fund strategies responded to the shocks.

The remaining part of the analysis of the most significant risk exposures underlying the hedge fund styles: Directional funds or equity hedge strategy take long/short positions. Literature like from Billio et al. (2018); Stafylas et al. (2017). evaluate the following group of factors using the model: (a) Equity factors, (b) Volatility factors, (c) Interest rate and credit risk factors, (d) Fama and French (1993) factors, (e) Commodity factors, (f) Currency factors, and (g) Emerging markets factors. The studies found that funds present exposures to various macro conditions. The analysis in the study section aims to track the behavior using the macroeconomic models.

Volatility Forecasting Variable

In financial markets, volatility refers to the changeable variance of asset returns. Bhowmik and Wang (2020) described volatility as the statistical measure of the standard deviation of dispersion around the mean. A unique trait of volatility is that it is not observable, making financial analysts eager to determine the approximate conditional variance (Bhowmik & Wang, 2020). Other researchers define volatility as a measure to which asset prices variate randomly as a time series component (Emenogu et al., 2020; Schreder, 2018). Thus, volatility mainly describes the rate and magnitude of changes in prices.

The frequent fluctuation of the broad capital market may cause uncertainty and impact investors' confidence about the value of assets (Maqsood et al., 2017). The authors also suggested that the public and investors believe the volatility is the cause of the market-wide movements, especially the down market movement. However, the down-market movements do not always relate to a specific news event. Manyang et al. (2017) showed that risk-averse and neutral investors generally pull back from the market during high price fluctuation market movements, thereby distorting the capital market. Market volatility is unavoidable in the financial system, and modeling, volatility, forecasting, and correlations are fundamentally crucial for all market participants (Schreder, 2018). Studies focusing on volatility have been increasing in importance because it contributes to liquidity to the financial system (Agarwal et al., 2017a, 2019; Lee & Nguyen, 2017). The primary motivators to conduct volatility forecasts are the prominent role of volatility as a risk management tool and portfolio management.

Volatility makes investors more risk-averse because of uncertainty (Rupande et al., 2019). Forecasting volatility can help risk-averse investors make decisions (Ahmad et al., 2017). For example, a high volatility investment could present a possible opportunity for a risk-tolerant investor with higher risk and possible significant profits (Markowitz, 1952). Therefore, knowing or predicting the volatility benefits the investors, especially those willing to potentially take a high risk to earn high returns. There are two basic approaches to forecasting volatility. The first approach is a time series or parametric, extracting information about the variance of future returns from historical volatility returns (Grable & Heo, 2017). Also, it uses non-constant volatility techniques such as generalized autoregressive conditional heteroscedasticity (GARCH), ARCH, and stochastic volatility models, to capture the clustering in volatility over time. The second approach is non-parametric or implied volatility and extracts the market's expectation about future volatility from observable option prices using implied volatility indices (Liu et al., 2021). The implied methods employ techniques such as Black-Scholes, introduced by Black and Scholes (1973). Furthermore, the model uses high-frequency data on volatility trading.

Some authors believe that the time series models are superior because they capture stylized parametric volatility characteristics, including persistence, a prominent trait of financial volatility (El Jebari, & Hakmaoui, 2017; Emenogu et al., 2020). On the other hand, others believe the implied volatility approach outranks the time series models because it cannot accurately forecast high-frequency volatility (Balcilar et al., 2017; Yang et al., 2019). For this reason, it has led researchers to propose combining both models for favorable results. Among the challenges a researcher may face in modeling volatility are the stylized facts or financial market volatility patterns. Financial market volatility has several characteristics that are acknowledgeable in the literature. For instance, Baltas and Kosowski (2019) reinforced the existence of volatility clustering and supported the ARCH behavior of financial time series. Grable and Heo (2017) also found that volatilities vary across time and asset classes.

Stylized Market Volatility

The financial time series has some established characteristics of financial market volatility. Most volatility forecasting models incorporate the salient features of the design (Kaya & Yarbaşi, 2021; Xaba et al., 2017). This section highlights and briefly describes some of the characteristics relating to this study. The features include asymmetry (leverage), volatility clustering, fat tail (leptokurtic) distribution, and autocorrelation (Ardia et al., 2018, 2019). Forecasting volatility includes selecting stylized properties such as asymmetry, leverage, persistence, and mean reversion (Dai et al., 2020).

Fat Tail or Leptokurtic Distribution. Leptokurtic refers to the return distribution curve with higher peaks that deviate from the median. Racicot and Théoret (2018) show that long-term negative increases the downside risk and failure. Skewness values higher than 3 lead to leptokurtic, and higher kurtosis values lead leptokurtic (Swartz & Emami-Langroodi, 2018). Hedge fund returns deviate from the median and left-skewed (negative), and have leptokurtic distribution because of the nonlinear investment style (Baker et al., 2017). Also, Fang and Almeida (2018) recommend allowing for skewness and kurtosis to improve the forecasting analysis.

Volatility Clustering. Clustering refers to the fluctuations of uneven financial asset returns in contrast to even variations (Bhowmik & Wang, 2020). With volatility clustering, significant price changes can follow another large price change in an unpredictable direction (Kumar & Biswal, 2019). Volatility clustering and persistence produce leptokurtic distribution in financial series (Racicot & Théoret, 2018). Also, volatility clustering implies that present-day volatility shocks may influence the expectations of future volatilities. Herbert et al. (2018) found the existence of volatility clustering and asymmetry (leverage effect) in the Nigerian stock market and that the clustering is persistent. Similarly, Oseifuah and Korkpoe (2019) found that the Johannesburg Stock Market (JSE) market returns' volatility features include clustering and leptokurtic.

Volatility Asymmetry. Volatility asymmetry is another essential characteristic in the financial markets, especially in the equity markets (Racicot & Théoret, 2018). According to Xie and Wang (2018), volatility asymmetry reacts to declining markets by rising. The leverage effect if volatility increases because previous day returns are negative (El Jebari & Hakmaoui, 2017). The leverage effect is the asymmetric reaction to fluctuating returns of the same size. Bhowmik and Wang (2020) stated that leverage indicates negative news, and stock falls, leading to rising leverage effect and thus, an increase of the degree of stock volatility. Zaiane and Jrad (2020) used APARCH to investigate the dynamic linkages between the exchange rate (US Dollar) and theTunisia stock market. The APARCH model was appropriate to study persistent long memory and asymmetry in both markets. The study results showed that volatility shocks could create sudden changes in the dynamic correlations. Mashamba and Magweva (2019) evidenced leverage effects in the market in South Africa. Mohohlo and Hall (2018) found that operational leverage has no impact on the capital structure in South Africa except for the industrial sector of the economy.

Autocorrelation. When stock returns are uncorrelated or exhibit weak autocorrelation, they are dependent (El Jebari & Hakmaoui, 2017). Also, high autocorrelation values indicate long memory of volatility persistence. The slow decay in autocorrelation in returns is a sign of long memory. Persistency of volatility poses a direct threat to the prices of assets (Emenogu & Adenomon, 2018). Volatility persistence goes against the main principle of EMH, which is that stock prices incorporate all available information making it impossible to forecast the prices. However, the long memory process implies that the current prices could be predetermined by previous prices, which results from autocorrelations rates in prices. Also, the autocorrelation rate takes a long time to decay; thus, the current shock to the volatility would have long-lasting effects. Amudha and Muthukamu (2018) used GARCH models to estimate the volatility of the trends within India Stock Exchange from April 2003 to Sept 2015. The results showed volatility which displays the clustering and persistence of stocks.

Volatility Forecasting Models

An accurate estimate and forecasting of volatility depend on capturing the most stylized facts (Di Sanzo, 2018; Pan et al., 2017). According to Gaetano (2018), the variance of a sample data set σ^2 can be used to measure the volatility statistically. Additionally, the volatility can be calculated from several serial observations as follows:

$$\sigma^2 = \frac{1}{T-1}\sum_{t=1}^{T}\left(R_t - \mu\right)^2$$

Where μ is the average return, T is the forecasting period, and R_t, is the excess on hedge fund return. Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model when analyzing and forecasting financial volatility and economic time series data (Engle, 1982). Engle (1982) 's ARCH model is a linear function aimed to capture volatility clustering. The following formulae represent the ARCH (q) model:

$r_t = \mu + \varepsilon_t$ and $\varepsilon_t = \sigma_t z_t$

Where r_t = return on an asset at time t, μ = average returns, and ε_t = residual returns at time t, z_t is independent and evenly distributed with N (0,1) with mean zero and variance of 1. The formula below shows the conditional variance of ARCH as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-i}^2$$

The limitations of the model are ω > 0 and $\alpha \geq 0$ (for all i = 1, , q) to ensure s_t^2 is positive. The parameter is the conditional variance (volatility) at time t, is the squared error at time *t-1* from the mean equation, and q represents the number of lags. According to Engle (1982), the error variance subject to q logs of the squared residual terms is necessary to determine the volatility clustering. Bollerslev (1986) extended the ARCH to the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model that combines the mean equation and the conditional variance. The GARCH model is specified as follows:

The mean equation: $r_t = \mu + \varepsilon_t$

Where r_t = return on asset at time t, μ = average returns, ε_t = residual returns at time t. The conditional variance is shown below:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_1 \varepsilon_{t-i}^2 \beta_1 \sigma_{t-1}^2$$

Where s_t^2 denotes to the conditional variance at time t, ω defines the unconditional variance, e_{t-i}^2 denotes to the squared residual at time t-1 from the mean (ARCH) equation, α_1 is the first ARCH parameter, β_1 is the first GARCH parameter, and s_t^2 is the last period forecast variance in the GARCH equation. The limitations for the GARCH model specify $\alpha_1 \geq 0$ and $\beta_1 \geq 0$ must be met for e_{t-i}^2 to be positive (Nelson, 1991). Researchers could use the total of the two terms to determine the short- term dynamic volatility time series (Gaetano, 2018). Also, the conditional variance has persistent attribute, and the parameters add up to 1. The GARCH and GARCH-M models capture leptokurtosis and volatility clustering attributes in financial time series (Gaetano, 2018). However, GARCH models cannot capture the asymmetry of the financial data; the symmetric models assume that bad and good news of the same magnitude has the same effect on the market (Wu & Hou, 2019). Ndei et al. (2019) used GARCH (1,1) to model the market return from the Nairobi securities exchange in the presence of structural breaks. The findings from the study revealed that the GARCH (1,1) model could capture volatility symmetric and asymmetric effects. Al Rahahleh and Kao (2018) found that the GARCH (1,1) model overestimates the asymmetry during high volatility periods.

