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Systematic Investing: Momentum and Volatility as Indicator for Market-Timing?

A better Alternative to the traditional 60/40 Multi-Asset Portfolio

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Abstract

In Financial Markets, academic questions revolve around the assumption that asset prices reflect all available information and exhibit a random walk. Direct implications of this hypotheses are that no market participant can consistently earn excess returns on a risk-adjusted basis, except by luck or by using non-public information. This thesis examines whether the assumption that historical data cannot be enough to consistently outperform the market holds. Based on the evidence that asset returns are negatively skewed with few fat-tails, the systematic multi-asset strategy presented in this thesis more than triples the risk-reward compared to the traditional 60/40 portfolio by incorporating trend-following and market risk assessments.

Key words: Financial Markets, Asset Management, Portfolio Allocation and Performance Analysis, Mutual Funds and ETFs

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All remaining errors are of course in my sole responsibility.

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Abbreviations

APT	Arbitrage Pricing Theory
AMH	Adaptive Market Hypothesis
ATH	All-Time High
Bps	Basis points
CAL	Capital Allocation Line
CAPM	Capital Asset Pricing Model
ETF	Exchange-traded Fund
EMH	Efficient Market Hypothesis
FI	Fixed Income
GDP	Gross Domestic Product
HY	High Yield
IG	Investment Grade
IR	Information Ratio
JA	Jensen’s alpha
Max DD	Maximum Drawdown
MACD	Moving Average Convergence/Divergence
MPT	Modern Portfolio Theory
REITs	Real Estate Investment Trusts
Rf	Risk-free rate (1-month US Libor)
RP	Risk Parity
RSI	Relative Strength Index
RWH	Random-Walk Hypothesis
SMA	Simple Moving Average
SR	Sharpe Ratio
TAA	Tactical Asset Allocation
T-Notes	10-year Treasury Notes
TE	Tracking Error
TR	Total Return
VaR	Value-at-Risk
VIX	Volatility Index
$\land$	Logical conjunction (“AND”)
$\lor$	Logical disjunction (“OR”)

1. Introduction

Over the past decades, systematic investment strategies have grown to be a force the in the portfolio selection process of institutional investors (Harvey, 2021). While bond and equity markets are showing increasingly correlated behaviour, the traditional 60/40 portfolio is being challenged. Both major liquid asset classes are suffering in 2022 from rising interest rates and increasing recession fears. With the emerge of technology, new quantitative and rules-based strategies gaining popularity among investors due to their cost efficiencies, lack of psychological biases, rigorous risk management and data-driven decision-making processes (Richardson, 2022). The purpose of this thesis is to present a systematic approach to investing, which delivers consistent performance, avoids large drawdowns, and increases an investor's risk-reward. Previous research in the field of quantitative finance has lagged in providing an easily replicable investment approach to investors. Furthermore, research has not fully explored how to benefit from the momentum puzzle while avoiding the downside risks. Hence, this thesis fills the gap and contributes to the existing research, as it is, to the author's best knowledge, one of the first empirical studies investigating a Value-at-Risk based trend-following trading strategy. This paper is structured as follow. First, the literature review summarizes the most relevant research done in asset pricing to build a theoretical framework. Second, this paper illustrates how to exploit market inefficiencies and utilize the negative skewness in asset returns with the use of systematic trading strategies. Therefore, arguing against prevailing theories in finance, such as the efficient market hypothesis. Third, the importance of the backtesting process and awareness of psychological and statistical biases is presented. Forth, a systematic trading strategy is introduced achieving a Sharpe ratio of 1.40 compared to the 60/40 portfolio with only 0.43 over the period of Jan-2000 and Nov-2022. Fifth, the results are discussed and set into context. Finally, this work illustrates the limitations, provides suggestions for future research, and draws a conclusion to the assumption that financial markets are efficient.

