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Active vs Passive Investing: A risk-adjusted performance comparison

Rodrigo de Aragão Barros e Alvim Boto

Master's in Management

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BUSINESS
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Resumo

O crescimento do investimento passivo e a dificuldade dos gestores em superar o índice após custos realçam a questão sobre o real valor da gestão ativa. Esta dissertação compara fundos ativos e passivos entre 2016 e 2025 nos Estados Unidos, na Europa e nos Mercados Emergentes e incorpora métricas de risco de cauda, como o Value at Risk e o Expected Shortfall, a par das medidas tradicionais. O estudo utiliza dados diários de doze fundos (um ETF passivo e três ativos por região). As crises pandémica de 2020 e inflacionista de 2022 são analisadas em detalhe para avaliar a reação a períodos de elevada volatilidade.

Os resultados descritivos mostram que a gestão ativa superou a passiva numa base ajustada ao risco, com força decrescente dos EUA até à Europa. Contudo, apenas dois fundos obtiveram alfas estatisticamente significativos, limitando a evidência de capacidade superior generalizada. A maioria dos fundos ativos registou um risco de cauda inferior ao do ETF devido aos seus betas mais baixos. O estudo revelou ainda um claro efeito de rotação de crises: o fundo mais resistente em 2020 foi o mais frágil em 2022.

Concluindo, não existe uma resposta única. O investimento passivo é uma escolha padrão na Europa, enquanto a gestão ativa retém valor em mercados menos eficientes e na diversificação de estilo, com a ressalva do enviesamento de sobrevivência inerente à amostra.

Keywords: Active management, Passive investing, Exchange Traded Funds, Risk-adjusted performance, Value-at-Risk, Expected Shortfall

JEL Classification: G11, G15, G17, G23

Abstract

The growth of passive investing and the difficulty for managers to beat the index after costs keep alive the question of active management's true value. This dissertation compares active and passive funds between 2016 and 2025 across the United States, Europe, and Emerging Markets from the perspective of a dollar-denominated investor, and incorporates tail-risk metrics such as Value at Risk and Expected Shortfall alongside traditional measures. Additionally, the 2020 pandemic and 2022 inflation crises are further examined to assess how each of the strategies reacted to high-volatility periods.

The methodology uses daily data from twelve funds (one passive ETF and three active ones per region). The evaluation combines traditional metrics, like Sharpe and Sortino, with tail metrics validated by backtesting. Descriptive results show that active management outperformed passive on a risk-adjusted basis, with decreasing strength from the US to Europe. However, formal testing revealed that only two funds generated statistically significant alphas, limiting the evidence of widespread manager skill. Most active funds recorded lower tail risk than the ETF due to their lower betas. The study also revealed a clear crisis rotation effect: the most resilient fund in 2020 was the most fragile during the 2022 inflation crisis.

In conclusion, there is no single answer. Passive investing is a default in Europe, while active management retains value in less efficient markets and in style diversification, subject to the survivorship bias inherent to the sample.

Keywords: Active management, Passive investing, Exchange Traded Funds, Risk-adjusted performance, Value-at-Risk, Expected Shortfall

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CHAPTER 1

INTRODUCTION

The question of how to invest efficiently has become increasingly relevant for individual investors across Europe. In Portugal, demographic projections and growing uncertainty around the sustainability of public pension systems have reinforced the need for personal financial planning (European Commission, 2024). For a generation of young professionals entering the job market, understanding how to allocate savings in a way that balances long-term growth with acceptable levels of risk has become increasingly important.

This leads to one of the older, but still unresolved, questions in modern finance: should an investor allocate their capital to a professional fund manager who actively selects securities looking for above-market returns, or should they simply replicate a market index at minimal cost? This debate between active and passive investing has shaped the asset management industry for decades and continues to divide academics and regulators.

The rise of passive investing has been one of the biggest trends in global finance. In 2019, passively managed assets in U.S. equity funds surpassed actively managed assets for the first time (Bloomberg, 2019), a milestone that reflected a change in investor behaviour. Exchange-traded funds (ETFs), which replicate benchmark indices at a fraction of the cost of traditional mutual funds, have grown from a niche product to the dominant investment vehicle for retail and institutional investors. The appeal is straightforward: if markets are efficient and most active managers fail to outperform after fees (Fama & French, 2010; Sharpe, 1991), why pay for a strategy that is statistically more unlikely to succeed?

The case for active management is, however, more complex than statistics suggest. Funds with a significant deviation from their benchmarks, those with high Active Share as defined by Cremers and Petajisto (2009), have historically outperformed, while "closet indexers" that closely mimic the index while charging active fees have mostly lagged. The relative advantage of active management appears to depend on market conditions: in less efficient markets, such as emerging economies, active managers have been shown to add meaningful value (Dyck et al., 2013), and during periods of market stress the flexibility of active management may provide downside protection that passive cannot.

Despite the extensive literature on this topic, two important gaps will be focused on this thesis. The first is that most empirical studies have focused on the U.S. market, with comparatively less attention given to European and Emerging Market funds. The second is that the risk dimension of the active-versus-passive comparison has been largely confined to traditional metrics such as standard deviation, beta and the Sharpe ratio. These measures treat upside and downside variability equally, which does not reflect

how investors actually experience risk. Behavioural finance research has consistently shown that investors are more sensitive to losses than to gains (Kahneman & Tversky, 1979), suggesting that risk measures focused on loss outcomes, such as Value-at-Risk (VaR) and Expected Shortfall, would provide a more relevant basis for comparison. These comparisons between active and passive strategies are lacking in the academic literature.

The analysis is organised around those two points. Its main goal is to analyse and compare the risk-adjusted performance of actively and passively managed investment funds across three geographic regions, the United States, Europe and Emerging Markets, over the period from 2016 to 2025. For each region, one passive ETF is compared against three actively managed mutual funds, selected among the largest in their respective geography. The comparison includes both traditional performance metrics (Sharpe ratio, Sortino ratio, Jensen's alpha, Treynor ratio, Information Ratio) and downside risk measures (Historical VaR, Skewed Generalised Student-t VaR and Expected Shortfall), with the VaR models validated through formal backtesting using the Kupiec Unconditional Coverage (Kupiec, 1995) and BCP tests.

Fund behaviour during market crisis will be addressed during two very different types of market crisis: the COVID-19 pandemic of 2020, which represented a sudden demand-side shock, and the 2022 inflation crisis caused by aggressive monetary tightening. These two episodes provide a natural experiment for testing whether active management offers superior downside protection during periods of stress, and, critically, whether the answer depends on the nature of the shock and the investment style of the manager.

This dissertation aims to contribute to existing literature in three ways. Extending the geographic scope of the active versus passive comparison by analysing European and Emerging Market funds alongside U.S. funds, from the perspective of a dollar-denominated investor with access to global markets. Introducing VaR and Expected Shortfall as complementary risk metrics for this comparison, addressing the limitation of traditional measures that do not distinguish between upside and downside volatility. Finally, by addressing the Crisis rotation effect: the empirical observation that the best-performing fund during one type of crisis tends to be the worst performer during a different type of crisis, caused by the contrasting impact of demand-side versus monetary-policy shocks on growth-oriented and value-oriented investment styles.

The remainder of this thesis is organised as follows. Chapter 2 reviews the existing literature on active and passive investing, performance evaluation and Value-at-Risk. Chapter 3 describes the methodology, including the performance metrics, VaR models and backtesting procedures used in the analysis. Chapter 4 presents the data, fund selection criteria and the macroeconomic context of the sample period. Chapter 5 reports the empirical results, covering full-period performance, VaR and Expected Shortfall estimates, and the analysis of high-volatility sub-periods. Chapter 6 discusses the results and their practical implications. Chapter 7 concludes the thesis and outlines directions for future research.

CHAPTER 2

LITERATURE REVIEW

Over the past few decades, the debate between investment styles has become one of the central discussions in portfolio management, particularly in terms of long-term and risk-adjusted performance. Active and passive portfolio management approaches are often seen as the two main investment styles (Malkiel, 2003).

2.1. Active investing

The active investing strategy involves the ongoing buying and selling of assets by an investment manager, aiming to achieve greater returns that exceed those of a benchmark (Gârleanu & Pedersen, 2022). This strategy has a clear objective: to try to beat and exploit the market for profitable opportunities. To do so, professional portfolio managers rely on their fundamental analysis, indicators and macroeconomic forecasts to identify undervalued assets or exit overvalued positions (Han & Hirshleifer, 2012).

That is why investment funds were created: to allow investors to access this expertise and benefit from professional management. They allow individuals to pool their resources with other investors, gaining advantages such as risk reduction and access to professional managers who may deliver better returns and more effective risk management. The composition of an actively managed fund therefore reflects the manager's own judgment and discretion (Barclays Bank, 2022), which introduces two key uncertainties: the risk of hiring an underperforming manager and the risk of that manager selecting the wrong securities. The performance of active investing is, in this sense, closely linked to the manager's expertise.

This logic challenges the assumptions of traditional portfolio theory, which presumes that investors behave rationally. Behavioural finance research shows that real-time investment decisions are frequently influenced by psychological biases and heuristics (Barber & Odean, 2001), which indicates that investors rely on mental shortcuts rather than purely rational analysis. If managers made entirely rational decisions, they would only use analytical tools to select securities or sectors most likely to grow faster than the market, aiming to maximise returns, especially during short-term fluctuations (Azouagh & Daoui, 2023). In practice, even rational decision-making is not enough to guarantee superior results.

As Ferri (2010) notes, strong past performance does not ensure future success. The author argues that the best predictor of an investor's long-term performance is the level of costs associated with their investments. In active strategies, the additional returns that investors aim for can therefore be largely reduced by high management and trading costs.

According to Fama (1970), it is very difficult for active managers to outperform the market after accounting for fees and risks. Fama and Litterman (2012) observed that, after costs, only the top 3% of managers generate returns sufficient to merely cover their expenses, which implies that the remaining 97% are likely to underperform. In this context, active strategies resemble a zero-sum game before costs, where gains for some investors come at the expense of others, and a negative-sum game once trading and management expenses are considered (Sharpe, 1991).

2.1.1. Active Share and the Heterogeneity of Active Management

While aggregate evidence suggests that the average actively managed fund underperforms its benchmark after costs, it is important to recognise that active funds are not a homogeneous group. Cremers and Petajisto (2009) introduced the concept of Active Share, which measures the proportion of a fund's holdings that differs from its benchmark index. Their research demonstrated that funds with the highest Active Share, those whose portfolio composition deviates most significantly from the index, tend to outperform their benchmarks even after fees. Funds with low Active Share, often referred to as "closet indexers", essentially replicate the index while charging active management fees, which naturally leads to underperformance after costs.