The ARCH and GARCH models cannot eliminate excess kurtosis in the return series and fail to capture skewness (Brooks, 2019). Nelson (1991) introduced asymmetric GARCH models (EGARCH, TGARCH, and APGARCH) to address the limitations of the ARCH and GARCH models. The GARCH variant models can capture the asymmetry of financial returns (Abdennadher & Hallara, 2018). According to Oseifuah and Korkpoe (2019), EGARCH, TGARCH, and APGARCH models are nonlinear and can model time-varying volatilities. Nelson (1991) 's EGARCH model extends the GARCH model of Bollerslev (1986) by accounting for skewness/asymmetric effect or leverage and persistence of shocks in conditional variance. The following equation shows the EGARCH model:

$$y_t = \mu + \varepsilon_t, with\, \varepsilon_t = \sigma_t z_t$$

$$\ln\left(\sigma_t^2\right) = \omega + \alpha_1 \left\{ \left| \varepsilon_{t-1} / \sigma_{t-1} \right| - \sqrt{2}/\pi \right\} + \beta_1 \log\left(\sigma_{t-1}^2\right) - \gamma\left(\varepsilon_{t-1}/\sigma_{t-1}\right)$$

Where γ measures the asymmetry, or the leverage, and α_i stands for the magnitude or the symmetric effect. If $\gamma_i = 0$, or the coefficient is 0, the implication is that both positive and negative shocks of the same magnitude have the same effect on the volatility. If $\gamma_i \neq 0$, implies the presence of the effect asymmetry. The leverage effect is exponential rather than quadratic, forecasting the conditional variance will be positive (Fernando, 2018). To test for leverage effects in the volatility by the hypothesis that $\gamma_i >$ 0, a positive coefficient means positive shocks tend to produce high volatility in the short term than negative shocks of the same magnitude (Fernando, 2018). The opposite would apply in the case of $\gamma_i < 0$. Ewing and Malik (2016) studied the presence of volatility spillover between oil prices and the U.S. stock market using the EGARCH model. Initially, the results from the study showed no volatility spillover. However, when the authors added structural breaks, they found volatility spillover between the U.S and China markets. Though the EGARCH model is applicable to forecast various financial features, it reacts slowly to market shifts (Emenogu et al., 2020). Also, the dynamics of risk exposures limit the EGARCH model by not changing regimes, which characterize hedge fund returns.

The TGARCH model presented by Rabemananjara and Zakoian (1993) and Glosten et al. (1993) captures both the positive and negative effects of asymmetry. The TGARCH equation has an artificial variable, *d* to account for the asymmetry or leverage effect. The conditional variance is given by:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_t^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

In this model, if $e_{t-1} \geq 0$, then good news, and if $e_{t-1} < 0$, bad news, and total effects are given by $(\alpha_i + \gamma_i)\, \varepsilon^2_{t-1}$. Also, e_{t-1} and e_{t-1} have a differential effect on the conditional variance. Good news impacts α, while bad news impacts $(\alpha_i + \gamma_i)$ (Ndei et al., 2019). The γ parameter represents the asymmetry or leverage. If $\gamma > 0$ indicates the leverage effect is present, the parameter represents the asymmetry or leverage, and bad news has a more powerful effect on volatility than good news (Saranya & Prasanna, 2018). On the other hand, if $\gamma \neq 0$, the news impact is asymmetric. Ding et al. (1993) introduced the APARCH model as an extension of the GARCH model. The conditional variance is shown as follows:

$$\sigma_t^{\delta} = \omega + \alpha_1\left(\left|\varepsilon_{t-1}\right| - \gamma_1\varepsilon_{t-1}\right)^{\delta} + \beta_1\sigma_{t-1}^{\delta}$$

Where δ denotes the asymmetric power term, enhances the model's flexibility. The leverage effect parameter γ tests the asymmetry up to order r (Ndei et al., 2019). Also, the main advantage of APARCH model is its flexibility and that it captures all features by EGARCH, and TGARCH. The limitations to the model are $\delta > 0, |\gamma_i| \leq 1$ for $i = 1, r$, $\gamma_i = 0$ for all $i > r$, and $r \leq p$.

Hamilton (1989) proposed the Markov Regime-Switching (MRS) as a time series technique to capture the shifts in the market during a recession. Gray (1996) further generalized the Markov regime-switching methods to ARCH models. Klaassen (2002) introduced the MRS GARCH by differentiating two regimes with different volatilities levels. The Markov regime-switching model makes it possible to analyze time-varying hedge fund risk exposures to different market regimes that include risk factors (Balcilar et al., 2017). A simple regime-switching model does not account for market risk factor regimes. The results identify different regimes with periods of levels of volatilities for most hedge fund indices. The out-of-sample forecasting shows the accuracy of the MS-GARCH regime-switching model. Forecast volatility, the hedge fund risk factors are necessary. The multifactor models are the foundation of the valuation process in asset management applications (Lambert & Platania, 2020). Following Billio et al. (2012), the baseline for the analysis is the Fama and French (1996) eight factors: All-World Index (market proxy), small-large risk (to capture liquidity risk), credit spread (credit risk proxy), and VIX (volatility proxy) risk factors. The hedge fund strategies will be on the index list.

In this section, I examined the relationship between the hedge fund performance and the forecast of the volatility of the hedge fund returns across different volatility regimes. Furthermore, I will investigate the exposure in hedge funds to a selection of market risk factors. Camacho et al. (2018) describe the MRS as a technique to capture discrete shifts and structural breaks. The focus of this section is to examine hedge fund excess return to adjust for exposure based on market volatility forecasts. I employed two different models to conduct the analysis. First, I tested the nonlinear TGARCH model to assess the asymmetric reaction of the performance of hedge funds to a positive and negative change in volatility. The second model will use the Markov regime-switching state-dependent volatility timing model (Hamilton, 1989):

$$R_{i,t+1} = \alpha_i + \beta_{i,} I_{t+1} + \lambda^{\sigma}_{i,} S_t \left(\sigma^{I}_{m,t+1} - \sigma^{T}_{m} \right) * I_{t+1}$$

$$+ \sum_{k=1}^{k} \beta_{i,k} F_{k,t_{+1}} + \varepsilon_{i,t+1} \sim i.i.d.N\left(0, \sigma^2_{\varepsilon_i}\right)$$

If the value l^{s}_{i,S_t} of state-dependent volatility-timing is negative, it indicates that the manager has sufficient market volatility timing skills and can adjust the fund's performance's market exposure before the market volatility level fluctuates. The conditional error term is $\varepsilon_{i,t+1} \sim i.i.d.\mathrm{N}\left(0, \sigma^2_{\varepsilon_i}\right)$, and the state-dependent volatility-timing is as follows:

$$\lambda^{\sigma}_{i,s_t} = \lambda^{\sigma}_{i,0}\left(1 - \mathrm{S}_t\right) + \lambda^{\sigma}_{i,1} S_t$$

According to Billio et al. (2018), the state-dependent market volatility timing I^{s}_{i,S_t}, is identified by two conditional regimes as follows:

$R_{it-1} = \alpha + \beta_{St} I_t + \omega\mu_t$ $\qquad$ $I = \mu_{S_t} + \sigma_{S_t}\varepsilon_t$

According to Camacho et al. (2018), the Markov regime model has the following parameters: $S_t\left(S_t \in \{0,1\}\right)$, S_t is Markov chain, n is the number of states, and P is the transition probability matrix. For n = 2 states, S_t = {0,1}. Camacho et al. (2018) revealed that that the Markov chain S_t is presented by the following transition probability matrix P.

$$P\left[S_{1t} = S_{1t} \middle| S_{1t-1} = S_{1t-1}\right] = \begin{pmatrix} P_{00} & P_{10} \\ P_{01} & P_{11} \end{pmatrix}$$

Table 7 below has the term description for the parameters.

Table 7

Terms of Description for the Equations

Term	Description
$R_{i,t+1}$	monthly excess return on hedge fund styles at time $t + 1$
α_t	Adjusted performance of hedge fund securities in time interval, t
I_{t+1}	Market factor in month $t + 1$
t	time interval in months
s_m^m	Average market volatility level
l_{i,S_t}^s	State-dependent volatility-timing
Z_t,	Markov chain proxy for non-linear factors not captured by hedge funds and market risk factors.
σ_{t+1}^2	Market volatility level at time $t + 1$
Θ_{k},	Linear factor loading of the hedge fund on the k-th risk factor
F_{kt+1},	Systematic factor on the k-th factor at time $t + 1$.(See table 10)
β,	Coefficient of exposure, and varies in various n state regimes H
S_t,	Regime indicator, Markov chain for n states, total n=2 (state 0, 1,)
σ^2	Conditional variance
σ	Actual observed volatility
μ_t	Average return over T periods
ϵ_t	Residual term or deviated return value from estimated mean return at time, t.
ω,	Idiosyncratic risk factor

Forecasting Performance Evaluation

This study follows Poon and Granger's (2003) work to evaluate the adequacy of the fitted model using the in-sample. For the in-sample, the goodness fit statistics method is appropriate to evaluate the models such as Akaike Information Criteria (AIC) and the Bayesian Information Criteria (BIC) (Bayer & Cribari-Neto, 2017). In this study, the significance of the second regime is not a comparison, but goodness-of-fit is the focus of this forecasting performance. According to Bayer and Cribari-Neto (2017), different models are only suitable for various loss functions. To quantify the forecasting performance of each model, a regression of the volatility forecasts the observed volatility and derives the coefficient value of (R^2).

The out-of-sample analyses comprise a period from January 2020 to December 2020 for twelve months. In this study, I will employ two loss functions to assess the out-of-sample forecasting performance of the models: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The out-of-sample and in-sample performance from the TGARCH and MRS models will be measured using the RMSE and MAE loss functions. If the in-sample output value from RMSE and MAE is greater than the out-of-sample, the forecast model is adequate (Khattak & Wali, 2017).

Financial Performance of Hedge Funds Variable

There is two strands of performance measures in the literature of hedge fund performance analysis (Stafylas & Andrikopoulos, 2020): (1) returns-based performance evaluation and (2) portfolio holdings-based performance evaluation (Stafylas et al., 2017). The returns-based approach is beta premium. In the returns-based method, the volatility of the returns relates to the risk exposure to the market (Agarwal et al., 2018a). The portfolio holdings-based approach generates alpha, designed to evaluate the manager's skill. A manager can use the return-based performance technique to evaluate systematic risk exposures of hedge funds (Frydenberg et al., 2017). Hedge fund returns exhibit nonlinear and option-based strategies, and the analysis focuses on regression approaches to regress the factors that proxy the strategies (Stafylas et al., 2017). The portfolio holdings-based performance approach focuses on unsystematic risks, making it appropriate for evaluating a fund manager's skill. This study includes combining both approaches to evaluate the variables of the research.

Benchmarking

Unlike mutual funds, where the benchmarks are relative, such as the S&P 500, hedge funds use indices (Pilbeam & Preston, 2019). Joenväärä et al. (2021a) cautioned on the importance of selecting the appropriate benchmark and technique because using the wrong methods could lead to error. Almeida et al. (2020) propose using a set of assets as benchmarks to evaluate hedge fund performance. The most basic performance measurement model is Jensen's alpha based on CAPM, where the fund's return is monthly risk-adjusted (Fama & French, 1993). The CAPM as the market proxy is the only factor as a benchmark. From here, the CAPM extends to the Fung and Hsieh (2001, 2004) multi-factor model to capture the abnormal performance of hedge funds, given the many strategies and risk factors. Also, the Sharpe ratio can assess risk-adjusted performance (Stafylas et al., 2018a). The Sharpe ratio is equal to the monthly return of the hedge fund index. The Sharpe ratio is scaled by the fund's return volatility as measured by the standard deviation. The Sharpe and CAPM models evaluate and rank hedge fund managers and are subject to criticism because they ignore their characteristics (Agarwal et al., 2018a). Platanakis and Sutcliffe (2017); Oikonomou et al. (2018) provide robust and innovative ways to manage the risk inherent in hedge fund returns. Silva et al. (2017) employed the Black-litterman portfolio model (BL) benchmark to estimate risk and make forecasts efficiently. The BL model weighs the portfolios to evaluate the returns.

Performance Persistence

Persistence in performance is a sought-after skill by fund managers and investors, as it is a direct test of the hedge fund manager's skill. However, past studies' conflicting results have weakened the certainty of performance persistence (Sun et al., 2018). Literature on hedge fund performance persistence is in three parts: (1) analysis of hedge fund performance and persistence in up and down markets and sustainability, (2) analysis of hedge fund market exposure, such as neutral market funds, and (3) hedge funds as diversification tool (Joenväärä et al., 2018).