2. Literature Review

2.1 Efficient Market Hypothesis

According to the Efficient-Market Hypothesis (EMH), a market is *efficient,* when prices of securities always accurately represent *all currently available information* and consistent outperformance is impossible (Fama, 1969, Jones and Netter, 2019). These outlines are not favourable for the systematic trading approach provided in this thesis and therefore, a *passive investment* strategy that is implemented with index funds (ETF) should be the better option. Already the *weak-form efficiency* implies that no profits can be made by any *historical* price-based trading strategies such as the ones presented in chapter 4. However, if markets were not fully efficient, then such systematic trading strategies can be profitable after all.

2.2 Modern Portfolio Theory

In the 1950s, Harry Markowitz introduced a mathematical framework for *portfolio optimization* within a mean-variance setting based on the *benefits of diversification*, known as modern portfolio theory (MPT). His pioneering analysis demonstrated that although the expected portfolio return is the weighted average of the expected returns of the individual assets, the variance of portfolio returns is typically *lower* than the weighted average of the asset variances because portfolio risk depends on the correlations among individual assets (Markowitz, 1959). The less correlation there is between assets, the greater the diversification benefits.

2.3 Capital Asset Pricing Model

Sharpe (1964), Lintner (1965) and Mossin (1966) further developed the MPT by including two key assumptions for choosing *mean-variance efficient* portfolios. The first assumption states that all investors can borrow and lend at the same *risk-free rate* which is unaffected by the amount borrowed or lent. Therefore, unlike the MPT model, only the portfolio with the *highest Sharpe ratio* on the efficient frontier really matters to investors, which is typically represented by the *market portfolio* (Bodie et al., 2014). Investors optimize their portfolios in a mean-variance efficient way by dividing their capital between the risk-free rate and the market portfolio based on their risk aversion, and consequently, find themselves on the *capital market line* (Figure 1). The second assumption is that investors have *homogeneous expectations* about returns and covariances/correlations for the same universe of tradeable assets over the same one-period planning horizon. In general, CAPM is based on the idea that the expected return of an asset is equal to the risk-free rate plus a risk premium, which depends on an asset's volatility in relation to the overall market, known as the beta of an asset (Treynor, 2004).

2.4 Factor Investing

Factor investing refers to an academic approach of explaining stock returns based on various *quantifiable characteristics* (Israel, et.al. 2014). As financial markets further evolved, so did academia, moving from the single-factor CAPM (Sharpe, 1964) to multifactor models. After years of study on arbitrage pricing theory (APT), Chen and others proposed in 1986 a multi-factor model with GDP and interest rate factors. Fama and French (1993) first split the systematic risk spectrum into three fundamental components, namely *market risk*, *size*, and *value*, before Carhart (1997) expanded the Fama-French three-factor model by adding a *momentum* factor to develop a four-factor model.

2.5 Momentum Puzzle

Momentum refers to the tendency of asset prices to continue moving in the same direction. Barroso and Santa-Clara (2012) conclude that momentum provides the *best risk-reward* compared to all other common factors. Hence, momentum strategies have attracted much research in the past decade. There are several studies that contradict the EMH and offer evidence that historical asset returns can predict the cross section of future asset returns to a certain extent (e.g., De Bondt & Thaler, 1987; Jegadeesh & Titman, 1993; Fama & French, 2012; Israel & Moskowitz, 2013). Research broadly divides the explanations as either risk based, or non-risk based. According to Ang, Chen and Xing (2001), it is *downside risk* that an investor gets rewarded for when applying a momentum strategy. In the category of non-risk-based explanations, there are several types of *behavioural explanations* that use either under-/overreaction effects or herd behaviour as explanations (Daniel et al., 1999). However, in times of market turmoil, momentum remains subject to large losses leading to the worst crashes (Barroso, 2012). Therefore, *risk management* is particularly important in momentum strategies.