This distinction is particularly relevant for the present study because the actively managed funds selected for analysis, such as Fidelity Contrafund and Dodge & Cox Stock, are generally regarded as high-conviction strategies with substantial deviation from their respective benchmarks. The performance comparison conducted in this thesis is between index replication and active managers who make meaningful allocation decisions.

2.1.2. The Central Role of Costs

Fees and transaction costs sit at the core of the active versus passive debate and require examination. As Bogle (2007) pointed out throughout his work, a fund's expense structure is generally the best indicator of its future relative performance. Over a long investment horizon, apparently minor differences in annual fees snowball into massive gaps in total returns. To put this in perspective, assuming the underlying gross returns are the same, a 1% higher fee applied annually over twenty years would decrease roughly 18% of an investor's final wealth.

This structural cost gap is a central element of the present study, particularly because the null hypothesis (H0) factors management fees directly into the performance equation. Within the selected sample, passive vehicles like the Vanguard S&P 500 ETF operate with extremely low expense ratios—around 0.03%. The actively managed funds, on the other hand, charge significantly more, usually falling between 0.50% and just over 1.00% per year. This analysis essentially asks whether the manager's active decisions generate enough excess return to cover their own fees. Malkiel (2013) highlighted how difficult this hurdle is, demonstrating that most active managers fail to beat their benchmarks once costs are deducted.

2.2. Passive investing

Given the difficulty of consistently outperforming the market after costs, over time many investors have turned towards a different philosophy: passive investing.

According to Bloomberg (2019), for the first time in history the value of assets managed passively surpassed those managed actively. The shift from about 1 percent of assets being managed passively in 1984 to more than 50 percent in 2019 reflects a clear and sustained movement toward passive investment strategies.

Passive investment is an approach designed to replicate the returns of a market index, such as an established market benchmark, and offers diversification at relatively low cost (Sushko & Turner, 2018). It involves holding the same securities that make up the index over a long-term horizon, with the objective of earning steady and consistent returns over a period (Gârleanu & Pedersen, 2022). It requires no trading in the absence of changes in index composition and is periodically rebalanced to reflect companies entering or exiting the index (Strampelli, 2018).

This management style involves the strategic acquisition and retention of exchange-traded funds (ETFs), which are baskets of securities traded like individual stocks through brokerage firms, with the objective of closely replicating the returns of the underlying index (Ferri, 2010).

Passively managed portfolios are based on the Efficient Market Hypothesis (EMH), formalised by Fama (1970), which claims that markets are efficient and investors cannot beat the market. The EMH suggests that in a highly competitive market all available information is instantly and accurately reflected in assets' prices, making it extremely difficult for any single investor to consistently beat the market. Blitz (2014) questioned this hypothesis, arguing that although it is conceptually appealing, if all investors adopted passive investing, market liquidity would disappear. He also noted that passive investors may act as free riders, since they do not attempt to evaluate a security's fair value. Abrantes (2017) adds that, despite being a passive strategy, many investors who opt for indexing are in fact assuming the role of active managers, since they actively decide which index to follow and when to enter or exit a particular asset class.

2.3. Performance Metrics

The overlap between active and passive decisions makes performance evaluation important, particularly when returns and risks are considered together.

A widely used framework for this purpose is the Capital Asset Pricing Model (CAPM), considered a cornerstone of finance, which provides a way to assess the relationship between systematic risk and expected return. Developed by Sharpe (1964), the model determines that the expected return of any asset is a function of the risk-free rate of return plus a premium for bearing market-related (systematic) risk.

Building on this framework, Jensen (1968) evaluated the performance of 115 U.S. mutual funds and introduced Jensen's alpha, which represents the abnormal return of a portfolio relative to what would be predicted by the CAPM. Jensen's alpha captures a manager's ability to generate returns beyond those justified by the portfolio's systematic risk. A positive alpha indicates superior performance, while a negative alpha indicates underperformance against the benchmark provided by CAPM and reflects inefficiency in either the strategy or management in running the investment activities of the fund (Fabozzi et al., 2002). In his empirical analysis, Jensen found that the mutual funds from 1945 to 1964 exhibited negative or statistically insignificant alpha, indicating that, on average, the funds' trading activities were insufficient to cover their costs, including brokerage fees.

The findings of Jensen's study are consistent with those of Fama and French (2010), who analysed U.S. equity mutual fund performance over the period 1984 to 2006 using alphas from the CAPM, three-factor and four-factor models. By including market, size, value and momentum factors, they evaluated whether managers achieved returns beyond what those risks could explain. Their results showed that mutual funds underperformed all three benchmarks by about the same amount as their costs and fees, meaning that active management failed to generate additional value after expenses.

2.3.1. Active versus Passive in Different Market Conditions

Later research has shown that the effectiveness of active management depends largely on market conditions and efficiency. Most studies agree that active investing tends to perform better in emerging markets, mainly because these markets are less competitive and less efficient (Dyck et al., 2013). Dyck et al. found that between 1993 and 2008 active management beat passive management by more than 180 basis points per year in emerging markets. In the U.S., active management underperformed. This indicates that the benefits of active management depend largely on how efficient the market is.

Although investment performance is influenced by market efficiency, the market movements and phases also influence it. Volatility is the measure of how much an asset's price fluctuates over a specific period, showing its associated risk, and tends to be higher during bear markets (around 2.5%) than during bull markets (around 1.9%) (Kole & Van Dijk, 2017).

In emerging markets, Gopane et al. (2024) analysed 20 South African funds from 2010 to 2022 and found that actively managed funds outperformed passive strategies with higher Jensen's alpha during bear and normal market conditions, indicating superior risk-adjusted returns, while passive strategies performed better during bull markets.

In the European context, Ferreira et al. (2013) analysed mutual fund performance across ten European countries (among others) and found that active managers, on average, exhibited negative alphas, indicating they failed to generate statistically significant positive abnormal returns after fees during the 1999–2005 period. They also concluded that countries with more liquid markets generally exhibit better performance.

2.4. Gap on Existing Literature

Based on the reviewed literature, most studies comparing active and passive investment strategies have focused on performance evaluation and cost efficiency, using common metrics such as alpha, beta and Sharpe ratio to address whether active management delivers superior results relative to its passive benchmarks.

A major limitation of traditional risk metrics is that they treat all variability in the same way, assuming that positive and negative deviations from a benchmark are equally undesirable. This approach does not reflect how investors actually perceive risk. In practice, investors are generally not concerned with all fluctuations; they welcome unexpected gains, while their aversion is primarily focused on losses, a pattern supported by behavioural finance research on asymmetric risk perception (Kahneman & Tversky, 1979).

To address this issue, risk measures should concentrate on downside variability rather than total volatility. Value-at-Risk (VaR) fulfils this purpose by quantifying potential losses under a worst-case scenario, providing a risk measure that corresponds more closely with how investors experience and respond to risk. With the increasing demand for standardised tools to quantify market risk, VaR was first introduced in practice in the late 1980s by Bankers Trust as a statistical measure estimating the maximum potential loss over a given time horizon at a specified confidence level (Best, 2000).

In 1996, J.P. Morgan developed RiskMetrics (RM), which further standardised and popularised VaR for use in financial institutions. Bank for International Settlements (2023) also contributed to VaR's global adoption by allowing banks to use internally calculated VaR models to determine regulatory capital requirements (Linsmeier & Pearson, 1996).

In this study, VaR will serve as an additional risk metric for the comparison of both investment styles.

CHAPTER 3

METHODOLOGY

The main objective of this study is to analyse and compare the performance and risk-adjusted returns of actively and passively managed investment funds across different markets. The research focuses on funds and ETFs representing the United States, Europe and Emerging Markets between 2016 and 2025.

This research adopts a quantitative and comparative approach, as the purpose is to evaluate objectively the differences in performance and risk characteristics between active and passive investment strategies. The analysis is based on historical data and financial metrics, rather than on qualitative assessments or investor surveys.

The conceptual foundation of this study is based on comparing two distinct investment philosophies, active and passive management. Active funds rely on portfolio managers who aim to outperform a benchmark index through strategic asset selection and timing decisions. Passive funds replicate the composition and performance of a chosen index, offering investors lower costs and less exposure to individual manager skill or error.

The analysis is composed of two layers. The overall period (2016–2025) is evaluated first, to determine whether active or passive strategies deliver superior risk-adjusted performance. Two specific high-volatility sub-periods are then isolated, the COVID-19 pandemic (February–March 2020) and the 2022 inflation crisis, to test whether active management provides better downside protection during market stress.

3.1. Hypotheses

Based on the research objectives mentioned in Chapter 1 and the literature reviewed in Chapter 2, the following hypotheses are proposed:

H0: Passive funds achieve equal or better risk-adjusted performance than active funds after accounting for management costs.

H1: Passive funds demonstrate lower volatility and tail risk (measured by VaR) compared to active funds.

H2: Active funds perform better during periods of higher market volatility, reflecting potential advantages of active management in adapting to uncertain environments.

3.2. Performance and Risk Metrics

3.2.1. Historical Returns

The dataset consists of daily adjusted closing prices for ETFs. Unlike ETFs, which trade continuously on secondary markets, mutual funds are bought and sold directly through the fund provider at the end of each trading day, at the Net Asset Value (NAV) computed

after market close. Using the NAV as the price input assures that the actively managed funds are evaluated on the same standardised basis as the ETFs. Both are adjusted for dividends and splits, so that the returns analysed reflect the total return experienced by an investor reinvesting distributions over the period. This data was retrieved from Yahoo Finance and Bloomberg.

Daily returns are calculated as

$$r_t = \frac{P_t}{P_{t-1}} - 1, \tag{3.1}$$

where P_t is the adjusted closing price or NAV in Dollars on day t.

For longer-term performance analysis, daily returns are aggregated into cumulative and annualised returns. Cumulative returns over the full sample period are computed as

$$R_{\text{cum}} = \prod_{t=1}^{T}(1 + r_t) - 1. \tag{3.2}$$

Annualised returns are derived by scaling the cumulative return to a yearly horizon:

$$R_{\text{ann}} = (1 + R_{\text{cum}})^{\frac{252}{T}} - 1, \tag{3.3}$$

where T is the total number of trading days in the sample, and 252 represents the typical number of trading days in a year.

3.2.2. Risk-free rate

The risk-free rate used in the formulas presented next is represented by R_f. According to Damodaran (2008), the risk-free rate should be expressed in the same currency as the asset returns under analysis. As all funds and ETFs in this study are denominated in U.S. dollars and the entire performance analysis is conducted in dollar terms, the R_f used in this study is the 1-month U.S. Treasury Bill rate at daily frequency, consistent with the frequency of the return series, obtained from the Kenneth French Data Library, which is the standard proxy adopted in empirical asset pricing research (Fama & French, 1993, 2010).