The first field compares the performance of hedge funds to mutual funds (Agarwal et al., 2018b). Proponents of hedge funds argue that the low correlation of traditional alternative assets' returns makes a better risk-return trade-off (Cao et al., 2018a; Kolokolova et al., 2020; Stafylas et al., 2018a). Furthermore, this low correlation is with traditional assets enhanced by the exemption from the Security Exchange Act of 1934. Thus, providing more flexibility with different investment options to generate persistent returns. Other studies found no evidence of performance persistence for hedge funds (Barth et al., 2021; Bollen et al., 2021). The authors found that hedge funds positively correlated with the S & P 500 during bear or down markets.

Some studies found strong evidence of at least short-term performance persistence for hedge funds (Agarwal et al., 2018a; Joenväärä et al., 2021b). Agarwal et al. (2018a) combined four hedge fund databases: Eurekahedge, HFR, Lepper TASS, and Morningstar. The researchers examined the information from the data for persistence in returns. Evidence from the study showed the short-term persistence of alpha. Other studies challenged the short-term performance persistence of hedge funds (Cui & Kolokolova, 2020; Sun et al., 2018). Other studies found that performance persistence varies based on the market environment and investment strategies (Ilerisoy et al., 2018; Metzger & Shenai, 2019). While Agarwal et al. (2017b) found more substantial performance persistence when using monthly, quarterly, or semi-annual returns instead of annual data.

Liquidity

Another essential feature contributing to hedge fund performance persistence is illiquidity (Hwang et al., 2017). The authors found evidence of high stock prices resulting from hedge fund liquidity returns during the financial crisis of 2007-2009. Another study by Kolokolova et al. (2020) observed unstable corporate bond yields, resulting from hedge fund liquidity during that period. Ilerisoy et al. (2018) provide evidence of a relationship between hedge fund performance, market risk, and funding liquidity risk. The authors show that the funding liquidity risk is an influential factor in hedge fund performance.

Fee Structure

The hedge fund fee structure includes the annual operational fee of 2% of assets under management, and an incentive fee of 20% of the returns (Fung et al., 2021). The researchers observed that higher feed leads to higher performance for the institution, and the fee structure is a driving feature of liquidity. Kolokolova and Mattes (2018) argued that higher management fees lead to less aggressive risk styles. Low performance at the beginning of the year leads to conservative techniques to increase the chance of survival.

Gao et al. (2018a) show that management fee does not motivate managers to pursue performance as funds grow. The authors conclude that the size of the management fee exceeds the fund's profit.

Lock-Up and Restrictions

Lock-up and restrictions are policies or a period imposed on investors from withdrawing funds early (Getmansky et al., 2019). Lock-up and restriction are other components of illiquidity in hedge fund performance (Getmansky et al., 2019). The lock-up period is the outflow term of performance, and the inflow restriction is the closure to new investor periods (Getmansky et al., 2019). Giannetti and Kahraman (2018) found that hedge funds with excessive share restrictions are more likely to trade against mispricing equities than unrestricted funds. Aiken et al. (2021) confirmed that hedge fund performance positively correlates with restraining withdrawal capital.

Leverage

Hedge fund investors employ leverage in the strategies to increase returns and volatility of any strategy (Getmansky et al., 2019). Leverage involves borrowing money from banks or brokers to use individual hedge funds or strategy groups (Getmansky et al., 2019). Other studies suggest that high leverage affects hedge fund returns distribution (Baker et al., 2017; Molyboga et al., 2017). Baker et al. (2017) confirmed their first hypothesis that leverage correlates with negative skewness due to asymmetric payoff from derivatives. The authors also found that, despite controlling for persistence, the leverage variable predicts the future hedge fund return distribution.

Market Timing

Market conditions may affect the properties of assets and fund managers' investment strategies, affecting performance persistence. Cai et al. (2018) documented the market timing ability of hedge funds, especially during down and volatile market conditions. Agarwal et al.(2018a) investigate hedge funds' exposure to different financial and microeconomic risk factors by decomposing alpha, traditional beta return, and exotic beta return and examining investor flows' sensitivity to return components. Their results indicate a weak persistence to exposure. Like Crego and Galvez (2018), evidence from the study shows that market-neutral hedge funds can adjust their strategies according to the economic state. Finally, Falkowski et al. (2020) examine various hedge fund strategies' effectiveness during varying market conditions. Findings from the analysis indicate that the specific strategies were effective in a particular market condition, and others did well in another environment. Also, others performed well in hybrid conditions.

Performance Measurement Models

Hedge funds use a variety of dynamic trading strategies and use derivatives, short-selling, and leverage (Gao et al., 2018a; Zheng & Osmer, 2018). The hedge fund characteristics feature nonlinear returns, exposure to risk factors, and strategies that change over time (Agarwal et al., 2018a; Falkowski et al., 2020). This thesis aimed to examine the dynamic features.

Non-Parametric Models

Performance analysis for hedge funds differs from traditional assets because the returns have a low correlation with market indices (Canepa et al., 2020). Thus, using the

CAPM, or Jensen's (1968) ratio, is inappropriate as a measurement tool for hedge funds. The CAPM's alpha can be helpful as the market proxy or benchmark for hedge fund performance. Fama and French's (1993) model extends CAPM's model by using the size and the book price ratio to develop the three-factor model. The expected return is a linear combination of various factors and affiliates. Carhart (1997) added momentum to the Fama-French' (1993) model as a fourth factor to account for trend-following strategies in the stock market. However, hedge funds are flexible and can choose from various classes to employ dynamic strategies (Metzger & Shenai, 2019). Fung and Hsieh's (1997b, 2004) model captures eight standard fund asset classes when analyzing risk factors to explain the performances. The risk factors include (1) the market index factor (MKT), (2) the size spread factor (SMB) of Fama and French (1993), (3) the Book-to-market ratio factor (HMLt) by Fama and French (1993), (4) Book-to-market ratio factor (HMLt) by Fama and French (1993), (5) Moment factor (MOMt) by Cahart (1997), (6) Interest rate and credit risk factor, (7) MSCI Emerging Markets Equity Index, (MSCIEMt), and (8) Option risk factor (Agarwal & Naik, 2004).

Parametric Models

Linear asset models cannot account for the dynamic properties of hedge fund returns. To overcome the limitations of traditional or non-parametric approaches, several researchers have developed models to account for hedge fund characteristics (Cao et al., 2018a; Shin et al., 2018). Agarwal et al. (2017b) applied a factor model to investigate hedge fund index exposure. Mero (2016) created the Markov regime-switching (MRS) framework to account for macroeconomic indicators. The framework also has an investment decision-making process. Cai et al. (2018) studied equity-oriented hedge fund strategies to analyze hedge fund risks relating to nonlinear factor loading. The authors focused on the dynamic factors that switch from a regular regime or state to two other regimes with high or low volatility characteristics. This study analysis employs the Markov regime-switching model from (Hamilton, 1989). In this model, Chen and Liang (2007) combined the timing measure to Jensen's (1972) model relating to the Sharpe ratio to allow risk-adjusted performance measurement as follows:

$$R_{i,t+1} = \alpha_i + \lambda_i \left(\frac{R^s_{m,t+1}}{\sigma^s_{m,t+1}} \right)^2 + \sum_{k=1}^{k} \beta_{i,k} F_{k,t+1} + \varepsilon_{i,t+1},$$

$$\varepsilon_{i,t+1} \sim i.i.d.N\left(0, \sigma^2_{\varepsilon i}\right)$$

Where $R^s_{m,t+1}$ is the return from the stock market at time t + 1; $\sigma^s_{m,t+1}$ is the stock market volatility level; and λ_i is the timing skill of the manager. Chen and Liang (2007) proposed the timing term $\left(\frac{R^s_{m,t+1}}{\sigma^s_{m,t+1}} \right)^2$, which is associated with the Sharpe ratio of the market, which lead to risk adjusted returns.

Hedge Fund Data Bias

Some authors have reported biases in hedge fund data because of managers' voluntary reporting (Ben-David et al., 2020; Jorion & Schwarz, 2019). Ben-David et al. (2020) used data from BarclayHedge and TASS to study three return biases from 1994-1918: survivorship bias, delisting bias, and backfill bias. Survivorship bias occurs when hedge fund managers exclude liquidated/dead funds. Further, survivorship bias may cause liquidity bias, resulting in inhomogeneity data (Agarwal et al., 2017b). Ultimately, the lack of homogeneity of the database construction rules may impact the study's analysis and findings.

Backfill bias occurs when a hedge fund manager cherry picks surviving funds to report and drops low-performing funds (Jorion & Schwarz, 2019). The authors cautioned researchers to mitigate the biases as they may skew study analysis and results. Joenväärä et al. (2021b) discussed two approaches to address backfill bias. The first approach is the ad-hoc cut-off, where the researcher excludes the first 12-24 months of funds’ returns. The second approach is the listing date method, where the researcher removes all data before the listing date in the database. Jorion and Schwarz (2019) developed an algorithm to identify backfill listings and amputate them from the central funds to mitigate the backfill bias. In addition, hedge fund returns are subject to delisting bias (Aragon & Nanda, 2017). Delisting bias occurs when managers strategically report a selected group of returns late to vendors, sometimes months after occurrence (Aragon & Nanda, 2017). Furthermore, the manager may strategically drop the low-performing returns, making it difficult for researchers to sample the excluded data. Delisting returns become missing data, causing upward bias in returns. Forsberg et al. (2018) found that managers are more likely to delist funds that underperform. Forsberg et al. (2018) suggest finding and amputating the incomplete data to control for delisting bias.

Transition

In Section 1, I justified using a quantitative correlational research study to examine the relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds. Section 1 includes the background of the problem, highlighting the dynamic nature of hedge fund characteristics for managers to adapt to their trading strategies accordingly. Also included in Section1 is the problem statement for this study, discussing the general and specific business problem. A discussion on the purpose statement, assumptions, limitations, delimitations, nature of the study, and the academic literature review are also part of Section 1. The nature of the study discussion includes the research method and design. The academic literature review includes the theoretical framework, analysis, and literature synthesis on the variables.

In Section 2 of this doctoral study, I included a description of my role of as the researcher, justified the implementation of research methodologies and design to validate analysis. Also included in Section 2 is a discussion of ethical considerations, participants, target population, and data collection procedures. The final section, Section 3, includes pre-data analyzing procedures, findings, application to professional practice, implications for social change, recommendations for action, and conclusion.

Section 2: The Project

In Section 2, I provided an overview and justification of the chosen research methodology and design for this study. The section begins with a purpose restatement, followed by a description of my role as the researcher in the data collection procedure. This section also includes information about (a) population sampling, (b) data collection, (c) data collection technique, (d) data analysis technique, and (e) reliability and validity. The section concludes with a transition summary statement.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between risk exposure, volatility forecasting, and financial performance of hedge funds. The independent variables were volatility forecasting and risk exposure. The dependent variable was the financial performance of hedge funds. The targeted population comprises archival data from hedge fund databases in South Africa. The implication for positive social change includes the potential to provide organizational leaders who partner with hedge funds the ability to maximize profit by diversifying risk in volatile market conditions. Using an investment tool to dispel uncertainty in various market conditions is a financial means to foster positive change (Tarhani & Ameli, 2016). Accordingly, through partnerships, hedge funds may help leaders of foundations and nonprofit organizations fund projects in local communities.