2.6 Behavioural Finance

Financial decisions are influenced by *heuristics* and *psychological biases* (Kahneman et al., 1982). Today, there are a variety of cognitive biases and heuristics revealed by researchers, including loss aversion, herd behaviour, and confirmation bias, to name just a few. These findings argue that the EMH cannot be valid since it ignores irrational and emotional behaviour (Asness, 2014). Due to psychological hurdles and limited information-processing capabilities, market participants have only *bounded rationality* (Thaler, 2008). One prominent example of such a heuristic is the *disposition effect,* which states that people prefer to maintain the status quo and are reluctant to part with assets that have lost value (Burton & Shah, 2013).

2.7 Risk Parity

Risk parity is a relatively new method of constructing portfolios, first appeared in 1996 when the American hedge fund Bridgewater Associates developed a framework to protect its assets. The objective is to build a portfolio that performs well in all market periods, which they coined an "*All-Weather-Strategy*" (Ray Dalio, 2010). The fundamental ideas behind the Risk Parity method, dates back to the development of MPT and the notion of a mean-variance efficient portfolio. Today, portfolios that aim to *equalize the risk contribution* of their underlying assets are referred to risk parity strategies. However, when Bridgewater Associates started to work on their risk-weighted asset allocation, they have realized that this approach does not meet their performance objectives, as lower yielding assets are weighted more heavily, resulting in lower returns. However, an unconventional solution was found to address this problem – leverage.

3. In Search for Alpha

This section is divided into nine sub chapters and serves a bridge between the theoretical concepts from before, concluding some of the findings and insights, which are then applied in the underlying idea of the systematic investment strategies presented in chapter four. The first chapter takes on the concepts of behavioural finance and investigates empirical probability measures to argue against the efficient-market hypothesis. Since the systematic models are compared with a buy-and-hold strategy, the second and third chapters show some general thoughts about the purpose of active investing, the persistence of the random walk hypothesis and how an investor can exploit the negative skewness in asset returns using *market-timing* and *risk rebalancing*. The fourth chapter explains some of the key difference between *discretionary* and *systematic investing*. Chapter five discusses the importance of *backtesting* and the awareness of statistical biases. Followed by the sixth chapter, which shows some practical hurdles that might occur when implementing a systematic strategy. The seventh chapter defines the investment universe and justifies it accordingly. The eighth and ninth chapter present some useable ratios and figures to evaluate an investment strategy in both, absolute and relative terms.

3.1 Evidence against the Efficient-Market Hypothesis

According to the EMH, which is one of the prevailing theories about financial markets, prices of securities follow a random manner, so-called "Random Walk Hypothesis" (RWH), implying that asset returns are normally distributed and successful market timing exceedingly difficult. Although many finance theories and models are based on this assumption, empirical research shows something different (Chung et al., 2006). Analysing returns of the S&P500 index on its distribution shows, asset returns exhibit a *negative skewness* with a leptokurtic distribution (Table 1). Skewness measures the level of asymmetry within the data set. A left-skewed distribution is called negatively skewed and indicates frequent small gains, but also a few large losses, so-called *fat-tails* (Figure 2). Hence, the metaphor: "markets take the stairs up and the elevator down” (Jiang, 2015). Furthermore, even though the EMH assumes that all investors are rational, in reality investors are subject to their own psychological biases, such as the status quo bias, in which people fall into lazy decision making and prefer not to change the situation even if market conditions changed and adjustment would be appropriate (Malkiel, 2006). More recent hypotheses apply principles of behavioural economics to the financial markets by taking competition, adaptation, and selection into account (Clowes, 2005). The so-called *Adaptive Market Hypothesis* (AMH) first coined by Andrew Lo in 2004, argues that investors can achieve an optimal dynamic allocation, by adapting to their own psychological biases such as status quo bias, over-/underreaction or overconfidence. One way to avoid such *adverse behaviour* is by using a systematic trading system that executes trades based on pre-defined rules, allowing investment decisions to be done in a methodical manner and portfolios to be continuously adjusted without the need for further human effort or the presence of emotional biases.