3.2.3. Sharpe Ratio

The Sharpe ratio evaluates the total risk-adjusted performance of the portfolio. It is defined as the excess return of the portfolio over the risk-free rate per unit of total risk:

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma_p}, \tag{3.4}$$

where R_p represents the average return of the portfolio, R_f is the risk-free rate, and σ_p is the standard deviation of portfolio returns. A higher Sharpe ratio indicates a more favourable risk-adjusted performance, as it reflects a higher excess return relative to the amount of volatility experienced.

3.2.4. Jensen's Alpha

Jensen's alpha, represented by α, is the excess return of a portfolio relative to its expected return given its systematic risk according to the Capital Asset Pricing Model (CAPM). It is defined as:

$$\alpha_p = R_p - [R_f + \beta_p(R_m - R_f)], \tag{3.5}$$

where R_p is the portfolio return, R_f is the risk-free rate, β_p is the portfolio beta, and R_m is the return of the market benchmark, which in this study is the corresponding regional passive ETF (VOO, EEM or VGK). A positive alpha indicates that the portfolio has outperformed its expected return based on its systematic risk. To distinguish genuine manager skill from statistical noise, the significance of Jensen's alpha is evaluated using the t-statistic of the regression intercept. The fund's excess return is regressed against the regional ETF's excess return, and statistical significance is assessed at the 1%, 5%, and 10% levels.

3.2.5. Treynor Ratio

The Treynor ratio, as explained earlier, is like the Sharpe ratio but takes into account the systematic risk, which is more useful when looking at well-diversified portfolios. It is calculated as:

$$\text{Treynor Ratio} = \frac{R_p - R_f}{\beta_p}, \tag{3.6}$$

where R_p is the portfolio return, R_f is the risk-free rate, and β_p is the portfolio's beta with respect to the benchmark index. A higher Treynor ratio indicates that the portfolio generates more excess return per unit of systematic risk.

3.2.6. Sortino Ratio

The Sortino ratio is used to evaluate risk-adjusted performance by focusing only on downside risk, ignoring positive volatility. It is defined as:

$$\text{Sortino Ratio} = \frac{R_p - R_f}{\sigma_{\text{downside}}}, \tag{3.7}$$

where R_p is the portfolio return, R_f is the risk-free rate, and σ_{downside} is the standard deviation of negative (downside) returns only. A higher Sortino ratio indicates better risk-adjusted performance, as it measures how much excess return is earned per unit of downside volatility.

3.2.7. Information Ratio

The Information Ratio measures the consistency of a portfolio's active return relative to its benchmark, expressing the excess return over the benchmark per unit of tracking error. It is defined as:

$$\text{Information Ratio} = \frac{R_p - R_m}{\sigma_{(R_p - R_m)}}, \tag{3.8}$$

where R_p is the portfolio return, R_m is the return of the benchmark (the corresponding regional passive ETF), and $\sigma_{(R_p - R_m)}$ is the tracking error, defined as the standard deviation of the active return (the difference between the portfolio and benchmark returns). A higher Information Ratio indicates that the portfolio generates excess returns over its benchmark more consistently.

3.2.8. Value-at-Risk

Value-at-Risk (VaR) estimates the maximum loss that is not expected to be exceeded over a given holding period, at a specified confidence level. Formally, the α-VaR corresponds to the negative of the α-quantile of the return distribution (Jorion, 2007):

$$\text{VaR}_\alpha = -F^{-1}(\alpha), \tag{3.9}$$

where F^{-1} is the inverse cumulative distribution function of the portfolio return. In this study, VaR is computed at the 99% confidence level over a one-day horizon for each of the twelve assets individually.

Two approaches are adopted to estimate VaR: the volatility-adjusted Historical Simulation and the Skewed Generalised Student-t (SGSt) parametric model. These are complemented by the Expected Shortfall (ES), which captures the average loss conditional on the loss exceeding the VaR threshold.

3.2.8.1. EWMA Volatility Estimation

Both VaR models rely on time-varying volatility estimates obtained through the Exponentially Weighted Moving Average (EWMA) model, as introduced by the RiskMetrics framework (J.P. Morgan, 1996). The EWMA variance at time t is defined as:

$$\hat{\sigma}_t^2 = \lambda \hat{\sigma}_{t-1}^2 + (1 - \lambda) r_{t-1}^2, \tag{3.10}$$

where λ is the decay factor, which determines the relative weight assigned to recent versus older observations. A lower λ places more emphasis on recent returns, allowing the model to react faster to sudden changes in volatility.

Following the RiskMetrics recommendation for daily data (Jorion, 2001), this study sets $\lambda = 0.94$. Under this parameterisation, the most recent observation receives a weight of approximately 6% (1- λ), while an observation one month earlier (21 trading days) receives only 1.74%. Observations older than two to three months have a negligible effect on the estimate. This choice guarantees that the volatility forecast is responsive to market shocks while still incorporating sufficient historical information.

3.2.8.2. Volatility-Adjusted Historical Simulation

The Historical Simulation approach estimates VaR directly from the empirical distribution of past returns, without imposing any parametric assumptions (Best, 2000). VaR is obtained as the α-quantile of the observed return series, ordered from worst to best.

A limitation of the standard Historical Simulation is that it assigns equal weight to all past observations, meaning that periods of low volatility influence the VaR estimate to the same extent as more recent high-volatility periods. To address this, Hull and White (1998) proposed the volatility-adjusted Historical Simulation, which rescales each historical return to reflect the current level of market volatility:

$$\hat{r}_t = r_t \times \frac{\hat{\sigma}_T}{\hat{\sigma}_t}, \tag{3.11}$$

where $\hat{r}_t$ is the adjusted return, $\hat{\sigma}_T$ is the EWMA volatility estimate at the VaR measurement date, and $\hat{\sigma}_t$ is the volatility at the date of the historical observation. This ensures that the entire sample reflects current market conditions while preserving the empirical distribution's fat tails and asymmetry.

3.2.8.3. Skewed Generalised Student-t VaR

Financial return distributions are known to exhibit negative skewness, excess kurtosis and fat tails, features that the normal distribution cannot adequately capture (Theodossiou, 1998). To model these characteristics, this study adopts the Skewed Generalised Student-t (SGSt) distribution, which extends the traditional Student-t distribution by incorporating a skewness parameter.

The SGSt distribution is characterised by three shape parameters: $\lambda \in (-1, 1)$, which controls asymmetry; $p > 0$, which shapes the central region; and $q > 0$, which governs the thickness of the tails. The one-day SGSt VaR is defined as:

$$\text{VaR}_\alpha^{\text{SGSt}} = -T^{-1}_{0,1,\lambda,p,q}(\alpha) \times \sigma_t, \tag{3.12}$$

where $T^{-1}_{0,1,\lambda,p,q}(\alpha)$ denotes the α-quantile of the standardised SGSt distribution and σ_t is the EWMA volatility forecast. The drift term μ is set to zero for a one-day horizon, as it is negligibly small relative to the volatility component (Alexander, 2008). The distribution parameters are estimated by maximum likelihood and re-estimated on each trading day to maintain responsiveness to changing market conditions, as proposed by Giot and Laurent (2003).

3.2.8.4. Expected Shortfall

While VaR identifies the loss threshold at a given confidence level, it does not quantify the severity of losses beyond that threshold. Expected Shortfall (ES), also known as Conditional VaR, tackles this limitation by measuring the average loss conditional on the VaR being exceeded:

$$\mathrm{ES}_\alpha = -\mathbb{E}\left[r \mid r < -\mathrm{VaR}_\alpha\right], \tag{3.13}$$

ES is always greater than or equal to VaR at the same confidence level and provides a more complete picture of tail risk, particularly during extreme market events.

3.2.9. VaR Model Validation: Backtesting

Before presenting VaR and ES results, the reliability of each model must be validated through backtesting. The procedure compares the VaR forecasts produced by the model with the losses actually observed, using a rolling-window out-of-sample procedure.

3.2.9.1. Backtesting Procedure

For each asset, the backtesting is performed using a rolling window of a maximum of 1,000 trading days ($\approx$ 4 years). The realised return is then compared to the predicted VaR. An exceedance is recorded when the actual loss exceeds the VaR estimate:

$$I_t = \begin{cases} 1 & \text{if } r_t < -\mathrm{VaR}_{1,\alpha,t} \\ 0 & \text{otherwise} \end{cases}, \tag{3.14}$$

where $\mathrm{VaR}_{1,\alpha,t}$ is the estimated VaR for day t.

Several VaR model configurations are tested for each asset, but only the model that passes the backtesting criteria is retained, as the objective is not to compare VaR models but to obtain a reliable measure of downside risk for the active versus passive comparison.

3.2.9.2. Kupiec Unconditional Coverage Test

The Unconditional Coverage (UC) test, proposed by Kupiec (1995), evaluates whether the observed frequency of exceedances is consistent with the expected rate implied by the confidence level. For a 99% VaR, exceedances should occur in approximately 1% of observations.

The test statistic is:

$$LR_{\mathrm{uc}} = \left(\frac{\pi_{\mathrm{exp}}}{\pi_{\mathrm{obs}}}\right)^{n_1} \left(\frac{1-\pi_{\mathrm{exp}}}{1-\pi_{\mathrm{obs}}}\right)^{n_0}, \tag{3.15}$$

where n_1 is the number of exceedances, $n_0 = n - n_1$ is the number of non-exceedances, $\pi_{\mathrm{obs}} = n_1/n$ is the observed exceedance rate, and π_{exp} is the expected rate (1% for a 99% VaR). Under the null hypothesis that the observed exceedances are statistically consistent with the significance level, $-2\ln(LR_{\mathrm{uc}}) \sim \chi^2_1$. A model is not rejected if the p-value exceeds 5%.

3.2.9.3. BCP Independence Test

The UC test evaluates the total number of exceedances but ignores their temporal structure. The BCP test, introduced by Berkowitz et al. (2011), complements the UC test by examining whether exceedances are independent over time, testing the null hypothesis that the autocorrelation of the exceedance series is zero across K lags:

$$\text{BCP}(K) = n(n+2)\sum_{k=1}^{K}\frac{\hat{\rho}_k^2}{n-k}, \tag{3.16}$$

where $\hat{\rho}_k$ is the sample autocorrelation at lag k of the exceedance indicator series I_t. In this study, the BCP test is computed for lags from 1 to 10. A rejection indicates that exceedances cluster, meaning the model cannot adapt quickly enough to changing market conditions. During periods of extreme turbulence, such as the COVID-19 crash of March 2020, even sophisticated models tend to produce clustered exceedances, which may lead to rejection of the BCP test regardless of overall model quality (Berkowitz et al., 2011).