Role of the Researcher

As the researcher in this study, my role included collecting, organizing, analyzing the secondary data, and interpreting the findings objectively. Using existing data is cost-effective and convenient if the researcher can analyze the data to address the research question (Martins et al., 2018). Part of performing my role included collecting secondary numerical data from website sources. Köhler et al. (2017) confirmed the use of statistical software in data analysis. I analyzed the data to determine if a relationship existed between the variables relating to the financial performance of hedge funds. In addition, I identified the effect of independent variables on the dependent variable in the financial performance of hedge funds. Finally, I used statistical analysis to make valid inferences and conclusions.

In a qualitative research study, the researcher is the primary data collection instrument because the researcher gathers the data through interviews, observations, and focus groups (Mason-Bish, 2019). In this study, I was not the data collection instrument because I used secondary data to perform the study data analysis. My role was to comply with the ethical principles and guidelines in the Belmont Report. The Belmont Report of 1979 provides an ethical framework that includes respect, beneficence, and justice as virtues researchers must follow when working with participants (U.S. Department of Health and Human Services, 2016). During this research, I did not use human participants and the ethical concerns identified in the Belmont Report did not apply.

My role as a quantitative researcher was to remain objective from my interests, bias, and experiences when interpreting and presenting the study results. Furthermore, the quantitative researcher is to practice ethical conduct and avoid influence by any organization to maintain the integrity of the research (Edwards, 2020). In this study, there were no boundary issues because I did not have any association with the industry or topic of study. Also, I did not associate with hedge fund managers in this profession. In addition, as the researcher, I did not provide investment advice on hedge funds related to this study. Ultimately, my role as a researcher was to uphold the highest ethical standards throughout the research process.

Participants

For this doctoral study, there were no human participants. Data for this study came from secondary sources relating to South Africa-based hedge funds. The data included historical monthly returns for hedge fund indices from the online database. The choice to use monthly returns was because hedge fund managers' report performance monthly to hedge fund databases (Shin et al., 2017). The retrieved data assisted in addressing the research question. Other data for this study included the financial information from Bloomberg as used in the performance evaluation variable.

For a quantitative correlational study, secondary data is an acceptable strategy (Queirós et al., 2017). Queirós et al. (2017) explained that using archival data is both more cost and time effective when compared to using primary data. Martins et al. (2018) highlighted the advantages of using secondary data, which include providing easier access to international data that would have been costly and time-consuming. In addition, by using secondary data, the researcher can access a large volume of historical data to conduct several statistical analyses (Cave & Stumm, 2021). The absence of human participants limits the risks identified in the 1976 Belmont Report and compliance requirements; however, I followed the report's guidance when in contact with humans during of the study.

Research Method and Design

Research Method

Research methodology is a technique that researchers use to collect, analyze, and interpret information to reach conclusions (Scholtz et al., 2020). Research methods can be quantitative, qualitative, or mixed method (Morgan, 2018; Zoellner & Harris, 2017). The researcher selects any one of the methods to conduct a study and address the research question (Williamson et al., 2020). The quantitative research method is an objective and systematic process of using numeric data to measure a phenomenon and produce findings (Ghauri et al., 2020). Researchers use the quantitative approach to examine the relationships between variables by statistically analyzing numerical data to make inferences (Köhler et al., 2017). Köhler et al. (2017) explained that the statistical inferences are generalizable to the larger population to answer the research question. I used the quantitative method for this study because I sought to examine the relationship between the variables.

The focus of researchers using qualitative method is to explore a phenomenon using non-numerical data (Nowell et al., 2017; Williamson et al., 2020). The qualitative research method is appropriate for understanding a social or human problem from multiple perspectives (Mohajan, 2018). Similarly, researchers use the mixed study approach to combine the qualitative and quantitative methodologies to analyze textual and numerical data (Brannen, 2017). Neither the mixed method nor the qualitative method were appropriate for this study because I did not explore people's experiences or attitudes. Therefore, the qualitative method and the qualitative portion of a mixed-method approach were not appropriate for this study, and the quantitative was the logical choice.

Research Design

Quantitative researchers can use correlational, experimental, or quasi-experimental designs to conduct research (Podsakoff & Podsakoff, 2019). Researchers use the correlational design to measure the strength of the relationship between two variables (Zyphur & Pierides, 2020). Researchers also use the correlational design to identify an association between variables (Yang et al., 2021). The correlational design was applicable for this study because the objective was to assess the relationship between independent variables (risk exposure and volatility forecasting) and a dependent variable (financial performance).

The causal-comparative design appeared to be an option for this study, but it was not suitable. Researchers use causal-comparative design to compare groups in order to explain existing differences between them on the same variable of interest (Gøtzsche-Astrup, 2018). Gøtzsche-Astrup (2018) explained that researchers use causal-comparative design to show that a relationship exists between variables and the consequences of differences that already exist between two groups. In this quantitative correlational design, I did not seek to understand the differences between groups; rather, I examined the relationship within a group. Furthermore, causal-comparative design allows the researcher to make inferences about causation and the correlational design does not.

The experimental designs involve manipulating variables to assess the cause-and-effect relationship between them (Podsakoff & Podsakoff, 2019). Researchers conduct the experimental design to determine the ideal values of variables that support the cause-and-effect relationship rather than an association between variables (Cortina, 2020). Furthermore, researchers using the true-experimental design assign variables to a group or manipulate an independent variable. In a quasi-experimental design, the researcher does not assign the variables randomly, and instead, uses a control group (Yang et al., 2021). However, in correlational studies, there is no manipulation of variables (Yang et al., 2021). Therefore, the experimental design was not suitable to address the research question for this study.

Population and Sampling

Population

A population refers to the summation of elements that the researcher wants to generate for the results (Hickey & Sollmann, 2018). The general population of this study encompasses all the asset classes under management in the hedge fund industry. The target population of this doctoral study includes monthly returns of hedge funds in South Africa between July 2007 to December 2020 from databases. The data also include the annual performance of the Johannesburg Stock Exchange (JSE) All Share Index (ALSI) as the market proxy to measure the surplus return of each hedge fund, along with the Morgan Stanley Capital International Index (MSCI) performance over the same period for robust analysis of risk exposure analysis.

Population Alignment with Research Question

The target population for this quantitative correlational study aligned with the research question with the variables of risk exposure, volatility forecasting, and financial performance. I regressed the monthly returns over the study period to determine the financial performance (dependent variable). Also, running the style analysis on the monthly returns allowed me to examine the hedge fund strategies' exposures relative to risk factors during the study period (independent variable). Finally, I used the indices from monthly returns to explain the hedge fund volatility and forecasting (independent variable). A sampling approach is essential for researchers when exploring datasets, including determining the appropriate sample size (Trafimow & Myüz, 2019).

Sampling

The two methods of collecting samples include probabilistic and nonprobabilistic sampling (Sharma, 2017). I used the probabilistic sampling strategy in selecting a sample of South Africa hedge fund data from databases. I did not use the nonprobabilistic sampling technique because it does not allow to make inferences about the population (West, 2017). Quantitative researchers use probabilistic sampling approach to generalize the findings from the sample to the study population (Sharma, 2017). The probabilistic sampling strategy was appropriate because the goal was to draw inferences of the entire population of hedge funds based upon the study sample. However, some there are some disadvantages for using the probabilistic sampling technique which include being tedious and time consuming, especially when the sample size is large (Schuster et al., 2022; West, 2017).

A simple random sampling was the suitable probabilistic sampling method for this study. The simple random sampling strategy allows every member of the population an equal chance of selection (Muneer et al., 2017). The sample comprised of time series data between July 2007 and December 2020. The data yielded 150 observations of monthly returns of hedge fund indices. The sample comprised of both live and dead funds from HedgeNews Africa database. In this study, survivorship bias in the sample may affect the study findings by inflating the performance (Gao et al., 2018a). Furthermore, potential survivorship bias may produce false conclusions about the relationship between volatility and performance. To mitigate survivorship bias, the dataset comprised post-1994 data, consisting of dead and live funds (Barth et al., 2021; Jiang et al., 2022; Joenväärä et al., 2021a). In addition, backfill bias in the sample may create upward biased time-series returns for macro funds (Joenväärä et al., 2018; Jorion & Schwarz, 2019). Backfill bias could also lead to incorrect relationship findings between hedge fund performance, systematic risks, and volatility. Following the approach by Barth et al. (2021), Forsberg et al. (2018), Gao et al. (2018b), and Jiang et al. (2022), to address backfill bias, I eliminated the first 24 month return observations of each fund.

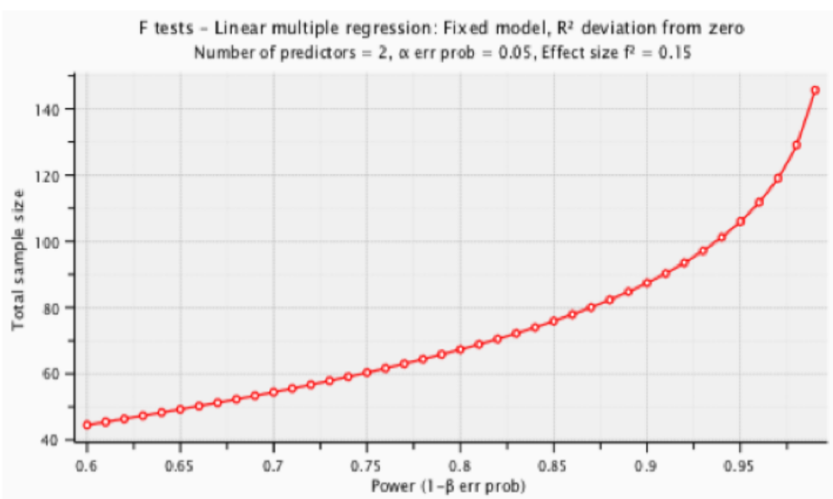
The reason for selecting the simple random sampling technique is because it enables the use of historical data. The advantage of using the simple random sampling technique is that it enables the researcher to reduce possible selection bias and minimize the potential for findings with skewness (Mahalua et al., 2019). Mahalua et al. (2019) also suggested that researchers use the probabilistic simple random technique when they require minimal knowledge of the target population. Furthermore, the probabilistic simple random technique could make a strong representation of the target population. Another advantage of using the probabilistic simple random technique is that selecting an individual member in the sample does not affect other members in the sample (Ali &

Shukla, 2020). The sampling choice aligned with the sample in this study because the data comprised of a monthly return time series. However, the simple random technique has a potential weakness of requiring a large sample to attain a representative population (Serdar et al., 2021).

G* Power is the statistical software package researchers use to perform a priori sample size analysis (Faul et al., 2009). I used the G*Power Version 3.1 to determine the appropriate sample size for this study. A priori power analysis with the assumptions of medium effect size (f^2 = .15), type I error (α = .05), and two predictor variables. The priori analysis indicates a minimum size of 68 sample observations to attain the power of 0.8 (Fig. 1). Increasing the power to 0.99 leads to 146 sample observations (see Table 8).

Figure 1

Relationship between effect size and the sample size at power 0.8 for F-Tests Linear Multiple Regression



Also see the minimum sample size for a different range of powers and effect sizes, shown in the table below.

Table 8

Minimum Sample Size for Selected Powers and Effect Size

	Power			
Effective Size	0.8	0.85	0.95	0.99
Small (0.02)	485	550	776	1073
Medium (0.15)	68	76	107	146
Large (0.35)	31	35	48	65

A sample size between 68 and 146 observations was acceptable for this study. The sample of 146 observations yields a study period of 12years, between July 2007 and December 2019. Therefore, the sample of 150 observations ranging between July 2007 and December 2020 was the appropriate size for this study.