3.2 Purpose of Active Investing

Active investing is characterized by the objective to time the market in the short run, in order to produce an excess return above a benchmark, which is often defined by a market index or ETF (Sommer, 2022). This excess return can be achieved through trading activity and rebalancing based on an investor’s own market judgments. If an investor would not care about market timing and excess return, he would follow a buy-and-hold strategy with a passive index fund of his desired asset class (e.g., for U.S. Large Cap Equities: S&P500 Index). In contrast, an investor who seeks to achieve *alpha*, or at least a higher risk-reward, must inevitably go *beyond beta*, and therefore beyond a passive market investment (Sommer, 2022). Further, if no one would trade actively, market prices would move away from their fundamentals, which would lead to inefficient allocation of resources and thus a decline in social welfare (Soros, 2012). Hence, active investing keeps tradable assets in their equilibrium, with deviations that, following to the EMH, only occur randomly (Lamont, 2015). According to a study by Standard

& Poor's (SPIVA Report, 2021), which examined more than 25,000 active funds over a 10-year period, only 20% of the fund managers were able to achieve their goal of beating their benchmark after costs. This circumstance does not make it easier to develop a systematic strategy which outperforms the market consistently, achieves a higher risk-reward and limits its downside risks. However, even if most fund managers fail to beat their benchmark, the trading models presented in this paper provide an effective way to leverage the insights of a negatively skewed return distribution, the assessment of fat-tail risks, and the persistence of the momentum puzzle.

3.3 Market Timing

According to academia, market timing involves shifting capital between the optimal portfolio, for example a market-index portfolio and a risk-free asset in hopes of capturing good and missing bad performing periods (Sharpe, 1975). By knowing that asset returns are usually negatively skewed with fat-tails, an investor can try to avoid periods with rising volatility, as such periods result in a worse risk-reward and increase the overall probability of extremely large losses. Moreover, an investor can respond to the current quantified risk environment by adapting his *risk appetite* and market exposure accordingly, a principle which is presented in the risk management approach in chapter 3.6 and applied in the trading models in chapter 4. The capital allocation between different asset classes is associated with different expectations regarding their future performance. These expectations can be formed based on historical data. For instance, an investor might weight the allocation differently based on past volatility, intending to limit the overall portfolio risk by shifting to less volatile assets. A principle that is applied in the *tactical asset allocation* (TAA) of this paper by targeting an annual volatility.

3.4 Systematic vs. Discretionary Investing

Discretionary investing refers to the traditional approach to investing and depends on the knowledge and expertise of an investor and his ability to analyse an almost endless number of securities with a variety of indicators in a limited timeframe. Due to practical reasons, the number of securities and indicators that can be considered in a discretionary investment approach must be relatively low. There are dozens of metrics an investor must evaluate in real-time with an almost infinite amount of data. Hence, when comparing all these data manually, the work quickly becomes overwhelming, the pace of decision-making stagnates, and misunderstanding often occurs (Carver, 2022). On the other hand, systematic investing is a technique for establishing *trading objectives*, risk controls, and rules that enables investment decisions to be made in an automated and *methodological way* (Nilsson, 2020). Today, with low-cost computation and vast data, rule-based investing is becoming increasingly popular (Harvey, 2021). This approach has the advantage that all investment decisions are made in a transparent and clearly comprehensible manner, which are not influenced by personal opinions and feelings. Psychological biases, such as the disposition effect or status quo bias, can not only be avoided, but systematic models also provide a convenient way to make investment decisions done and execute more efficient and automated.

3.5 Backtesting

An important part of developing a systematic trading strategy, involves backtesting, which is the process of studying the behaviour of a security, asset class or investment strategy and analyse its performance based on *historical data*. According to the underlying idea of backtesting, any strategy that performed well in the past is likely to do so again in the future, and vice versa. There are several statistical biases that need special attention in the process of developing a viable backtesting. Survivorship bias, look-ahead bias, and data snooping are the most common ones (Chincarini et al., 2006). The *survivorship bias* ignores assets that have disappeared during the test period and only considers investments that are still present at the end of the test period. The *look ahead bias* occurs, when investment decisions are done based on information, which are not yet available at the time the signal is processed in real-time