CHAPTER 4

DATA

4.1. Portfolio Composition

The objective is to empirically determine which investment vehicle provides the best value when considering both performance and risk. For this purpose, one ETF and three Actively Managed Funds were selected for each of three distinct geographic regions:

- **United States**: the largest economy in the world, representing 50.2% of the world's stock market capitalisation (The Globalist, 2025), which makes it a central market for any global investment comparison. Its large and liquid market, combined with a long history of research and data availability, makes it ideal for evaluating the efficiency of active and passive strategies.
- **Europe**: provides a meaningful comparison with the U.S. market. Unlike the American market, Europe is made up of several economies that differ in size, structure and regulatory approach. These differences can affect how funds behave in terms of both return and risk. There is still relatively little empirical work focused specifically on European equity funds, which makes this region interesting for exploring whether active managers can add value under such diverse and fragmented market conditions.
- **Emerging Markets**: offer wider global exposure and capture potential differences in performance within less developed but rapidly growing economies. The region includes countries such as China, India, Brazil, South Korea, Mexico and Taiwan, known for their high volatility, delivering valuable insights on how active and passive strategies perform under conditions of high risk and market inefficiency.

4.1.1. Selection Criteria

All funds included in the sample were required to satisfy the following conditions: availability of daily pricing data for the full period from 2011 to 2025 (with the analysis period starting in 2016, and 2011–2015 serving as the lookback window for VaR backtesting); use of accumulation share classes; and benchmark alignment, meaning that the actively managed funds in each geographic region are benchmarked against the corresponding passive ETF.

The selection was guided by Assets Under Management (AuM) and overall popularity among investors, ensuring that the funds are liquid, investable and representative of their respective categories.

The following table presents the selected funds by region:

Ticker	Fund Name	Benchmark	Expense Ratio	AuM (in Bn$)
United States				
VOO	Vanguard S&P 500 ETF	S&P 500	0.03%	811
AMRMX	American Mutual Fund	S&P 500	0.59%	93
FCNTX	Fidelity Contrafund	S&P 500	0.72%	155
DODGX	Dodge & Cox Stock Fund	S&P 500	0.51%	104
Emerging Markets				
EEM	iShares MSCI EM ETF	MSCI EM	0.70%	25
FEMKX	Fidelity Emerging Markets	MSCI EM	0.89%	7
NEWFX	American New World Fund	MSCI EM	0.72%	43
PRMSX	T. Rowe Price EM Stock	MSCI EM	1.04%	10
Europe				
VGK	Vanguard FTSE Europe ETF	MSCI Europe	0.06%	37
FIEUX	Fidelity Europe Fund	MSCI Europe	0.77%	1
PRESX	T. Rowe Price Eur. Stock	MSCI Europe	0.88%	1
MEURX	Franklin Mutual Intl. Value	MSCI Europe	0.97%	1

Table 4.1. Selected Funds and Respective Characteristics

4.2. Data Contextualisation

The data span used in this study aims to reflect long-term investment and to capture periods of volatility and uncertainty. The period between 2016 and 2025 includes several events that substantially impacted financial markets across the United States, Europe and Emerging Markets.

In 2016 the Brexit referendum created market uncertainty. When the United Kingdom unexpectedly voted to leave the European Union on 23 June 2016, investor confidence fell massively, leading to an immediate sell-off and a negative impact on liquidity across European equities.

The outbreak of COVID-19 caused one of the most abrupt and dramatic market declines in modern history. Governments imposed lockdowns, travel restrictions and controlled exports, economic activity contracted sharply, leading to panic and uncertainty. Between February and March 2020, the S&P500 fell about 34% while the MSCI Europe and MSCI Emerging Markets ETFs fell by approximately 35% and 30% respectively. To combat this, the Central Banks cut interest rates to near zero. These interventions sparked a rapid recovery in asset prices, and by the end of the year markets had regained their losses and the technology sector hit all-time highs. Overall, the COVID-19 pandemic reshaped the global economy.

By 2022, rising inflation and aggressive monetary tightening by central banks input a new form of crisis. Interest rates spiked, leading to significant losses in growth-oriented and long-duration assets. This period provides a meaningful contrast to the COVID-19 crisis, since the nature of the shock, and therefore the funds most affected were drastically different.

These events show that shocks, crashes, recoveries and structural changes are natural and shape the economy.

4.2.1. Survivorship Bias

In empirical studies of mutual fund performance, a common concern is survivorship bias, which arises when the sample includes only funds that have survived throughout the entire analysis period, thereby excluding funds that were closed, merged or liquidated due to poor performance (Elton et al., 1996). Since underperforming funds are more likely to be closed, a sample composed exclusively of surviving funds may overstate the average performance of active management.

In this study, the selection of funds with a continuous track record introduces a degree of survivorship bias. Choosing high AuM funds contributes to this as well. This bias is more likely to affect the actively managed fund sample than the passive ETF sample, since ETFs tracking major indices are rarely closed. As a result, the performance comparison may be slightly favourable to the active funds. This will be further documented in Section 6.3.

CHAPTER 5

EMPIRICAL RESULTS

In Chapter 3, the methodology used to compare active and passive investment strategies was documented. This chapter presents the empirical findings of the study and analyses whether active management delivers superior risk-adjusted performance relative to passive investing across the United States, Emerging Markets and Europe, according to the hypotheses defined earlier in Chapter 3.

Sections 5.1 through 5.3 present the full-period performance results for each geographic region, together with the risk-adjusted metrics. In addition to the traditional performance measures, the analysis also incorporates in Section 5.6 the downside risk evaluation through Value-at-Risk and Expected Shortfall.

Section 5.7 provides a cross-regional summary of the results, while Section 5.8 examines fund behaviour during two high-volatility sub-periods and Section 5.9 discusses the crisis rotation effect.

5.1. United States

The United States represents the most developed and efficient market included in the sample, making it an important benchmark for evaluating whether active managers are capable of consistently outperforming passive strategies after costs. The analysis compares VOO, the passive S&P 500 ETF, with three actively managed funds: AMRMX, FCNTX and DODGX.

Figure 5.1 illustrates the evolution of a hypothetical $10,000 investment made at the beginning of 2016 in each of the selected funds.

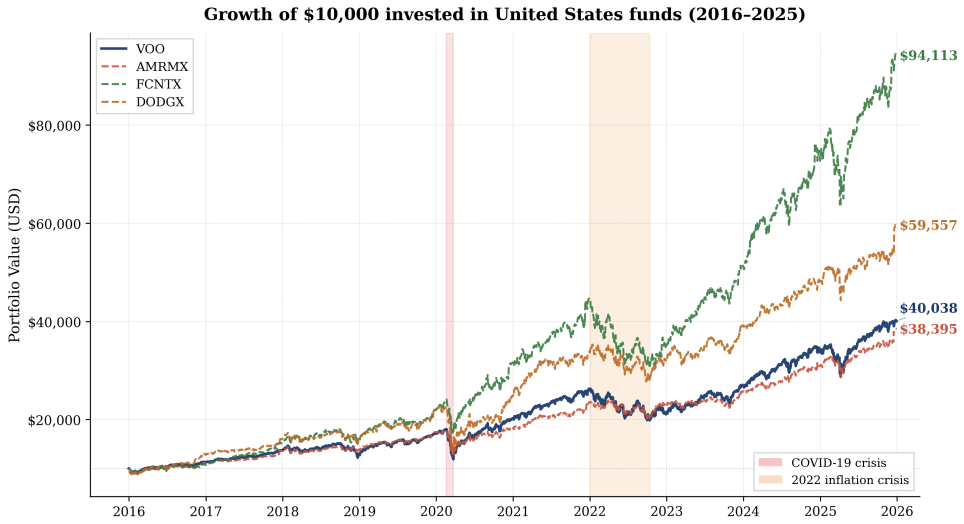


Figure 5.1. Growth of $10,000 invested in U.S. funds (2016–2025). AMRMX's initial price reflects a 5.75% front-end sales load applied at entry; the remaining funds are no load. Source: own elaboration based on data from Yahoo Finance

Although all four investments benefited from the strong performance of U.S. equity markets during the sample period, the differences in long-term outcomes are considerable. An investor who placed $10,000 in VOO in January 2016 would have accumulated $40,038 by the end of the sample period. The same investment in AMRMX would have grown to $38,395 (after the 5.75% front-end sales load applied at entry), in DODGX to $59,557, and in FCNTX to $94,113. FCNTX displayed an advantage of more than double over the passive benchmark. Table 5.1 formalises these differences through standard risk-adjusted measures.

Metric	VOO (ETF)	AMRMX	FCNTX	DODGX
Annualised Return	14.93%	15.12%	25.21%	19.59%
Cumulative Return	300.4%	307.4%	841.1%	495.6%
Std. Deviation (daily)	1.139%	0.924%	1.303%	1.260%
Beta	1.000	0.749	1.029	0.979
Jensen's Alpha (ann.)	—	2.97%*	8.68%***	4.63%
(t-statistic)		(1.66)	(3.03)	(1.57)
Sharpe Ratio	0.738	0.884	1.084	0.885
Sortino Ratio	1.035	1.266	1.600	1.274
Treynor Ratio	0.134	0.173	0.218	0.181
Information Ratio	—	−0.054	1.003	0.466

Table 5.1. U.S. Market: Performance and Risk Metrics (2016–2025)

Note: The value in parentheses beneath Jensen's alpha is the t-statistic of the regression intercept (fund excess return regressed on the regional ETF excess return; $n = 2{,}513$). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The results show that all three actively managed funds outperform the passive ETF across the main risk-adjusted performance measures, including the Sharpe, Sortino and Treynor ratios.

FCNTX delivers the strongest performance among every metric. Its annualised return of 25.21% more than compensates for its higher volatility (daily standard deviation of 1.303% versus 1.139% for VOO), producing a Sharpe ratio of 1.084 and a Sortino of 1.600. The annualised alpha of 8.68% and the Information Ratio of 1.003 indicate substantial outperformance along with consistency. Managed by Will Danoff, a manager with one of the longest sustained outperformance records in U.S. mutual fund history, the fund represents an exceptional case in the active management universe. AMRMX and DODGX follow a different pattern because of their Value focus investment strategy. AMRMX operates with a low beta of 0.749, indicating that it takes on approximately 25% less systematic risk than the market. Its daily volatility (0.924%) is the lowest in the group, below both the ETF and the other active funds. Despite generating a mean daily return slightly below the ETF (0.060% versus 0.062%), the lower volatility translates into a Sharpe ratio of 0.884, significantly higher than VOO's 0.738. These results tell us that outperformance on a risk-adjusted basis does not necessarily require higher absolute returns. It can also be achieved through lower risk exposure.

DODGX, with a beta of 0.979 that is almost identical to the market, provides the most direct comparison to the ETF. Its annualised alpha of 4.63% is positive but not statistically distinguishable from zero (t = 1.57). Its realised Sharpe of 0.885 and Treynor of 0.181 exceed VOO's on a descriptive basis, but the evidence does not support a claim of genuine stock-selection skill over the period.