Ethical Research

Researchers have an ethical responsibility to conduct research with integrity, regardless of the research methodology (Zyphur & Pierides, 2017). I obtained the IRB approval from Walden University before collecting and analyzing data, with the licence number 02-03-22-0552772. I obtained secondary data from public and private electronic data sources. The ethical protocols in the Belmont Report (U.S. Department of Health, 2016) apply to human research subjects (Friesen et al., 2017). The Belmont Report of 1979 provides an ethical framework that includes respect, beneficence, and justice that researchers must follow when working with participants (U.S. Department of Health, 2016). I did not use human subjects in this study.

Consequently, the consent documents include (a) informing participants about the study purpose, (b) possible risks in the study, (c) potential benefits, (d) voluntary participation, and (e) the process for withdrawal from the study. I maintained confidentiality by limiting access to the data and securely storing and protecting data in electronic folders with a password. Finally, I will delete the data five years after the study's publication.

Data Collection Instruments

I did not use a data collection instrument in this study. The data originate from secondary sources. Martins et al. (2018) described secondary data as information from existing sources. Quantitative researchers may use secondary data for statistical analysis (Queirós et al., 2017). Theofanidis and Fountouki (2018) also reported that researchers set boundaries for the research by establishing delimitations for a framework for recording and analyzing the information. This study involved scaling each variable based on measurement techniques researchers used to measure variables in previous studies. The data for this study included monthly time series from the online HedgeNews Africa (HNA) database from July 2007 to December 2020 (HNA, 2021). The HNA database provides the most timely, accurate, and independent source of information covering alternative investment space across the emerging African continent and the South African hedge fund industry (HNA, 2021). I converted the hedge fund return rates from South African Rand terms (ZAR) to U.S Dollars (USD) for all strategies for analysis.

Other secondary data sources were the Bloomberg database using the Bloomberg terminal, I-Net Bridge, and the South African Reserve Bank (SARB). Bloomberg is among the most global providers of timely, accurate, and high-quality financial news and information to more than 300,000 trading desks (Guidotti, 2019). Beyond information, the Bloomberg terminal system allows market participants to monitor and analyze real-time financial market data for informed decisions. I-Net Bridge is a South African financial services company that provides electronic economic data, financial market data, and market intelligence (I-Net Bridge, 2021). The SARB provides high-quality economic, policy-relevant, and financial statistics that present a holistic view of the South African equities market (SARB, 2021).

The purpose of this study was to examine the relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds. The datasets incorporated the variables, and I utilized them to determine the relationship between the three variables. Risk exposure is one of the variables in this study. Several studies applied the style analysis to investigate the risk exposure of funds to gain insight into the impact of factors on performance (Billio et al., 2018; Hespeler & Loiacono, 2017; Stafylas & Andrikopoulos, 2020). The style analysis includes a regression process between fund returns against risk factors (Frydenberg et al., 2017). The HNA database provided the source for monthly hedge fund returns. Using the Bloomberg terminal, I sourced the JSE (ALSI) returns and the Morgan Stanley Capital International (MSCI) index from the Bloomberg database for the study period. I also sourced sample data for risk factors from I-Net Bridge. The beta coefficient represents a standard measure of a fund's exposure to movements in the market's return (Frydenberg et al., 2017). If the market beta coefficient value is zero and an asset contains a beta coefficient of zero, it indicates no correlation with the market index (Mestre, 2021). Also, a positive beta of the asset shows that the asset follows the market movements and has higher risk exposure. Several researchers used the beta coefficient to measure risk exposure in various areas of financial studies

(Agarwal et al., 2018a; Gerhard & Rupert, 2017; Hwang et al., 2017; Yurteri Kösedağli et al., 2021).

Volatility forecasting is the second independent variable in this study. Previous research indicates that volatility forecasting in financial instruments demonstrates a direct association with performance (Gaetano, 2018; Limam et al., 2017). In this study, I used an autoregressive model to perform volatility forecasting. Autoregressive Conditional Heteroskedasticity models (ARCH) are statistical techniques that suggest the subsequent period volatility is conditional on the current period volatility, including the time-varying nature of volatility (Ndei et al., 2019). Researchers may use ARCH and its variant of family models to forecast volatility in time-series data with a non-linear model without assuming constant variance (Mashamba & Magweva, 2019). The HNA database served as the source for the hedge fund returns for the study period. I sourced the returns on the JSE (ALSI), MSCI index, South African Volatility Index (SAVI), and MSCI Emerging Market Stock Index from the Bloomberg database for the study period using the Bloomberg terminal. In addition, I sourced the exogenous factors from I-Net Bridge and SARB. The asset return volatility measures how much the returns move around their mean (Greaves, 2018). Some volatility measures include standard deviation, beta, R-squared, and alpha (Ardia et al., 2018). Previous researchers have supported the standard deviation or variance as a measurement of uncertainty or risk (Ardia et al., 2018; Gaetano, 2018; Greaves, 2018; Siddiqui & Roy, 2019). The standard deviation has advantages because extreme values do not affect how it functions (Greaves, 2018). Furthermore, it indicates its magnitude by the cluster level or shocks, and it is more precise and reliable than the other measurements. I used the Root Mean Square Error (RMSE) to assess the accuracy of the forecasting performance of the models. The RMSE compares the out-of-sample of forecast performance of the models. The forecasting model with the lowest value of RMSE is the most accurate (Al Rahahleh & Kao, 2018).

The financial performance of hedge funds represents the dependent variable in this study. Like the independent variables, I retrieved secondary data from HNA, Bloomberg database, I-Net Bridge, and SARB. Alpha represents the measurement of funds' performance (Kapil & Gupta, 2019). Also, the regression intercept of several market factors on the hedge fund excess returns to measure the performance. Risk-adjusted performance measures include the Sharpe, Sortino, omega, and Calmar ratios (Newton et al., 2021). The Sharpe ratio is inappropriate to measure hedge funds' performance because it assumes that returns produce a normal distribution (Metzger & Shenai, 2019). The Sortino, omega, and Calmar ratios use volatility as risk, making them unsuitable for measuring hedge fund performance (Kapil & Gupta, 2019). This study included evaluating the hedge fund performance measure by augmenting the Capital Asset Pricing Model (CAPM) of the Sharpe ratio by factoring in the changing state of the economy, systematic risk factors, and market timing component. Previous researchers have supported the time-varying factor approach to evaluate alpha (Bouamara et al., 2017; Chen & Kawaguchi, 2018; Metzger & Shenai, 2019; Newton et al., 2021)

In this study, the measurement scale for the dependent variable, the financial performance of hedge funds, is the ratio scale. The basis for financial performance of hedge funds is the time series returns from assets measured as ratio scale. Also, the measurement for the independent variable, the volatility forecasting variable was ratio scale. The second independent variable, the risk exposure variable, was an ordinal scale with eleven sub-variables: (a) market index (ALSI), (b) size spread factor (SMB), (c) book-to-market factor (HML), (d) moment factor (MOM), (e) equity markets index (MSCI), (f) emerging markets equity index (MSCIEM), (g) option risk factor (SAVI), (h) 10- year government bond (10-Yr-bond), (i) 3- month T-Bill (j) metal commodities (k) exchange rate risk (US/ZAR). Content validity, criterion-related validity, and construct validity did not apply in this study because I did not use instruments.

Data Collection Technique

The research question of this quantitative correlational study is as follows: Is there a statistically significant relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds? The data collection method for this study involved sourcing data from secondary sources. I collected secondary data for this study from websites linking to HNA, Bloomberg terminal, SARB, and I-NET Bridge databases between 2007 and 2020. Yerpude and Singhal (2017) revealed that collecting data using automated real-time systems increases the accuracy of forecasting output. The SARB distributes data through an online terminal which allows users to download data (SARB, 2021). The data terminal allows users to download time series data and easily export it to excel. Significantly, the system provides the researcher with a time series code and uses keywords to search (SARB, 2021).

The Bloomberg terminal includes an online tutorial and data acquisition instructions (Guidotti, 2019). In addition, a researcher can transfer data from the

Bloomberg terminal to other software programs like Excel and SPSS for sorting and analysis. I-NET service provides a workstation for users to access electronic data and support operating the terminal (I-Net Bridge, 2021). Furthermore, the electronic terminal incorporates a web application and a data feed system with analytic tools. Finally, the HNA database provides an online terminal for users to download and transfer data to various programs, like the Excel spreadsheet (HedgeNews Africa, 2021).

After obtaining the IRB's approval, I extracted the data through the electronic terminals from the databases for the study period between 2007 and 2020. The first step was to ensure that sources comprised the relevant data to answer the research question (Olabode et al., 2018). I used the variables in this study to filter the data from respective database terminals. The study variables include risk exposure, volatility forecasting, and the financial performance of hedge funds. The data from sources aligned with variables as presented in Table 9.

Table 9

Systematic Risks Data, Sources, for Risk Exposure Variables

Factors (Data)	Source
Monthly returns net-of-all-fees, relating to the hedge fund strategy indices	HNA
Equity factors:	
1. Market (MKT) JSE (ALSI)	Bloomberg
2. Morgan Stanley Capital International (MSCI) index	Bloomberg
3. MSCI Emerging Markets Equity Index, ($MSCIEM_t$)	Bloomberg
4. Size factor (SMB_t) by Fama and French (1993)	I-NET
5.Book-to-market ratio factor (HML_t) by Fama and French (1993)	I-NET
6. Moment factor (MOM_t) by Cahart (1997)	I-NET
Option risk factor (Agarwal and Naik (2004):	
7. South African Volatility Index (SAVI)-implied volatility	I-NET
Interest rate and credit risk factor:	
8. ZAR 10-year South Africa government yields	SARB
Exchange rate factor:	
9. Fluctuations in the Rand-Dollar exchange rate (USD_t)	Bloomberg
Commodity factor:	
10. World metal prices (MET_t)	I-NET
Spread:	
11. Spread: the difference between market return and the 3-month treasury bill (risk-free rate, rf)	SARB

The second step included:(a) downloading the data onto an Excel spreadsheet, (b) organizing the data for all variables, and (d) importing the data into SPSS for statistical analysis. Weston et al. (2019) recommended that secondary researchers document the data using code, including precise instructions, before the statistical analysis. Arslan (2019) also proposed code-creating tools such as the codebook package. Tools like the codebook help secondary researchers with reliability procedures, missing patterns, storage, plot data, and web interface. Further, the auto code tool includes meta-data, such as variable names and labels (Arslan, 2019).

Retrieving secondary data from electronic databases has both advantages and disadvantages for this study. Olabode et al. (2018) stated that collecting electronic data allows unrestricted access to broad international samples at a limited cost. According to Yerpude and Singhal (2017), automated secondary data collection is more appropriate for time series forecasting. Furthermore, the web interface and storage systems grant researchers unlimited access to data and transfer it to statistical software for analysis (Arslan, 2019). There is some drawback to employing secondary data. Pernollet et al. (2017) opined that preparation errors in archival data might affect the study results' reliability. Because of the voluntary nature of reporting, there is a possibility of missing or incomplete data in hedge fund databases (Aragon & Nanda, 2017). The missing data set might exclude the researcher's vital information to address the research question (Weston et al., 2019). Furthermore, missing or incomplete data may generate bias, affecting the relationship between the variables (Olabode et al., 2018). Cheng et al. (2017) suggested that pilot studies are significant steps to evaluate the possible threats to the validity of empirical research. Fink et al. (2021) pointed out that the primary purpose of a pilot study is to assess the measurement characteristics of the instruments. However, a pilot study was not appropriate for this study because of the use of secondary data.