(Chincarini et al., 2006). For example, if the 200-day moving average triggers a new buy/sell signal based on historical close prices, this information would be just usable in the subsequent period (t_{+1}). When strategies rely solely on historical performance data without proof of similar results in the future, they are subject to *data snooping.* (Chincarini et al., 2006). Although historical data does not guarantee futures performance, it helps to evaluate a strategy and to understand its performance in different periods and market events. The level of confidence depends on the stability of the backtest result and further out-of-sample tests. Such out-of-sample tests confirm the effectiveness of the systematic strategy and reveal a system's genuine capabilities before actual money is on the line. For a trading system to be considered reliable, backtesting and out-of-sample results must all show a high degree of correlation (Sommer, 2022).

3.6 Biases in Systematic Strategies

After avoiding statistical biases and securing the validity of the backtesting, implementing an actual systematic investment strategy poses new challenges for an investor. While the absence of emotions and cognitive biases in risk-taking and decision-making is advantageous for systematic trading (Guzun, 2020), there are still some common mistakes, including *cognitive biases*, that can occur in the process of defining and developing a systematic trading strategy.

3.6.1 Overconfidence

According to Kaastrup-Larsen and Carver (2020), being overconfident is one of the biggest mistakes an investor can make. Both in absolute terms and relative to others, people have the tendency to overestimate their own capabilities and skills. In behavioural finance overconfidence is called *illusory superiority.* When an investor believes he is better than the rest of the market, he tends to trade too often and take excessive risks. According to Craver (2020), the best discretionary traders are those who have the courage and humility to admit when they are wrong and to close a position when it goes against them. A similar humble attitude is required for those who develop systematic strategies, where such risk and trading limits can be implemented in a rigors and rule-based manner. Nevertheless, an investor must admit that historical data only provide *limited informational value* for future outcomes. For instance, exogenous shocks and fat-tail risks, such as a global pandemic, can be considered only to a certain extent in a systematic model.

3.6.2 Overtrading

Another manifestation of overconfidence is overtrading. An unrealistic backtest show that buying and selling frequently might profitable and paired with unrealistically low assumptions of trading cost, provides satisfactory results but is useless in practice. Therefore, it is important to have realistic expectations of the model's trading frequency and cover a conservative estimate of *trading costs.*

3.6.3 Overfitting

Overfitting a trading system is the process of figuring out which collection of trading rules and parameters will result in the best trading system when tested using historical data (Leinweber, 2007). In this case, the model is trained to perform incredibly well in the historical data sample but does not provide reliable results if the market environment is changing, leading to ineffective results in the future. It happens when a systematic investor is looking for the right perfect parameter setting instead of defining a hypothesis for why those parameters would be good candidates (Aronson, 2006). Hence, further out-of-sample tests and *walk-forward analyses* are necessary to keep the strategy viable (Prado, 2008).

3.6.4 Overcomplexity

Over complicating a model happens when an investor starts with a rather simple trading system, but after backtesting, it seems to perform worse than expected. By adapting new parameters and fine tuning, the model improves its performance, leading to a similar inaccurate result as the prior point about overfitting. Further, according to Fenton-O'Creevy (2003), complexity also makes a system opaque, so that the trading approach becomes obscure to outside investors.

A reliable trading strategy is predictable. An investor should be able to roughly predict what the strategy will do when the market moves in a certain direction. Additionally, if an investor understands the trading system, he is more likely to believe in it, and allow it to operate and execute unhindered. Therefore, the strategy presented in this work keeps its trading fundamentals very simple by limiting its investment universe to ETFs, based on only two indicators, namely momentum (moving averages) and volatility (Value-at-Risk).