5.2. Emerging Markets

The Emerging Markets analysis presents a different dynamic from the U.S. market, reflecting the higher volatility and lower informational efficiency associated with developing economies. This comparison includes EEM, the passive MSCI EM ETF, with three actively managed funds: FEMKX, NEWFX and PRMSX. Figure 5.2 shows the hypothetical investment of $10,000 placed in each fund at the beginning of 2016.

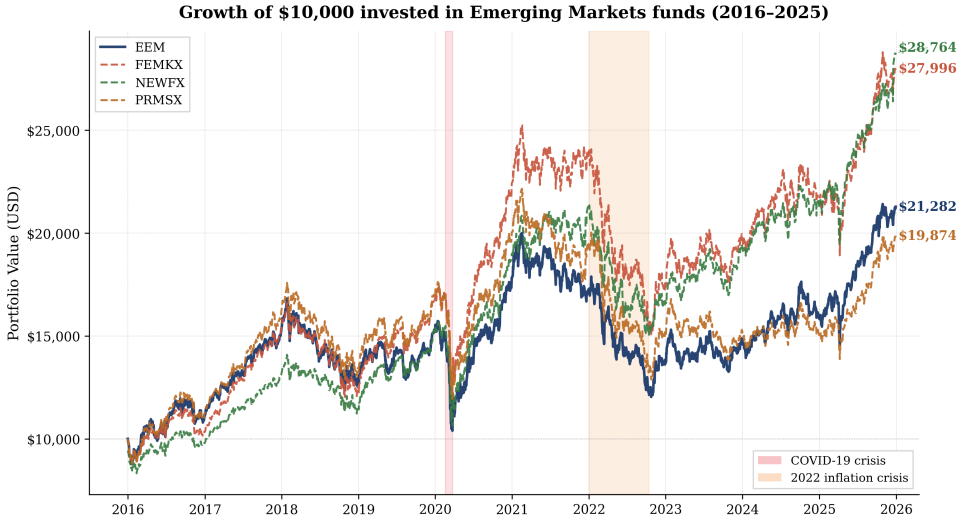


Figure 5.2. Growth of $10,000 invested in Emerging Markets funds (2016–2025). NEWFX's initial price reflects a 5.75% front-end sales load applied at entry; the remaining funds are no load. Source: own elaboration based on data from Yahoo Finance.

Compared with the U.S. sample, the cumulative returns are lower overall, but the dispersion between funds is still significant. An investment in EEM (ETF) in January 2016 would have accumulated $21,282 by the end of period. The same investment in FEMKX would have grown to $27,996, in NEWFX to $28,764 (despite absorbing the 5.75% front-end sales load at entry), while PRMSX produced a final value slightly below the ETF at $19,874. Table 5.2 reinforces these differences through standard risk-adjusted measures.

Metric	EEM (ETF)	FEMKX	NEWFX	PRMSX
Annualised Return	7.87%	10.88%	11.84%	7.13%
Cumulative Return	112.8%	180.0%	205.2%	98.7%
Std. Deviation (daily)	1.282%	1.156%	1.025%	1.162%
Beta	1.000	0.849	0.717	0.850
Jensen's Alpha (ann.)	—	3.48%*	4.98%**	0.05%
(t-statistic)		(1.78)	(2.18)	(0.03)
Sharpe Ratio	0.366	0.535	0.634	0.347
Sortino Ratio	0.508	0.749	0.886	0.484
Treynor Ratio	0.075	0.116	0.144	0.075
Information Ratio	—	0.342	0.310	−0.150

Table 5.2. Emerging Markets: Performance and Risk Metrics (2016–2025)

Note: The value in parentheses beneath Jensen's alpha is the t-statistic of the regression intercept (fund excess return regressed on the regional ETF excess return; $n = 2{,}513$). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

The Emerging Markets region presents a more diverse picture than the United States. Two of the three active funds clearly outperform the passive ETF, while the third basically matches it.

NEWFX delivers the best risk-adjusted performance in this region, with a Sharpe ratio of 0.634 compared to 0.366 for EEM, an annualised alpha of 4.98%, and the lowest daily volatility in the group (1.025%). This combination of higher returns and lower volatility is unusual. Part of the explanation is in the fund's investment approach: by design NEWFX is invested in some developed-market companies that derive significant revenues from emerging economies. This partial exposure to more liquid and less volatile developed-market securities may explain its lower beta (0.717) and reduced volatility, while still capturing the growth opportunities offered by emerging markets. FEMKX also outperforms the ETF convincingly, with a Sharpe of 0.535, an alpha of 3.48%, and a Sortino ratio that is nearly 50% higher than EEM's (0.749 versus 0.508). The cumulative return of 180.0% over the period translates into an annualised return of 10.88%, substantially above EEM's 7.87%.

PRMSX, however, tells a different story. With a Sharpe of 0.347, a negligible alpha of 0.05% and a negative Information Ratio (−0.150), this fund has essentially delivered the same risk-adjusted performance as the passive ETF, but at a higher cost given its expense ratio of 1.04%. An investor choosing PRMSX over EEM would have paid more in fees without receiving any meaningful improvement in either returns or risk management.

This dispersion within the active fund group reinforces the argument made by Cremers and Petajisto (2009): the performance of active management is not uniform. The finding that active management can add value in emerging markets is consistent with Dyck et al. (2013), who demonstrated that active managers tend to outperform in less efficient markets where informational advantages can be more easily exploited.

5.3. Europe

For European analysis, a more fragmented and regulated economy, the comparison is between VGK, the passive Europe ETF, with the actively managed funds FIEUX, PRESX and MEURX. Figure 5.3 illustrates the evolution of a hypothetical $10,000 investment across the four funds.

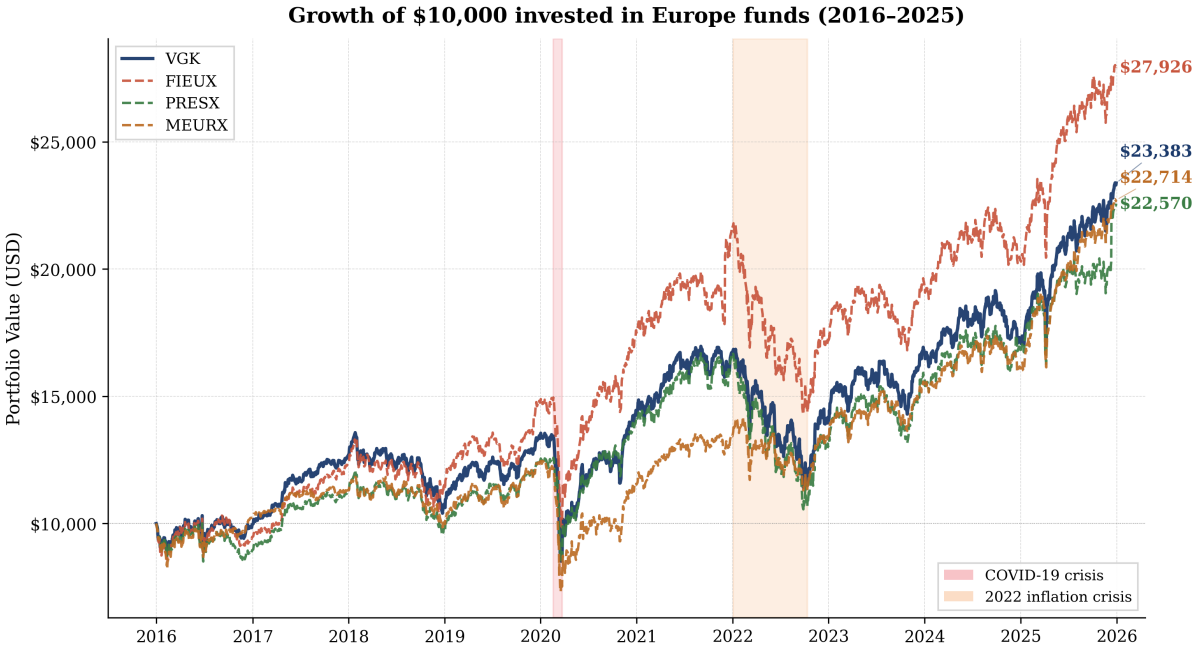


Figure 5.3. Growth of $10,000 invested in European funds (2016–2025). Source: own elaboration based on data from Yahoo Finance.

An investment in VGK (ETF) would have grown to $23,383 by the end of the sample period. FIEUX achieved the strongest result, reaching $27,926, while PRESX and MEURX produced final values broadly like the passive benchmark, $22,570 and $22,714, respectively. This indicates that the European sample produced more balanced results, with only one actively managed fund clearly outperforming the passive strategy. Table 5.3 confirms this pattern through standard risk-adjusted measures.

Metric	VGK (ETF)	FIEUX	PRESX	MEURX
Annualised Return	8.89%	10.85%	8.51%	8.57%
Cumulative Return	133.8%	179.3%	125.7%	127.1%
Std. Deviation (daily)	1.194%	1.177%	1.145%	1.101%
Beta	1.000	0.887	0.908	0.821
Jensen's Alpha (ann.)	—	2.64%	0.24%	0.90%
(t-statistic)		(1.02)	(0.13)	(0.36)
Sharpe Ratio	0.429	0.527	0.420	0.433
Sortino Ratio	0.582	0.748	0.583	0.582
Treynor Ratio	0.081	0.111	0.084	0.092
Information Ratio	—	0.203	−0.083	−0.064

Table 5.3. European Market: Performance and Risk Metrics (2016–2025)

Note: The value in parentheses beneath Jensen's alpha is the t-statistic of the regression intercept (fund excess return regressed on the regional ETF excess return; $n = 2{,}513$). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Europe produces the most balanced results of the three regions, with smaller differences between active and passive strategies than those observed in the United States or Emerging Markets.

FIEUX (Fidelity Europe) is the only active fund that clearly outperforms the ETF on the risk-adjusted ratios, with a Sharpe ratio of 0.527 versus 0.429 and the highest Sortino ratio in the group (0.748). Its cumulative return of 179.3% over the period is substantially above VGK's 133.8%, achieved with slightly lower volatility than the ETF (daily standard deviation of 1.177% versus 1.194%). Descriptively, this combination of higher returns and lower volatility is consistent with effective security selection and risk control. Its alpha of 2.64%, however, is not statistically significant (t = 1.02); in line with the rest of the European sample, no fund delivers a statistically significant alpha.

PRESX and MEURX present a contrast between two funds that achieve similar overall results through different approaches. PRESX has a Sharpe ratio of 0.420, an alpha of just 0.24% and a negative Information Ratio, indicating that it does not outperform the passive benchmark on a risk-adjusted basis after the full period. MEURX, on the other hand, has a slightly higher Sharpe (0.433) and a modest alpha of 0.90%, with the lowest daily volatility of any fund in the European sample (1.101%) and the lowest beta (0.821). Neither fund justifies its higher expense ratio relative to the ETF over the full period.