Data Analysis

The research question of this study is as follows: Is there a statistically significant relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds? The independent variables are risk exposure and volatility forecasting.

The dependent variable is the financial performance of hedge funds. This study involved answering the research question by testing the following hypotheses:

H_0: There is no statistically significant relationship between risk exposure, volatility forecasting, and financial performance of hedge funds.

H_a: There is a statistically significant relationship between risk exposure, volatility forecasting, and financial performance of hedge funds.

I used the multiple regression model to analyze the data in this study. Multiple regression is a statistical technique that allows researchers to examine relationships between one dependent variable and several independent variables (Green & Salkind, 2017). According to Jelusic (2017), the multiple regression method is valuable in quantifying the degree of association between variables. The multiple regression analysis is appropriate for this study because the research question is about a predictive relationship between one dependent variable and two independent variables. While I opted to use the multiple regression approach, I did consider using other techniques like the Analysis of Variance (ANOVA) and logistic regression.

The ANOVA is a statistical technique that researchers can use to measure the statistical mean difference between samples (Green & Salkind, 2017). Furthermore, Green and Salkind (2017) also noted that the ANOVA test applies when the dependent variable is continuous while the independent variables are categorical. The focus of this study was not to examine the mean and group differences between samples. Moreover, the independent variables are not categorical. Therefore, the ANOVA test was not applicable to this study. Another option was logistic regression. Logistic regression analysis is another statistical technique that researchers use to examine the relationship between a dichotomous, binary dependent variable and independent explanatory variables (Bergtold et al., 2018). Given that the focus of this study did not predict the binary dependent variable, this made the logistic regression approach unsuitable for this study.

Quantitative researchers use data cleaning and screening procedures to refine raw data to a suitable format for statistical analysis (Kiss et al., 2017). Data cleaning refers to the process data analysts use to edit invalid data from the dataset (Bashir & Wei, 2018). Kiss et al. (2017) also recommend performing data cleaning methods to improve the quality to minimize the possibility of false positives in the study results. At the same time, screening involves detecting the anomaly in the dataset (Arslan, 2019). Data screening starts with establishing the raw data characteristics (Wang & Wang, 2020). Arslan (2019) suggested performing data screening to ensure that data are ready for analysis. Furthermore, the quality of acceptable analysis is subjective to the initial phase of data screening. Data cleaning and screening include standardization, coding, and reporting (Arslan, 2019). The data cleaning and screening procedures suitable for this study include scanning, coding, identifying missing values, validation, and implementing treatment techniques.

Missing data is inevitable in secondary datasets (Coertjens et al., 2017). Most databases contain duplicate, incomplete, and missing values (Agbehadji et al., 2018). This research included employing archival information from hedge fund databases. Agarwal et al. (2017b) noted that managers' voluntary disclosure of hedge funds provides the source of missing and incomplete data in hedge fund databases. Furthermore, missing data are problematic when a researcher intends to examine events' occurrence or variations of change over time (Bashir & Wei, 2018). There are various methods to mitigate missing data, including imputation techniques. According to Kiss et al. (2017), methods to consider addressing missing data include (a) listwise deletion, (b) pairwise deletion and, (c) Expectation-Maximization (EM). The listwise deletion method excludes all data cases with missing values (Bashir & Wei, 2018). The listwise deletion approach involves excluding all data cases with missing values. However, time series data involve removing the time intervals when there is missing data for specific data. The downside to the listwise deletion method is that it can cause bias and fragment time series data, distorting the study results (Agbehadji et al., 2018).

The pairwise deletion approach involves deleting the whole variable with the missing values and substituting it with the median or unconditional mean (Kiss et al., 2017). Kiss et al. (2017) also noted that a drawback of the pairwise method could compromise the power of statistical tests because the estimated data could exhibit bias. The EM approach reconstructs the missing data by estimating the variance or covariance (Bashir & Wei, 2018). However, Kiss et al. (2017) argued that the EM approach would affect time series more under multivariate applications. I adopted the listwise approach for this study to identify the contaminated data and address missing data.

There are assumptions in any statistical analysis (Plonsky & Ghanbar, 2018). Bergtold et al. (2018) reported that the assumptions associated with using multiple regression are as follows: (a) multicollinearity, (b) linearity, (c) outliers, (d) normality, (e) homoscedasticity and (f) independence of residuals. Multicollinearity occurs when two independent variables are highly correlated, as high as 0.8 to 0.9 (Green & Salkind, 2017). The violation of the multicollinearity assumption in a study may inflate the variances of the parameter estimates, which may result in questionable p-values (Plonsky & Ghanbar, 2018). Consequently, incorrect conclusions about relationships between the independent and dependent variables. Theoretically, it would be challenging to determine which highly correlated predictor variable is related to the hedge fund's performance. I examined a bivariate correlation matrix of the predictor variables from the SPSS software output. A correlation coefficient less than 0.8 is acceptable (Hirk et al., 2019).

Linearity assumes a linear relationship between independent and dependent variables (Josephat & Ame, 2018). To check for linearity, I visually inspect the scatterplot of the relationship between the variables using SPSS. A straight line indicates that the assumption is present. Outliers represent observations or scores whose values highly differ from the data set under study (Ernst & Albers, 2017). Yuen and Ortiz (2017) stated that outliers could arise from various sources, like incorrect recording observations of data. To locate outliers, I visually inspected the scatterplot, histograms, box plot, or frequency distributions using the SPSS software. Another method to locate outliers includes converting data to z-scores (Ernst & Albers, 2017). One solution is removing the outliers from data analysis (Green & Salkind, 2017). However, dropping the data or outliers may cause bias in the study results (Yuen & Ortiz, 2017). Dropping outliers can be justified when: (a) they are out-of-range, and misentered data and (b) missing. Normality assumes that the distribution of residuals is normal (Hirk et al., 2019). Some of the tests for normality include the following: (a) observing the normal probability-

probability plot (Q-Q), (b) histogram, or (c) a Shapiro-Wilk and Kolmogorov-Snairnov tests using the SPSS software (Ernst & Albers, 2017).

Homoscedasticity refers to assuming the variability in scores should be constant across all independent variable levels (Ernst & Albers, 2017). Homoscedasticity assumption can lead to bias in the findings, and alter the overall analysis, thus weaken the statistical power (Dattalo, 2018). Ernst and Albers (2017) observed that a weak power increases the potential occurrence of Type I error. Consequently, Type I error results in inaccurate *F-test* results and discrepant conclusions. To assess the presence of homoscedasticity, a visual inspection of the Normal Probability Plot (P-P) of the Regression Standardized Residual using the SPSS software (Dattalo, 2018). Also, I observed the scatterplot from SPSS software. A funnel shape indicates the assumption is unacceptable, and a random array of dots indicates that the homoscedasticity assumption is acceptable (Green & Salkind, 2017). Finally, the independence of residuals refers to the residual difference between each observed and the average predicted value of the dependent variables (Hirk et al., 2019). Ernst and Albers (2017) suggested using the Durbin-Watson test to determine autocorrelation for serial correlation between errors. Thus, I used the same procedure to test for the independence of the residual assumption.

To combat the possible influence of violations of statistical assumptions, I employed a bootstrapping technique. Researchers use the bootstrapping technique to address the violation of assumptions (Dattalo, 2018). According to Dattalo (2018), the bootstrapping technique is equally appropriate as an alternative to statistical inference without relying on assumptions to quantify the uncertainty. Violating assumptions could lead to an unreliable and invalid analysis of data (Ernst, & Albers, 2017). Therefore, I used the bootstrapping technique to address the possible influence of assumption violations. I employed the Statistical Packages for Social Science (SPSS), version 25, for this doctoral study to analyze the data. The SPSS software translates numerical and non-numerical information into data for statistical analysis (Green & Salkind, 2017). The SPSS software provides specific output parameters for interpretation as follows: (a) *F* value, (b) *B, (c) R2, (d) β,* (e) *SE B,* (f) *Sig (p)*, and (g) *t* results.

F value or the *F*-ratio of the analysis of variance, including the sig *p* values, applies to ascertain if the null hypothesis is accepted or rejected (Shyti & Valera, 2018). A sig *p-value* less than 0.05 could lead to the rejection of the null hypothesis (Shyti & Valera, 2018). *B* refers to the unstandardized coefficient of the predictor variable of the study (Josephat & Ame, 2018). Researchers use the *B* value to predict that the magnitude of a factor of the dependent variable will change by a unit change in the independent variable, given that all other independent variables stay constant (Josephat & Ame, 2018). *β* refers to the standardized coefficient of the predictor variable and is the slope of the regression line that mathematically represents the linear regression equation (Davino et al., 2020). The *β* coefficient represents the magnitude of change related to a one-unit change in each independent variable (Davino et al., 2020). *SE B* represents the standard error for the predictor variable's unstandardized coefficient, which indicates the degree of irregularity in the data (Hirk et al., 2019). The standard error of the estimate refers to the standard deviation of the error term and is derived by the square root of the mean square residual (Hirk et al., 2019). R^2 is the percentage measure of the variance in the dependent variable that relates to the independent variable (Josephat & Ame, 2018). The *t* statistic measures the distance of a parameter from its notional value and standard error (Andronov, 2017). Researchers determine the *t*-statistic when the parameter estimate value in a regression model differs from the actual parameter estimate and is divided by the standard error (Andronov, 2017). *Sig (p)* represents the statistical significance of each independent variable (Pfeiffer et al., 2017). The *p-value* is the likelihood that the actual value associated with the independent variable in the population is zero. A sig *p-value* less than 0.05 could lead to the rejection of the null hypothesis (Pfeiffer et al., 2017).

I used the Markov regime-switching model to compute the risk-adjusted performance of hedge funds (Hamilton, 1989). In this model, Chen and Liang (2007) combined the timing measure to Jensen's (1972) model relating to the Sharpe ratio to allow risk-adjusted performance measurement as follows:

$$R_{i,t+1} = \alpha_i + \lambda_i \left(\frac{R^s_{m,t+1}}{\sigma^s_{m,t+1}} \right)^2 + \sum_{k=1}^{k} \beta_{i,k} F_{k,t+1} + \varepsilon_{i,t+1},$$

$$e_{i,t+1} \square\ i.i.d.N\left(0, s^2_{ei}\right)$$

(see Table 7 for terms of description)

Study Validity

The two types of study validity are internal and external (Sürücü & Maslakçi, 2020). According to Thomas et al. (2018), internal validity represents the extent to which the results of a study support a causal relationship between variables. When researchers use an experimental design, there is a potential risk of internal validity (Rahi, 2017). For a quantitative correlational study, internal validity does not apply. However, there are potential threats to statistical conclusion validity.

A researcher could attain statistical conclusion validity by using appropriate statistics to infer the association between dependent and independent variables (West, 2017). According to Muneer et al. (2017), failing to address threats to statistical conclusion validity could lead to inaccurate inferences like type I or type II errors. Serdar et al. (2021) described type I error as the probability of rejecting a true null hypothesis and type II as the probability of accepting a factually false null hypothesis. Factors that could affect the statistical conclusion validity include (a) reliability of the instruments, (b) data assumptions, and (c) sample size (Bergtold et al., 2018). The reliability of instruments relates to the internal consistency of the instruments of the study. I did not use an instrument to collect data; I employed secondary data. Therefore, internal consistency in this study should not be a concern.