3.7 Investment Universe

Traditionally, there are two kinds of market investments an investor considers, stocks and bonds. Apart from this traditional investment universe, an investor might look for further diversification benefits in alternative investments like commodities, currencies, private equity/debt, or real estate. Due to the scope, this thesis limits its investment universe to the traditional two asset classes of stocks and bonds. Since the US financial markets are the most matured and researched, the systematic strategy presented in this thesis, focuses on the US market, and choose the traditional 60/40 portfolio as its benchmark, with 60% US large cap stocks and 40% US government bonds, represented by an investment of 60% in a S&P500 index fund and 40% in US Treasury index fund with daily rebalancing and the exclusion of transaction and rebalancing costs (contrary to the actual systematic strategy). Stocks have delivered remarkable returns over the past century. Most of these returns are not fully explainable by academic models in finance, which is known as the *equity premium puzzle*. There is a significant divergence of 6 to 7% between the returns of US treasury bills and US equities (Kenton, 2022). On the other hand, fixed-income securities offer *yielding income* and move in a relatively negative manner to the equity market, thus also acting as a *hedging factor* when uncertainty in the equity market increases. Such diversification effects, discussed in chapter 2, allow a higher risk-reward, since the portfolio volatility decreases, depending on the correlation of the underlying assets. Moreover, treasury notes can be considered as a better equivalent to cash, as they have no default risk, are highly liquid and pay ongoing coupons (Kon, 2022).

3.8 Risk Management

Effective risk management is characterized by taking proactive measures to reduce both the *probability* of a risk occurring and the potential negative *impact* (Dionne, 2013). Within a portfolio, risk management comprises identifying, measuring, assessing, and managing risks within and across asset classes, and focuses on limiting such potential risk-drivers. Risk controls and limits are also essential for systematic strategies, as this approach allows to set pre-defined limits and thresholds that the model should adhere to. In the following, the approach to risk management of the systematic strategy in chapter 4 is presented. To better diversify the overall risk, a risk-weighted allocation is used, with a pre-defined target annual portfolio volatility, as well as different Value-at-Risk thresholds within the risky asset class of equities.

3.8.1 Risk

The most common risk measure of an asset or portfolio (σ_i) is the *standard deviation* its daily returns. Volatility and risk are used synonymously in this analysis, while other risk indicators including Value-at-Risk, maximum drawdown, tracking error, and beta are also considered.

$$\sigma_i = \sqrt{\frac{\sum(r_i - \bar{r})}{N}}, \tag{1}$$

3.8.2 Risk Parity

Within a traditional 60/40 allocation, risk is heavily weighted on stocks, since they cover most of the volatility, which leads to concentration of risk (Maillard et al., 2009). To diversify a portfolio more adequately to the inherent risk of the underlying asset, an investor can decide to allocation capital according to the respective risk. This asset allocation principle as introduced in chapter 2.6, comes into practice within our tactical asset allocation (TAA) model in chapter 4.4, allocating the portfolio between its equity and fixed income strategy based on their current volatility. Further, this approach allows to set volatility targets to determine an investors risk appetite. This dynamic tactical asset allocation method helps to avoid high volatile periods, as it shifts from assets with rising volatility to assets with the lowest volatility, thus avoids relatively risky assets.

3.8.3 Value-at-Risk

Value-at-Risk (VaR) is among the most relevant and commonly used statistics to indicate the downside risk of a financial asset over a given period based on its historical volatility (Benninga & Wiener, 1998). VaR can be expressed as a prospective loss from the current value and corresponds to a percentile of returns. VaR provides a response to the question, "How much can I lose over a certain horizon with a probability of x%?" For instance, a VaR of one million USD at a 99% confidence level and a 1-day horizon means that in 1 of 100 days, an investor could expect to lose more than one million dollars due to market volatility. In other words, with 99% probability, the expected maximum loss over the next day will be not more than one million USD. VaR is calculated for a specific degree of confidence 1-α and is expressed as the lower negative quantile q of the return distribution, such as in the example above.

$$VaR_{\alpha} = -q_{\alpha}(X) = -\{x | P(X \leq x) \geq \alpha\}, \tag{2}$$

The equity trading model presented in chapter 4.2 uses the VaR figure to better assess the current market environment, adjust its trading strategy accordingly and reduce its exposure if necessary. In this case of the equity model, a daily 99%-VaR is used with α = 1% as the given confidence level, such as in the example above.