These results are broadly consistent with Ferreira et al. (2013), who found that active managers in European markets generally struggle to generate positive alphas. The European market, characterised by greater regulatory fragmentation but generally high liquidity in its largest constituents, offers fewer inefficiencies than emerging markets. The fact that one fund (FIEUX) does outperform on the risk-adjusted ratios suggests that outperformance remains possible, but that the standards are higher.

5.4. VaR Model Validation

Following the performance analysis, this section focuses on downside risk using the Value-at-Risk models. Before comparing the VaR estimates across the funds, it is necessary to evaluate whether the models produce reliable results throughout the sample period. Therefore, the following subsection describes the model selection process.

The VaR models are estimated at the 99% confidence level, which implies an expected exceedance rate of 1%. This means that, under a correctly specified model, the actual daily loss should exceed the predicted VaR on approximately 1 out of every 100 trading days. The choice of 99% confidence follows the Basel Committee on Banking Supervision framework (Bank for International Settlements, 2023), which recommends this level for internal risk models, and is consistent with the standard adopted in the VaR literature for measuring extreme tail risk.

The model selection is based on the Kupiec Unconditional Coverage (UC) test, which evaluates the number of exceedances observed during the backtesting period. More specifically, the test examines whether the observed exceedance rate is statistically consistent with the expected 1% rate, through the UC p-value. A model is considered well calibrated when the exceedance rate is close to 1% and the corresponding UC p-value does not lead to a rejection of the null hypothesis at the 5% significance level. However, the UC test is sensitive to the number of exceedances in the sample: during periods of extreme market stress, exceedances may become concentrated within short intervals, which can lead the UC test to reject models that otherwise perform reasonably well over the full sample period.

Following the UC test analysis, the BCP independence test is examined to provide additional information about the exceedances. Specifically, the BCP test reveals whether exceedances are autocorrelated, that is, whether they tend to cluster in time rather than occurring independently. This provides insight into the periods during which the models experienced the greatest difficulty.

5.5. Backtesting

The objective of the backtesting analysis is to determine which VaR model produced the most accurate risk estimates for each asset over the 2016–2025 backtesting period, being 2025-12-30 the backtesting date. This allows the identification of the model that provided the best overall performance throughout the sample period for each individual asset. Since the funds and ETFs differ in terms of portfolio composition and return characteristics, different sample sizes were tested for each asset. The sample size has a significant influence on the estimation of VaR, because larger datasets provide a broader range of observations and reduce the sensitivity of the estimates to extreme outliers. Table 5.4 presents the optimised results obtained from the backtesting analysis. The model selection is based primarily on the UC test results, with preference given to the specification that produces exceedance rates closest to the theoretical 1% threshold.

		SGSt VaR			Historical VaR			
Reg.	Fund	Exc. Rate%	UC p%	Worst BCP p%	Exc. Rate%	UC p%	Worst BCP p%	Selected
US	VOO	4.54	0.00%	0.00	1.50	1.70	0.02	Hist.
	AMRMX	2.08	0.00	0.00	1.69	0.12	0.00	Hist.
	FCNTX	1.27	18.54	1.59	1.65	0.22	5.09	SGSt
	DODGX	1.19	33.88	0.00	1.85	0.01	0.00	SGSt
EM	EEM	1.42	4.15	3.93	1.50	1.70	6.02	SGSt
	FEMKX	1.08	69.70	0.06	1.77	0.04	1.36	SGSt
	NEWFX	1.08	69.70	0.06	2.00	0.00	0.88	SGSt
	PRMSX	1.15	44.15	0.27	1.54	1.06	0.20	SGSt
EU	VGK	1.50	1.70	2.55	1.73	0.07	0.13	SGSt
	FIEUX	1.38	6.25	0.06	2.00	0.00	0.18	SGSt
	PRESX	1.08	69.70	0.00	1.96	0.00	0.21	SGSt
	MEURX	1.50	1.70	0.00	2.08	0.00	0.00	SGSt

Note: Expected exceedance rate = 1.00% (99% VaR). UC p = Kupiec Unconditional Coverage p-value. Worst BCP p = lowest p-value of the BCP independence test across lags 1 to 10 over the full sample period.

Table 5.4. VaR Model Comparison and Selection (99% VaR, Global Period)

Table 5.4 shows that, for most of the assets, the SGSt model provides the most accurate results. FEMKX, NEWFX, PRESX and DODGX record exceedance rates close to the expected level (1%) together with relatively stronger UC test results, indicating that the SGSt specification captures the tail behaviour of these assets more effectively.

The main exceptions are VOO and AMRMX. For these two assets, the SGSt model produces exceedance rates substantially above the theoretical threshold, especially in the case of VOO, where the exceedance frequency reaches 4.54%.

Therefore, based on the UC test results, the SGSt model is selected to estimate the Value-at-Risk for FCNTX, DODGX, FEMKX, NEWFX, FIEUX, PRMSX and PRESX, since the exceedance rates are closer to the expected level and the corresponding p-values are not rejected. For the remaining assets (VOO, AMRMX, EEM, VGK and MEURX), the UC test rejects both the Historical Simulation and SGSt models. The following subsection discusses the model selection for these assets in greater detail.

5.5.1. Independence of Exceedances

The BCP test provides additional information regarding the temporal behaviour of exceedances. For most assets, the null hypothesis of independence is rejected under both models, indicating that exceedances are not independently distributed over time and tend to occur in clusters rather than randomly throughout the sample period.

The sub-period analysis presented in Appendix A focuses on the periods that contributed most significantly to the global UC and BCP rejections, namely the COVID-19 crash (2020–2021) and the transition into the 2022 inflation crisis. The results show that exceedance became concentrated during these periods of extreme market stress, leading to weaker backtesting results for several assets.

5.5.2. Assets Where Both Models Fail the UC Test

For five assets (VOO, AMRMX, EEM, VGK, and MEURX) neither the SGSt nor the Historical Simulation achieves a UC p-value above the 5% rejection threshold over the global period. As shown in Table A.1 and in the full period results in Table 5.4, the cause of these failures is the concentration of exceedances during the 2020 to 2021 period. For VOO and AMRMX, the Historical VaR recorded exceedance rates between 2.3% and 3.5% during this window, while the SGSt performed considerably worse with rates exceeding 7% for AMRMX and 15% for VOO.

Outside the 2020 to 2022 window, both models maintain exceedance rates consistent with the expected 1% for all five assets. The global UC test failure therefore reflects the impact of a specific, historically exceptional period of market stress, rather than a fundamental problem with model calibration.

Given that the reasons for the failure have been identified and are attributable to the COVID-19 crisis rather than to structural model inadequacy, the model with the lower exceedance rate over the global period is selected for each of these five assets. For VOO and AMRMX, this is the Historical Simulation (exceedance rates of 1.50% and 1.69%). For EEM, VGK, and MEURX, this is the SGSt (exceedance rates of 1.42%, 1.50%, and 1.50%). The selected models for all twelve assets are indicated in the last column of Table 5.4.

The VaR estimates should primarily be interpreted as relative measures of tail risk between funds. Although periods such as the COVID-19 crisis affected the backtesting results, the same methodology is applied consistently within each region, allowing a reliable comparative analysis between active and passive strategies. However, the absolute VaR estimates should be interpreted with caution during periods of extreme market stress comparable to the COVID-19 crisis, where daily VaR models may underestimate downside risk.

5.6. Value-at-Risk and Expected Shortfall

As previously discussed, the VaR identifies the threshold of potential tail loss at the 99% confidence level. In other words, if a fund has a VaR of 1%, losses greater than 1% are expected to occur on approximately one out of every hundred trading days, under normal market conditions. Expected Shortfall complements the VaR by measuring the average loss observed during those exceedance days. Table 5.5 reports the average VaR and Expected Shortfall estimates over the full sample period at the 99% confidence level.

Region	Fund	VaR 99% (%)	ES 99% (%)	ES/VaR
US	VOO	2.63	3.48	1.32
	AMRMX	2.13	2.83	1.33
	FCNTX	3.27	4.26	1.30
	DODGX	2.82	4.77	1.69
EM	EEM	3.06	4.62	1.51
	FEMKX	2.91	4.03	1.38
	NEWFX	2.57	2.86	1.11
	PRMSX	2.84	3.87	1.36
EU	VGK	2.63	4.95	1.88
	FIEUX	2.73	3.58	1.31
	PRESX	2.65	5.48	2.07
	MEURX	2.53	4.70	1.86

Table 5.5. Daily VaR and Expected Shortfall at 99% Confidence

The VaR estimates reveal different patterns across the three regions. In the United States, AMRMX stands out with the lowest daily VaR in the sample (2.13%), comfortably below the 2.63% of the passive ETF VOO. This is consistent with the fund's defensive, low-beta orientation already identified in the performance results. At the other extreme, FCNTX records the highest U.S. VaR at 3.27%, in line with its growth profile and its larger exposure to high-volatility holdings. DODGX sits between the two, slightly above VOO at 2.82%. In Emerging Markets, the dispersion is closer, but all active funds record lower VaR estimates than the passive ETF EEM (3.06%). NEWFX records the lowest downside risk in the region at 2.57%, followed by PRMSX at 2.84% and FEMKX at 2.91%. This contrasts with the U.S. results, where FCNTX exhibits higher downside risk than the passive benchmark. The European group exhibits the most compressed range, with all four investments presenting VaR estimates between 2.53% and 2.73%. VGK remains broadly aligned with the active funds, while only MEURX records a noticeably lower VaR than the ETF.

In Emerging Markets, the differences between the active funds and the passive ETF become more evident when analysing Expected Shortfall instead of VaR. NEWFX stands

out with an ES of only 2.86% and an ES/VaR ratio of 1.11, the lowest in the sample, indicating comparatively limited tail risk. The European group, by contrast, exhibit the heaviest tails in the sample. PRESX records an ES of 5.48% against a VaR of 2.65%, producing the highest ES/VaR ratio in the study (2.07). VGK and MEURX also record elevated ratios of 1.88 and 1.86, respectively. These results suggest that European funds appear relatively stable during normal market conditions, but they can still experience sharp losses during periods of extreme market stress that are not fully reflected in the VaR estimates alone. The contrast between VaR and Expected Shortfall rankings is particularly relevant. DODGX, for example, appears only moderately risky in terms of VaR but becomes the riskiest U.S. fund once tail losses are considered through Expected Shortfall. Similarly, the European funds appear relatively stable under VaR but reveal substantially heavier tails when evaluated through ES. These results highlight the importance of analysing VaR and Expected Shortfall jointly when comparing downside risk across active and passive strategies.

5.7. Cross-Regional Comparison

Table 5.6 summarizes the results across the three regions by counting how many active funds outperform their corresponding ETF on each key metric.