When using multiple regression, the data assumptions are normality, linearity, homoscedasticity, and multicollinearity (Bergtold et al., 2018). According to Josephat and Ame (2018), the assumption for linearity indicates that the relationship between the dependent and independent variables is linear. The scatterplot feature on SPSS can help researchers check for normality, linearity, and homoscedasticity (West, 2017). I visually examined the scatterplot to determine the linearity of data in this study. According to Yuen and Ortiz (2017), outliers can impact the results of a regression analysis. Furthermore, researchers can use a histogram from the SPSS program to locate any outliers. Data assumptions are the primary threat to the validity of this doctoral study. Violating the data assumption may lead to Type I or Type II errors (West, 2017). To mitigate the violation of data assumptions, I ran a bootstrapping technique using SPSS.

The sample size in a quantitative study is essential to assist researchers in determining the statistical significance between variables (Rahi, 2017). Serdar et al. (2021) claimed that increasing the sample size would increase the power level, decreasing the probability of generating type I and II errors. Trafimow (2018) suggested that researchers use a priori power analysis to determine an adequate sample size. Thomas et al. (2018) suggested that researchers select an effective size to estimate the sample size for a specified power (1- β) and significance level (α) at the planning phase of the research. I performed an a priori power analysis using the G*Power software to select an adequate sample size of 150 observations in this study. Moreover, I employed a statistical power of 0.95 at an alpha of 0.5 to minimize the threat to the statistical conclusion validity.

External validity represents the extent to which the researcher can generalize the study findings to the broader populations, various settings, and different measurements (Sürücü & Maslakçi, 2020). Mahalua et al. (2019) explained that a probabilistic sampling strategy could improve the external validity of a study by increasing the generalizability. According to Trafimow & Myüz (2019), researchers can overcome threats to external validity by using an adequate sample size representing the target population. Palazón-Bru et al. (2017) also noted that a sample that does not represent the target population adequately could lead to selection bias, which may threaten external validity. Researchers cannot use a biased sample to generalize findings to a larger population (Mang et al., 2021). In addition, I used a random sampling technique to select the sample size because it represents the study population. I used inferential statistical techniques like hypothesis testing and regression analysis to generalize the study's population. The study's sample size comprised hedge funds that invest in South African financial markets. Similar to the selection process of Kumar and Kumar (2017), the sample included a monthly return time series of hedge fund indices from July 2007 to December 2020. The results may not represent the entire global hedge fund industry, threatening validity (Theofanidis & Fountouki, 2018). Consequently, the findings may include limitations due to the sample size, characteristics, and period chosen.

Transition and Summary

Section 2 contains narratives on the purpose of the research, my role as a researcher, the research method, design, and ethical procedures. Furthermore, in Section 2, I discussed sampling techniques, data collection methods and instruments, data analysis presentation, and the study validity. In Section 3, I presented the study findings, and discussed the implication for social change and business practices. In addition, I included recommendations for future research, reflections, and concluding remarks for the study.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative correlational study was to examine the relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds. The independent variables were risk exposure and volatility forecasting. The dependent variable was the financial performance of hedge funds compared to the benchmark performance of the Johannesburg stock exchange, ALSI. The model showed that at F (2, 149) = 238, p < 0.001, $R2$ = .950, risk exposure and volatility forecasting significantly predicted the financial performance of hedge funds. Hence, the null hypothesis was rejected, and the alternative hypothesis was accepted.

Presentation of the Findings

This subsection includes a discussion of assumptions testing, descriptive statistics, and inferential statistics results, provides a theoretical discussion about the findings, and concludes with a concise summary. I employed multiple linear regression, with a sample consisting of 150 monthly observations from July 2007 to December 2020, to address the relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds. The employment of bootstrapping with 1,000 samples was applied to address the violation of the assumptions where appropriate. Hence, bootstrapping of 95% confidence intervals is presented where applicable.

Test of Assumptions

For the multiple regression, I assessed six assumptions: independence of residuals (autocorrelation), linearity, normality, stationary, homoscedasticity, multicollinearity, outliners, and heteroskedasticity. I included all the cleaned samples in the analysis. It is necessary to meet all assumptions in regression analysis to avoid spurious regressions (Plonsky & Ghanbar, 2018).

Multicollinearity

Multicollinearity was evaluated by viewing the correlation coefficients between the predictor variables. All bivariate correlation coefficients between the predictor variables were small. Therefore, there was no evidence of multicollinearity assumption violation. Table 11 shows the correlation coefficients.

Table 10

Correlation Coefficients Among Study Variables

Variable	Sub-Variables	ALSI	SMB	HML	MOM	MSCI	EM	SAVI	10YR	3mth	COM	US/ZAR
Risk Exposure	ALSI	1										
	SMB	0.873	1									
	HML	0.630	0.179	1	-							
	MOM	-0.141	-0.146	-0.057	1							
	MSCI	0.715	0.671	0.130	-0.145	1						
	MSCIEM	0.720	0.734	0.201	-0.099	0.860	1					
	SAVI	0.096	0.110	0.023	0.061	-0.026	-0.096	1				
	10Y	-0.130	-0.274	-0.088	-0.017	-0.251	-0.307	-0.091	1			
	3mth	0.094	0.078	0.003	-0.026	-0.020	-0.065	-0.084	-0.047	1		
	COM	0.299	0.352	0.008	0.015	0.277	0.277	0.443	0.038	-0.257	1	
	US/ZAR	-0.295	-0.402	-0.165	0.061	-0.596	-0.714	0.144	0.571	-0.016	-0.401	1
Volatility Forecasting		0.021	-0.075	-0.083	0.076	0.068	0.060	0.011	0.032	-0.073	0.044	0.017

Outliers, Normality, Linearity, Homoscedasticity, and Independence of Residuals

I investigated outliers, normality, linearity, homoscedasticity, and independence of residuals by examining the normality P-P plots, box plots, and the scatterplot of the standardized residuals from SPSS. The examination indicated there was a violation of outliers' assumption. Figure 2 shows the normality P-P plots of the standardized residuals. The failure of the standardized residuals to lie in a straight line against the predicted value supports the presence of outliers and the normality assumption violation (Josephat & Ame, 2018). Figure 3 shows the scatterplot of the standard residuals. The lack of a clear or systematic pattern in the scatterplot supports the tenability of the violation of the linearity, homoscedasticity, and independence of residuals assumptions. I computed 1,000 bootstrapping samples to address any possible influence of assumption violations and reported 95% confidence intervals, based on the bootstrap samples where appropriate.

Figure 2

Normality of plot (P-P) of the regression standardized residuals

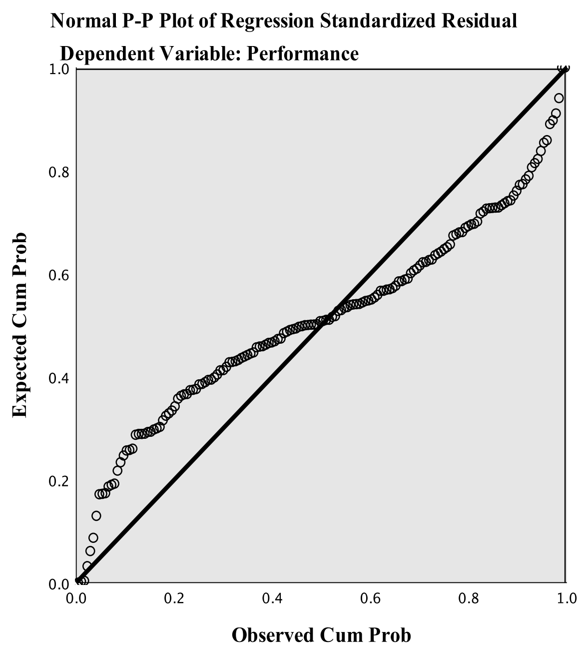
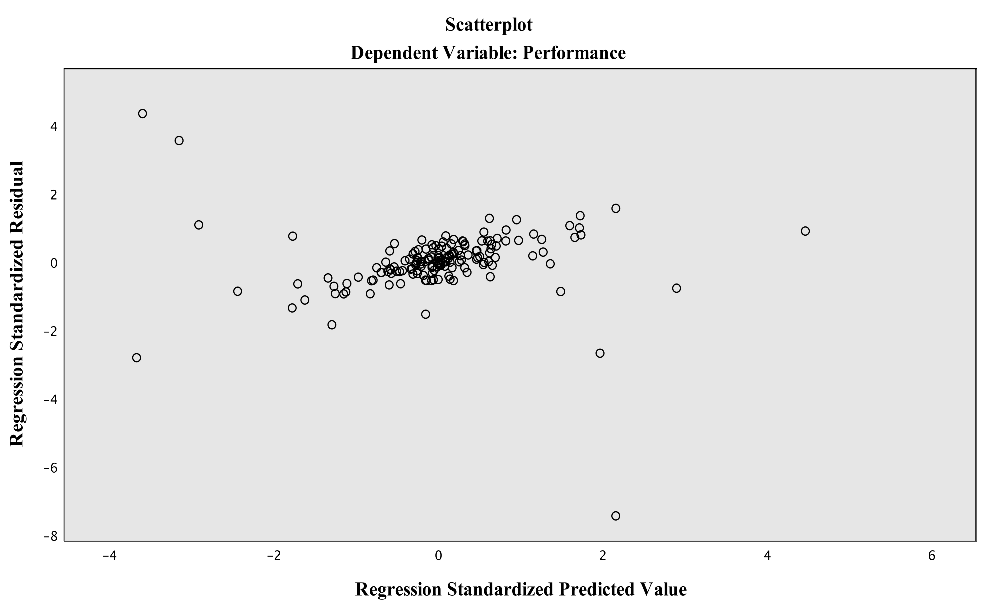


Figure 3

Scatterplot of the standardized residuals



Descriptive Statistics

The data consists of 150 observations of monthly returns from July 2007 to December 2020 and eliminated six because of missing data, which resulted in 144 observations. Table 12 presents descriptive statistics of study variables.

Table 11

Means and Standard Deviations for Quantitative Study Variables

Variable	*M*	*M* 95% Bootstrap CI	*SD*	*SD* 95% Bootstrap CI
Performance	0.123	[-0.02, 0.27]	1.00	[0.80, 1.19]
Volatility Forecasting	0.04	[0.04, 0.04]	0.004	[0.003, 0.005]
Risk Exposure	2.9	[2.05, 3.35]	.28	[.25, .44]

Note: *N = 144*

Inferential Results

The study involved using the standard multiple linear regression, α = 0.05 (two-tailed), to examine the efficacy of risk exposure, volatility forecasting, and the financial performance of hedge funds. The independent variables were risk exposure and volatility forecasting. The dependent variable was financial performance. The null hypothesis was that there was no statistically significant relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds. The alternative hypothesis was that there is a statistically significant relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds. The preliminary analysis took place to assess whether the assumptions of multicollinearity, outliers, normality, homoscedasticity, and independence of residuals were met. The results of the preliminary analyses included a violation of outliers, normality, and homoscedasticity assumptions.

However, they did not include any serious violation of the independence of residuals assumption (see *Tests of Assumptions* section).