3.8.4 Maximum Drawdown

The highest observable loss from a portfolio's prior peak to its low is known as the maximum drawdown (MDD) (Hayes, 2022). Maximum drawdown serves as a measure of downside risk over time. It is calculated by dividing the difference between the peak value and the subsequent low by the peak value, and phrased as follows:

$$MDD = \frac{Peak - Low}{Peak} = \min(0, \max(P_t - P_{t+n}), \tag{3}$$

According to the prospect theory, humans evaluate their losses and gains differently, which is known as loss aversion (Kahneman, 1979). Therefore, the potential downside risk should be visible and at best also limitable. The maximum drawdown is useful figure to illustrate how much an investor could have lost with the respective strategy or fund in the past.

3.8.5 Tracking Error

Tracking error (TE), also referred to *non-systematic risk*, is a measure of the difference between the price behaviour of a fund compared to its benchmark and shows how much the portfolio is aligned with its benchmark. The TE can be calculated as follows (Basilico et al., 2019):

$$TE \; = \; \sqrt{\sigma_P \, \sigma_{BMK}}, \tag{4}$$

3.9 Performance Measurement

There are several key figures and ratios to measure the success of a trading strategy. Portfolio managers are often asked how much alpha they have generated, i.e., how much excess return they have achieved over their benchmark. However, this number alone does not indicate how well an investor has performed. High alpha can come at the expense of high volatility since more risk usually means higher expected return. Therefore, a performance ratio should always consider the risk taken. The following part presents some metrics that will help evaluating and understanding the performance of the systematic trading strategy presented in this thesis.

3.9.1 Sharpe Ratio

One of the most used statistics for measuring *risk-reward* is the Sharpe ratio (Bender et al., 2014). Its development is based on the assumptions of mean-variance analysis, first proposed by William Sharpe (1966). By comparing the expected excess return of an investment with its volatility, it calculates an investor’s return per unit of volatility and can be expressed as the slope of the Capital Allocation Line (CAL) within the CAPM (Figure 1).

$$Sharpe\ Ratio = \frac{E(r_p - r_f)}{\sigma_p}, \tag{5}$$

3.9.2 Treynor Ratio

The Treynor ratio divides the excess return by the beta component to determine the risk premium per unit of systematic risk. The Treynor ratio, in contrast to the Sharpe ratio, substitutes systematic risk (beta) for overall risk (volatility) in the denominator and is denoted as follows:

$$Treynor\ Ratio = \frac{E(r_p - r_f)}{\beta_p}, \quad (6)$$

3.9.3 Jensen’s Alpha

The difference between the actual return and the return projected by the CAPM is measured by Jensen's Alpha. The investor is provided with a metric to evaluate the investment manager’s ability to perform above its theoretical *benchmark* presented by the CAPM. Jensen’s alpha is well suited for portfolios that are diversified to the point where idiosyncratic risk is negligible (Bodie et al., 2014).

$$Jensen's\ Alpha = r_p - [r_f + \beta \cdot (r_m - r_f)], \quad (7)$$

3.9.4 Information Ratio

The information ratio (IR) divides the excess return of a strategy, called alpha, by its tracking error. This metrics shows the abnormal return per unit of non-systematic (idiosyncratic) risk, which in principle could have been diversified away by holding a market index portfolio. Since many retail investors hold a portfolio of mutual funds, idiosyncratic risk matters and the contribution of each fund in the portfolio to reducing or increasing idiosyncratic risk matters. The lower the idiosyncratic risk, the more of the asset can be added to a diversified portfolio without affecting its variance much.

$$IR_p = \frac{\alpha_p}{TE}, \quad (8)$$

3.9.5 Risk Reward Multiplier

The Risk Reward Multiplier is a metric that measures the improvement of the risk-reward of an investment strategy compared to its benchmark. In this case, the risk-reward is measured by the