Metric	**United States**	**Emerging Markets**	**Europe**
Higher Sharpe Ratio	3/3	2/3	2/3
Higher Sortino Ratio	3/3	2/3	2/3
Positive Alpha	3/3	3/3	3/3
Higher Treynor Ratio	3/3	2/3	3/3
Lower Std. Deviation	1/3	3/3	3/3
Positive Info. Ratio	2/3	2/3	1/3
Lower VaR	1/3	3/3	1/3
Lower Expected Shortfall	1/3	3/3	2/3

Table 5.6. Number of Active Funds Outperforming the Passive ETF (out of 3 per region)

A consistent pattern emerges across all three regions: the active funds in this sample tend to exhibit lower volatility than their passive counterparts. In seven out of nine cases (one in the US, three in Emerging Markets and three in Europe) the active fund has a lower daily standard deviation than the ETF. This is partly explained by the lower betas observed in most active funds, which range from 0.717 (NEWFX) to 1.029 (FCNTX), with eight of the nine active funds showing a beta below 1.

The practical implication is that the risk-adjusted outperformance of the active funds in this sample comes not only from higher returns but also, and in some cases primarily, from lower volatility. An investor evaluating these funds solely on raw returns might

underestimate the advantage of active management, since the lower risk displayed by most active funds amplifies their Sharpe, Sortino and Treynor ratios relative to the ETFs.

The cross-regional comparison also reveals that market efficiency plays a role. In the United States, all three active funds outperform on every risk-adjusted metric. In Emerging Markets and Europe, the picture is more mixed, with active funds outperforming on some risk-adjusted metrics but not consistently across all of them. This gradient is consistent with the hypothesis that active managers add more value in less efficient markets, as documented by Dyck et al. (2013). The U.S. results, however, appear to contradict this relationship, as the most efficient market in the sample produces the strongest active outperformance. This apparent contradiction is examined further in Chapter 6 through the analysis of survivorship bias.

5.8. High-Volatility Sub-Periods

The previous analysis focused on performance over the full 2016–2025 period. However, looking only at the full sample can hide important differences in how funds behave during periods of severe market stress. The following section therefore isolates high-volatility episodes to examine whether the relative performance of active and passive strategies changes under crisis conditions.

5.8.1. The Nature of the Two Crises

The two high-volatility episodes examined in this study represent fundamentally different types of market shocks, and understanding this distinction is essential for interpreting the results that follow.

The two sub-periods were not selected after looking at the funds' return series, but on a observable benchmark: the CBOE Volatility Index (VIX). Derived from S&P 500 option prices, the VIX measures the market's expectation of 30-day forward volatility and has served as the standard reference in the empirical literature for identifying regimes of stress since Whaley (2000) characterised it as the "investor fear gauge", the overall sentiment of the market. For most of the 2016–2025 sample period the VIX averaged close to its historical average levels.

Two episodes stand out clearly from that pattern. On 16 March 2020, during the COVID-19 crash, the VIX closed at 82.69, the highest value in its entire history since 1990, exceeding even the 80.86 peak reached on 20 November 2008 during the Global Financial Crisis (John & Li, 2021). In contrast, the 2022 inflation crisis was characterised by lower but more persistent volatility, with the VIX remaining above 30 for extended periods throughout the year. Both periods recorded volatility levels consistent with high stress market environments, therefore they provide a suitable framework for analysing fund behaviour under adverse conditions.

The COVID-19 crash (February 19 to March 23, 2020) was a demand-side shock: a collapse in economic activity triggered by global lockdowns. The initial sell-off was universal, affecting all sectors and geographies simultaneously. The recovery, however,

was highly asymmetric. Technology and digital-economy companies, benefiting from the acceleration of remote work, e-commerce and digital infrastructure, rebounded rapidly and reached new highs by the end of 2020. The Central banks responded with emergency rate cuts to almost zero, which compressed bond yields and stimulated a big increase in growth-oriented equities. Cyclical sectors such as energy, financials and travel recovered much more slowly, remaining below pre-crisis levels well into 2021. The 2022 inflation crisis window (3 January to 12 October 2022) was the mirror image. Rather than facing a collapse in economic activity, markets were confronted with persistent inflation, and aggressive interest rate increases by central banks. As interest rates moved higher, growth-oriented assets came under significant pressure, while more defensive and value-oriented sectors generally performed better. These contrasting conditions provide a useful setting for analysing whether the relative performance of active and passive strategies depends on the type of market shock.

5.8.2. Performance Analysis

Table 5.7 compares the cumulative returns observed for each fund during the two high volatility sub-periods introduced previously.

Region	**Fund**	**COVID-19** (Feb–Mar 2020)	**2022 Inflation** (Jan–Oct 2022)
US	VOO	−34.0%	−24.5%
	AMRMX	−29.8%	−13.8%
	FCNTX*	**−29.4%**	**−30.2%**
	DODGX	−40.3%	−17.6%
EM	EEM	−30.8%	−29.0%
	FEMKX*	**−28.6%**	**−35.3%**
	NEWFX	−31.4%	−29.3%
	PRMSX	−29.4%	−32.1%
EU	VGK	−36.3%	−31.7%
	FIEUX	−34.2%	−33.8%
	PRESX*	**−31.6%**	**−36.0%**
	MEURX	−38.2%	−16.5%

Table 5.7. Performance During Crisis Periods: The Rotation Effect

Note: Values represent the cumulative returns observed for each fund during the respective crisis window. In each region, the active fund highlighted in **bold** delivered the smallest decrease during COVID-19 and simultaneously the largest decrease during the 2022 inflation crisis.

The cumulative drawdowns reported reveal two contrasting profiles of stress. The COVID-19 episode produced uniformly severe losses across the sample, with every fund declining by at least 28.6% (FEMKX) and the worst case reaching 40.3% (DODGX). Despite the severity of the sell-off, the differences between the best and worst performing

funds remained relatively small, at less than twelve percentage points. This suggests that the initial COVID-19 shock affected most investment styles in a broadly similar way. The 2022 inflation window produced a very different pattern, also due to the fact that this stress period wasn't a sharp crash but more of a consistent volatility period: the best outcomes were limited to losses of −13.8% (AMRMX) and −16.5% (MEURX), while the biggest losses approached the COVID levels at −36.0% (PRESX) and −35.3% (FEMKX). The 22-point spread between the most and least resilient funds during the inflation window is roughly double the spread observed during COVID, indicating that the second crisis discriminated between investment styles in a way that the first did not.

The comparison between each ETF and their respective active funds also differs across the two windows. During COVID-19, VOO (−34.0%) outperformed only one of the three U.S. active funds (DODGX, at −40.3%), while AMRMX and FCNTX held their losses close to −29%. In Emerging Markets the four funds clustered much closer between −28.6% and −31.4%, with EEM in the middle of the group. In Europe, VGK (−36.3%) was beaten by FIEUX and PRESX but did better than MEURX (−38.2%). The 2022 inflation window reversed the situation for the U.S. group: AMRMX (−13.8%) beat VOO (−24.5%) by more than ten percentage points, DODGX limited its losses to −17.6%, and only FCNTX deteriorated to −30.2% which was the worst U.S. result of the window. The European reversal is even more visible, with MEURX losing only −16.5% against the −31.7% of VGK, a 15-point advantage for the active fund while the other two European active funds fell behind the ETF.

Looking at the results, a clear trend is seen, the three funds that performed best during COVID-19 in their respective regions are the same three that performed worst during the 2022 inflation crisis. This reversal in relative fund performance across the two crises is examined further in Section 5.9.

5.8.3. VaR Results

This section complements the previous analysis by examining how estimated downside risk evolved across the same volatility periods. Table 5.8 reports the average daily VaR estimates at the 99% confidence level for the full sample, the COVID-19 crash and the 2022 inflation crisis.

Region	Fund	Average VaR 99% (%)		
		Full Sample	COVID-19	Inflation 2022
US	VOO	2.63	7.89	3.39
	AMRMX	2.13	6.24	2.65
	FCNTX	3.27	6.81	4.72
	DODGX	2.82	7.70	3.28
EM	EEM	3.06	7.21	3.55
	FEMKX	2.91	6.37	3.92
	NEWFX	2.57	6.60	3.69
	PRMSX	2.84	6.66	3.72
EU	VGK	2.63	7.44	3.61
	FIEUX	2.73	6.47	3.81
	PRESX	2.65	6.52	4.22
	MEURX	2.53	7.89	2.79

Table 5.8. Average Daily VaR at 99% Confidence Across Volatility Regimes

Notes: The full-sample column reproduces the reference VaR for ease of comparison. The COVID-19 window covers 19 February to 23 March 2020 (24 trading days); the Inflation 2022 window covers 3 January to 12 October 2022 (203 trading days). All values are averages of the daily VaR estimates inside each window.

The VaR estimates increase sharply during the COVID-19 period. Across the sample, the average daily VaR rises from 2.13%–3.27% to 6.24%–7.89% during the 24 trading days of the pandemic shock. The highest absolute readings are recorded by VOO and MEURX (both at 7.89%), followed by DODGX (7.70%) and VGK (7.44%), while AMRMX (6.24%) and FEMKX (6.37%) exhibit the lowest COVID-period VaR estimates in their respective regions. Despite these differences, the COVID-19 shock affected all funds in a relatively similar way. Regardless of region, investment style or active-passive classification, all funds experienced a substantial increase in downside risk during the pandemic crash. This reflects the highly systemic nature of the COVID-19 sell-off, where correlations across markets and sectors increased sharply.

The 2022 inflation window produces a different pattern. Although VaR estimates remain above their full-sample levels, the increase is considerably smaller than during

COVID-19, ranging from 2.65% (AMRMX) to 4.72% (FCNTX). For most funds, inflation-period VaR remains between 1.1 and 1.6 times the full-sample average, compared with increases of roughly 2.5 to 3 times during the pandemic crash. This indicates that the inflation crisis contributed to tail risk less through abrupt volatility spikes and more through the persistence of elevated market uncertainty over a much longer period.

In the United States, the COVID-19 VaR is highest for VOO and the value-oriented DODGX (7.89% and 7.70%), and lowest for the defensive AMRMX and the growth-oriented FCNTX (6.24% and 6.81%). During the inflation window the ordering shifts: FCNTX records the highest U.S. VaR at 4.72%, while DODGX falls to 3.28%. Europe displays the most extreme version of this pattern. MEURX records the highest VaR of the European group during COVID-19 (7.89%) and the lowest during inflation (2.79%), more than five percentage points for the same fund between regimes. In the Emerging Markets the same reversal observed in the drawdowns reappears in the VaR estimates. This consistency across two independent risk metrics points to a structural mechanism, which is examined in the next section.

5.9. The Crisis Rotation Effect

Tables 5.7 and 5.8 reveal a consistent pattern across two independent risk metrics: the fund that suffers the deepest drawdown in one crisis tends to be among the most resilient during the other, and the same reversal appears in the VaR estimates. The fact that the effect emerges in both drawdown and tail-risk measurements rules out the possibility of a metric-specific artefact and points to a structural mechanism. That mechanism lies in the interaction between fund investment style and the nature of the macroeconomic shock.