The model as a whole was able to significantly predict hedge funds' financial performance at F (2, 149) = 238, $p < 0.001$, $R^2 = 0.932$. The R^2 (0.932) value indicated that approximately 93% of hedge fund financial performance variations are accounted for by the linear combination of the predictor variables. Risk exposure and volatility forecasting were statistically significant in the final model. Table 12 shows the regression summary of the study. The final regression equation is as follows:

Performance = $\alpha + \beta_1$(Volatility forecasting) + β_3(ALSI) + β_4(SMB) + β_5(HML) + β_6(MOM) + β_7(MSCI) + β_8(MSCIEM) + β_9(SAVI) + β_{10}(10Yr-Bond) + β_{11}(3month T-Bill) + β_{12}(Commodities) + β_{13}(US/ZAR) + e

Table 12

Regression Analysis Summary for Predictor Variables

Variable	*B*	*SE B*	β	*t*	*p*	Lower Bound	Upper Bound
Volatility Forecasting	-3.685	4.444	-0.016	-0.829	0.408	-12.466	5.096
Risk Exposure	0.00	0.00	.00	.00	.00		
ALSI	1.421	1.021	0.136	1.393	0.166	-0.596	3.438
SMB	-0.012	0.055	-0.004	-0.209	0.835	-0.120	0.097
HML	-1.345	0.982	-0.059	-1.369	0.173	-3.285	0.596
MOM	0.013	0.198	0.001	0.068	0.946	-0.378	0.405
MSCI	0.894	0.834	0.090	1.073	0.285	-0.753	2.542
MSCIEM	-0.155	0.823	-0.017	-0.188	0.851	-1.780	1.471
SAVI	0.033	0.167	0.004	0.199	0.842	-0.296	0.363

(*table continues*)

Variable	*B*	*SE B*	β	*t*	*p*	Lower Bound	Upper Bound
10Yr-Bond	-0.438	0.493	-0.021	-0.889	0.376	-1.413	0.536
3-mth T-Bill	-8.947	0.950	-0.789	-9.417	<0.001	-10.824	-7.070
COM	-0.496	0.350	-0.030	-1.418	0.158	-1.187	0.195
US/ZAR	-0.061	0.755	-0.003	-0.081	0.936	-1.552	1.430

Note. N= 144; B = unstandardized coefficient; β = standardized coefficient

Volatility Forecasting

The negative slope for volatility forecasting (-3.685) as a predictor of hedge funds' financial performance indicated a 3.685 decrease in performance for each one-point increase in volatility forecasting. In other words, hedge funds' financial performance tends to decrease as volatility forecasting increases. The squared semi-partial coefficient (sr^2) that was an estimate of how much variance in hedge funds' financial performance was uniquely predictable from volatility forecasting at 0.03, indicating that 3% of the variance in hedge funds' financial performance is uniquely accounted for by volatility forecasting when risk exposure is controlled.

Risk Exposure

The categories of risk exposure variable (i.e., ALSI, SMB, HML, MOM, MSCI, MSCIEM, SAVI, 10Yr-bond, 3mth-bill, Commodities, and SA/ZAR Exchange rate) helped to determine the occurrence and magnitude of hedge funds financial performance. The 3-month T-bill rate was the significant predictor of hedge funds' financial performance at the 1% level, accounting for the highest contribution (B = -8.947).

Analysis Summary

The purpose of this quantitative correlational study was to examine the relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds. I used multiple linear regression to examine the risk exposure and volatility forecasting ability to predict the value of the financial performance of hedge funds. Assumptions surrounding multiple regression were assessed with the assessment results, including violations of outliers, normality, homoscedasticity, and independence of residual assumptions. The model used in this study, as a whole, was able to significantly predict the financial performance of hedge funds, F (2, 149) = 238, $p <$ 0.001, R^2 = .950. Volatility forecasting and risk exposure provide helpful predictive information about the financial performance of hedge funds

Theoretical Conversation on Findings

The findings of this study align with the findings of Markowitz (1952). For example, Stafylas et al. (2017) identified that investors could increase returns by taking more significant risks. Bedoui et al. (2020) concluded in this research that the MPT was valid for investigating the standard deviation optimization. Further, Joenväärä et al. (2021b) identified that hedge funds' returns move in the opposite directions if there is a positive or negative change in the stock market. The findings from this study extended and supported Markowitz's (1952) MPT. The premise of MPT is that the expected return and variances of assets in which a hedge fund manager constructs hedge funds is based on their customers' risk preferences (Moulya et al., 2019).

The findings of this study indicated no significant relationship between volatility forecasting and the financial performance of hedge funds. The model used in this study, as a whole, was able to significantly predict the financial performance of hedge funds, *F* (2, 149) = 238, $p < 0.001$, $R^2 = .950$. The negative slope of volatility forecasting (-0.016) as a predictor of hedge funds' financial performance indicated a 0.016 decrease in volatility forecasting for a unit's increase in performance. The findings of this study supported the findings of Abdennadher and Hallara (2018), who showed that the shifts explained changes in the return volatilities of equity hedge funds returns.

The findings of this study indicated varying relationships between risk exposure categories and the financial performance of hedge funds. In this study, the 3-month T-bill rate had a significant relationship with the financial performance of hedge funds at 1% from 2007 to 2020. The negative slope of the 3-month T-bill variable (-0.789) as a predictor of financial performance of hedge funds indicated there was 0.678. The market index (ALSI) did not contribute significantly to the model (B = 1.421) and had the highest slope $\beta = 0.136$, indicating the highest hedge fund exposure in the analysis. Frydenberg et al. (2017) findings indicated that the momentum effect (MOM) and market index (NYSE) were significant at the level of 1% during the recession period. However, MOM was also significant during the whole period of study, from 1994 to 2015. Frydenberg et al. (2017) confirmed that hedge fund managers vary the risk exposure of assets to changing market conditions, indicating managers' skills.

Similarly, Agarwal et al. (2018a) show that hedge fund managers vary the portfolio exposure timely by predicting the fluctuating macroeconomic variables. The outcome of this study contrasted with a study conducted by Gerhard and Rupert (2017). Gerhard and Rupert (2017) examined the relationship between commodity, equity indices, and hedge fund performance, reporting that MSCIEM and the market index (S&P 500) were highly significant during the analysis period from 1990 to 2010.

Applications to Professional Practice

The financial performance of hedge fund attracts market participants seeking higher returns in various market conditions (Schreder, 2018; Shin et al., 2017). One of the sources of the superior performance of hedge fund managers is skills in market timing and volatility to adapt the funds' market exposure (Cui & Kolokolova, 2020; Muteba Mwaba, 2017). The study's findings may be of practical significance to investors and fund managers because: (a) I based the study design on the decision-making to assess investment risk, and (b) I highlighted the movement of underlying macroeconomic variables that correlate with hedge fund performance.

Market participants should account for risks when making investment decisions (Stafylas & Andrikopoulos, 2020). The results of this study highlight the necessity of risk dynamics assessment. Simultaneously, timing the market and predicting future levels of volatility allows the managers to adapt the funds' risk exposure for higher performance or reduce losses (Cao et al., 2018a). Furthermore, the research findings may provide essential information to assist investors or managers in determining the impact of varying economic conditions on the risk dynamics of the hedge fund strategies.

Implications for Social Change

The implication of the study results could serve two potential purposes. The first is that leaders of investment corporations may: (a) factor in the importance of market pricing when making investment decisions and (b) ensure that superior performance relates to knowledge of market risks and volatility. Thus, the right timing of investments could increase a firm's profits and resources to drive social change. Firms that create profits or increase value have a competitive edge, which allows them to invest in socio-economic projects that drive change (Sosner & Steblea-Lora, 2022). The implications for a positive social change of this study include the potential to improve communities by providing more jobs for local people.

Another implication for a positive social change includes the potential to provide corporate leaders with a better understanding of factors that drive the financial performance of hedge funds. The possibility exists to improve the tools for managers to maximize financial performance by timing market returns and predicting levels of volatility. The social change implication includes the potential to improve relationships between leaders, fund managers of the corporation, investors, and shareholders.

Recommendations for Action

The results of this study are consistent with other research on hedge fund performance (Kapil & Gupta, 2019; Metzger & Shenai, 2019; Zhang et al., 2021). The performance of hedge funds is an indicator of the manager’s skill (Shin et al., 2017). Also, the findings from this study supported the validity of MPT, and I recommend that managers use MPT as a basis for portfolio management strategies. I found a significant relationship between risk exposure, volatility forecasting, and performance. Based on the findings on these variables, my recommendation for hedge fund managers includes the risk exposure to maximize financial performance. Risk exposure refers to using systematic risk factors of hedge funds to evaluate financial performance. I recommend hedge fund managers allocate strategies by adjusting the funds' performance market exposure.

The study results are relevant to fund managers and scholars. The results may help fund managers make investment decisions or portfolio selections under varying market conditions. Finally, scholars may use the findings as a foundation for further research or comparison to other areas of hedge fund literature or models. I intend to publish the results of this study in the Pro-Quest dissertation database and other scholarly journals so other scholars, practitioners, and business professionals can have access. Furthermore, I intend to present the findings to stakeholders via conferences, seminars, and training workshops.

Recommendations for Further Research

In this study, I examined the relationship between risk exposure, volatility forecasting, and the financial performance of hedge funds. This study has some limitations; therefore, recommendations for future studies are necessary. The performance variable focuses on hedge fund returns in South Africa from 2007 to 2020. Recommendations for future researchers include expanding to other markets or regions. Furthermore, I would recommend further research on using different techniques to analyze performance and increasing the number of years for data analysis. The findings of this study could improve business practices by providing managers with insight into asset selectivity.

Reflections

In concluding this study, my goal was to gain insight into market risk exposure of hedge funds, volatility, and the effect on performance. There were few surprises during the process, especially during the data collection phase. Unfortunately, unlike mutual funds, accessing hedge fund data from databases is extremely expensive. I had to acquire the necessary funds to purchase the data. After purchasing, there is a waiting period for a background check before downloading. In addition, for several weeks, I reviewed the fields that contained the data required for analysis. Though, this task was a grueling, the process yielded an effective source for the study.

Conclusion

The primary purpose of the quantitative correlational study was to examine hedge funds as a potential source of investment profits for individual and corporate investors without loss. The aim was to determine if a statistically significant relationship exists between risk exposure, volatility forecasting, and the financial performance of hedge funds. I examined the relationship between the variables using a multiple regression model, and a sample consisting of 144 observations of 86 managed funds.

The findings revealed a significant relationship between variables because the p-values were less than the alpha of 0.05. Consequently, I rejected the null hypothesis; H_0: There is no statistically significant relationship between risk exposure, volatility forecasting, and financial performance of hedge funds for the period 2007 and 2020.

According to the findings, investors and managers may use risk exposure and volatility as indicators of future hedge fund performance

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Appendix A: Total Number of Funds in the Study

Table A1

Total Number of Funds in the Study

Hedge Fund Strategy	Alive	Dead	Total
Long/Short	23	7	30
Market Neutral	12	3	15
Multi Strategies	12	6	18
Fixed Income	11	2	13
Event Driven	3	1	4
Total	61	19	80

Appendix B: Description of Hedge Funds Strategies in HNA

Table B1

Description of Hedge Fund Indices by HNA

Index	Description
Long Short Equity	Long short equity hedge fund strategies establish both long and short positions mostly in equity related securities.
Equity Market Neutral	Equity market neutral strategies aim to eliminate a fund's exposure to systematic risk in the market.
Multi-Strategies	Multi-strategies are characterized by their flexibility to invest in different hedge fund strategies to diversify their portfolio.
Fixed Income Arbitrage	Fixed income arbitrage strategies construct their portfolios by taking corresponding long and short positions in fixed income instruments to exploit temporary mispriced securities.
Event Driven	Event driven strategies focus on positions in companies currently or prospectively involved in some form of liquidation.

Appendix C: FTSE-JSE All-Share Index-monthly from 1995-2020 Chart

Figure C1

FTSE-JSE-All-Share-Index-TR-Monthly from 1995-2020 Chart