5.9.1. United States

The U.S. sample provides the clearest illustration. During COVID-19, DODGX (a deep-value fund) suffered the worst drawdown at -40.3%, more than six percentage points worse than the ETF (-34.0%). FCNTX (a growth fund) experienced the mildest drawdown at -29.4%. During the 2022 inflation crisis the rankings reversed almost perfectly: FCNTX fell -30.2% (the worst in the group), while AMRMX fell only -13.8% and DODGX -17.6%, both substantially better than the ETF at -24.5%.

The explanation is in the opposing mechanisms of the two crises. DODGX's portfolio of cyclical, financial and energy stocks was devastated by the sudden shock in economic activity during COVID, but these same sectors benefited from inflation, rising commodity prices and wider interest margins in 2022. FCNTX's technology-heavy portfolio benefited during COVID-era digital acceleration but was punished when rising discount rates compressed the valuations of long-duration growth stocks in 2022. The same opposition is visible in the VaR estimates of Table 5.8: DODGX records a high COVID VaR (7.70%) but a low inflation VaR (3.28%), while FCNTX shows the inverse profile (6.81% in COVID against 4.72% in inflation).

5.9.2. Europe

The European sample produces the strongest example of the crisis rotation effect. MEURX, a value-oriented fund with the lowest beta in the European group (0.821), suffered the worst COVID drawdown of any European fund at −38.2%, worse than the ETF VGK. During the 2022 inflation crisis, however, MEURX fell only −16.5% the best among European funds. The next-best European fund during the inflation crisis was VGK at −31.7%, nearly double MEURX's loss. This percentage gap between the worst and best funds during the same crisis shows how investment style affects crisis outcomes. The contrast also emerges in the VaR: MEURX shows the highest COVID VaR of the European group (7.89%) and the lowest inflation VaR (2.79%), while PRESX displays the opposite movement (6.52% in COVID against 4.22% in inflation).

5.9.3. Emerging Markets

In Emerging Markets the rotation is present but less pronounced, reflecting the more homogeneous geographic and sector exposures of the funds in this group. FEMKX had the smallest COVID drawdown (−28.6%) but the largest inflation-crisis drawdown (−35.3%). The spread between the best and worst funds is narrower than in the other regions, consistent with the observation that emerging-market funds tend to have more overlapping exposures due to the concentration of these markets in a smaller number of sectors and countries.

CHAPTER 6

DISCUSSION

This chapter interprets the empirical results presented in Chapter 5 in considering the hypotheses formulated in Chapter 3. It first summarises the main findings and the destination of each hypothesis, develops the interpretation of the crisis rotation effect, draws practical implications for investors, and acknowledges the main limitations of the analysis.

6.1. Summary of Main Findings

The actively managed funds in the sample outperformed their passive counterparts descriptively on a risk-adjusted basis, but the strength of this outperformance varied substantially across regions. In the United States, all three active funds delivered higher Sharpe, Sortino and Treynor ratios than VOO. In Emerging Markets, NEWFX and FEMKX outperformed EEM by a clear margin, while PRMSX produced similar results. In Europe, only FIEUX achieved a considerable descriptive outperformance over VGK. However, these descriptive findings must be qualified by formal tests of manager skill. Evaluated through the statistical significance of Jensen's alpha, genuine outperformance at the 5% level is limited to only two funds: FCNTX (US) and NEWFX (EM). This nuanced evidence partially challenges the hypothesis that passive funds achieve equal or better risk-adjusted performance after management costs. The evidence for active management is heavily reliant on isolated exceptional funds, is weaker in Emerging Markets, and is non-existent in Europe, where no fund achieved a statistically significant alpha.

The tail-risk results lead to the rejection of Hypothesis H1, which proposed that passive funds consistently exhibit lower volatility and tail risk than active funds. Across the sample, most active funds recorded lower volatility and lower Expected Shortfall than their passive counterparts, particularly in Emerging Markets and Europe. The Value-at-Risk advantage, while clear in Emerging Markets, was more limited in the United States and Europe.

The comparison between performance during the COVID-19 pandemic and the 2022 inflation crisis revealed a pattern that does not align with either of the simple alternatives proposed in Hypothesis H2. Active funds did not uniformly provide better downside protection during stress. Instead, the funds that performed best during one crisis consistently performed worst during the other. This crisis rotation effect emerges from a consequential observation. In each region of the sample, the active fund that suffered the smallest drawdown during the COVID-19 crash subsequently suffered the largest drawdown during the 2022 inflation crisis. The same inversion appears in the VaR estimates of Table 5.8, emphasising the differences of different portfolio strategies during different time periods.

The practical consequence is that an investor seeking crisis protection through active management must not only choose to invest actively but must also correctly anticipate the type of shock that will occur. This is a task at which Lynch and Rothchild (1989) considered both professionals and amateurs unlikely to succeed.

6.2. Style as a Dimension of Diversification

Crisis rotation effect has direct implications for portfolio construction. The traditional argument for diversification operates across asset classes and across geographies. The pattern documented suggests that a third dimension is relevant within an equity allocation: diversification across investment styles, particularly between growth and value. An investor who held both FCNTX and DODGX through the 2016 to 2025 period would have moderated the drawdowns in both crises, sacrificing some upside during the post-COVID growth.

6.3. Limitations of the Study

The most important limitation of the thesis is survivorship bias. As mentioned in Chapter 4 the sample consists exclusively of funds that survived the full sample period with continuous data availability and that maintained sufficient assets to be classified as large in their respective categories. Funds that were closed, merged or liquidated during the period are absent by construction, and Elton et al. (1996) demonstrated that this type of selection systematically overstates the average performance of active management.

A second limitation relates to the currency perspective adopted in the analysis. All returns were calculated in U.S. dollars, using the U.S. Treasury Bill as the risk-free rate. Therefore, the findings should be interpreted from the perspective of a dollar-denominated investor. Investors based in other regions may experience different outcomes due to exchange-rate fluctuations between the U.S. dollar and their domestic currency. Over a long investment horizon, currency movements can either amplify or reduce investment returns, particularly in international and emerging market funds. Since currency risk was not explicitly incorporated into the analysis, this dimension is not captured in the results.

CHAPTER 7

CONCLUSION

This dissertation investigated whether actively or passively managed investment funds deliver superior risk-adjusted performance, with a focus on downside risk and on behaviour during periods of market stress. The analysis covered twelve funds across three regions between 2016 and 2025, combining traditional performance metrics with Value-at-Risk and Expected Shortfall measures validated through formal backtesting.

The performance results are heterogeneous across regions. In the United States, all three active funds delivered higher risk-adjusted returns than VOO. In Emerging Markets, two of the three active funds outperformed EEM by a clear margin, while PRMSX matched it. In Europe, only FIEUX outperformed VGK. The strength of active outperformance therefore decreases as one moves from the U.S. towards the more fragmented European market, in a direction broadly consistent with the literature, although the particularly strong U.S. results should be interpreted with some caution, as they may partly reflect survivorship bias and the inclusion of FCNTX, a fund with an exceptional long-term track record.

The risk results were unexpected. Across all three regions, most of active funds recorded lower daily VaR and lower Expected Shortfall than their passive counterparts, contradicting the intuitive expectation that broad-based ETFs would offer more contained downside exposure. This is explained by the lower betas of the active funds in the sample and in the inability of standard deviation, by itself to distinguish between favourable and unfavourable variability.

The most distinctive finding of the study is the crisis rotation pattern observed in the selected sample. In each region, the active fund that suffered the smallest drawdown during the COVID-19 crash subsequently recorded the largest drawdown during the 2022 inflation crisis, with the same appearing in the VaR results. The mechanism is straightforward: a sudden contraction of real activity favours long-duration growth holdings, while a monetary tightening cycle favours cyclical and value-oriented portfolios. However, this pattern should not be interpreted as a universal law of fund performance, given the limited sample and the use of only two specific crises. Nevertheless, it provides useful evidence that downside protection is conditional on the interaction between portfolio style and nature of the shock.

These findings translate directly into the destination of the three hypotheses formulated in Chapter 3. Hypothesis H0 is rejected in the United States, partially rejected in Emerging Markets, and not rejected in Europe, primarily based on realised descriptive

ratios. However, in the dimension of proven manager capacity, statistical significance at the 5% level is restricted to FCNTX and NEWFX. Therefore, the rejection of H0 in the U.S. regarding manager skill is heavily driven by FCNTX alone. The strong U.S. results reflect survivorship bias and the inclusion of an exceptional fund: FCNTX, which is the only statistically significant alpha in the American group. Hypothesis H1 is rejected because most active funds in the sample exhibit lower tail risk than their passive benchmarks. Hypothesis H2 is only conditionally supported: active funds did not provide uniform downside protection during periods of stress, but some funds offered substantial protection when their investment style matched the nature of the shock.

The practical implication is that the active versus passive choice cannot be reduced to a single recommendation. Passive investing remains the default for European equities, while active management retains a meaningful role in less efficient markets and in portfolios where style diversification is an explicit objective. Future research could extend the present analysis to different funds and fund sizes, to currency-hedged funds, and to a broader set of crisis episodes that would test the generality of the rotation effect documented here.

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APPENDIX A

Sub-period Backtesting

Table A.1. Sub-period Backtesting for Assets Where Both Models Fail the UC Test

		SGSt VaR				Historical VaR			
Fund	Period	Exc.%	UC p	BCP p	Lag	Exc.%	UC p	BCP p	Lag
VOO	2021–2022	18.08	0.00%	0.10%	3	1.54	41.87%	79.92%	1
	2020–2021	15.38	0.00%	0.70%	7	3.08	0.69%	4.14%	4
AMRMX	2021–2022	1.92	18.44%	0.00%	3	1.54	41.87%	0.05%	2
	2020–2021	7.31	0.00%	0.00%	10	2.31	7.01%	0.01%	10
EEM	2021–2022	0.38	25.44%	94.99%	1	0.38	25.44%	94.99%	1
	2020–2021	2.31	7.01%	0.37%	5	2.69	2.34%	3.98%	5
VGK	2021–2022	0.77	69.67%	89.96%	1	0.77	69.67%	89.96%	1
	2020–2021	3.85	0.04%	1.97%	2	2.69	2.34%	0.00%	10
MEURX	2021–2022	2.31	7.01%	1.72%	1	1.92	18.44%	28.00%	1
	2020–2021	3.46	0.18%	0.01%	10	3.08	0.69%	0.00%	10

Note: Sub-periods correspond to annual backtesting windows within the full sample. Lag = the lag at which the BCP test records the lowest p-value, indicating the interval (in trading days) at which exceedances show the strongest autocorrelation.