Sharpe ratio (SR). This SR of an active trading strategy is then set in relation to the SR of its benchmark. This figure shows how many times higher the risk-reward of the active strategy is compared to its benchmark. This ratio has not been discussed in the financial literature so far but came up during the performance assessment process and appeared to be a useful figure to illustrate the progress of the risk-reward triggered by an active investment strategy. For instance, if an active strategy achieves a SR of 0.6 while its benchmark achieves only 0.2, then the fund manager tripled the risk reward. Therefore, the Risk Reward Multiplier is expressed as follow:

$$Risk\ Reward\ Multiplier = \frac{SR_P}{SR_{BMK}}, \tag{9}$$

4. Data and Model Methodology

This section explains the chosen methodological approach of constructing a portfolio based on two individual equity and fixed-income strategies. The methodological framework helps to understand and evaluate the empirical results discussed in chapter 5. This chapter is divided into four subchapters. The first section describes the data set, some pre-defined rules as well as trading objective for the subsequent systematic strategies. The second and third chapter present the underlying equity and fixed-income strategy, while the fourth section covers the asset allocation methodology, putting both strategies into one portfolio. Lastly, the fifth chapter covers the portfolio performance and statistics.

4.1 Data Set and Trading Rules

In the run-up to this paper, various strategies across a variety of asset classes have been tested. In the end, two different but similar strategies were developed for stocks and bond indices. The backtesting procedure and data set included the closing prices of the following indices between 01/10/1999 and 14/10/2022 and were retrieved from Bloomberg:

- ICE Libor 1-month Libor USD (Ticker: US0001m Index)

- Bloomberg US Treasury Bond Total Return ETF (Ticker: LUATTRUU Index)
- Bloomberg Barclays US High Yield Bond Total Return ETF (Ticker: LF98TRUU Index)
- SPDR S&P500 Index ETF (Ticker: SPY Index)
- S&P500 Total Return Index (Ticker: SPXT Index)

The following presents some methodological explanations of the empirical approach to the strategy and the backtesting results. For the daily returns, the logarithmic rate of change is calculated. The benefit of calculating the logarithmic return of an asset, is the *time-additivity* of a logarithmic scale (Hudson & Gregoriou, 2010). While arithmetic returns are not additive over time, and therefore do not yield the total return over a multi-period time length, logarithmic returns can be used to satisfy the property of *time-consistency* with calculating *compounded* returns. Another advantage over arithmetic returns is the *symmetry* of logarithmic returns. Logarithmic returns of the same magnitude but opposite signs will cancel each other out, which arithmetic returns do not (Hudson et al., 2021). Transactions costs are assumed to be 10 basis points (bps) per trade and represent foremost the bid-ask spread when buying and selling the assets. These costs are incurred each time the signal is changed. Signals are generated daily and need to be processed overnight, and therefore are executed in the subsequent period t+1 (*time-lag*). Both strategies are using price-based simple moving averages (SMA) with equally weighted prices. For the current risk-free rate, the 1-month USD Libor is assumed. Moreover, 252 trading days per year are used to annualize return, volatility, and other figures. To calculate the VaR figure in the equity strategy, the 99% confidence interval was chosen to calculate the daily VaR based on the past 50 returns.

4.2 Systematic Equity Trading Strategy

The equity strategy presented in this section is compared with the performance of the S&P500 total return index as its benchmark. To avoid over-complication in the model, short-selling and stock-picking strategies are excluded. Instead, the model narrows its investment decision to long-only investments in the S&P500 index and seeks to benefit only from market timing. In the beginning of this paper, it was found that stock prices are not perfectly normally distributed, but rather exhibit negative skewness with a few large fat-tails. Hence, the underlying idea is that if market volatility remains low, stock market trends are likely to continue. To measure the current market risk, the equity model calculates the daily 99%-VaR based on the past 50 returns. Moreover, if the price trend indicated by two SMA remain intact, the model assumes that this trend is likely to continue. Therefore, the model invests in the S&P500 index ETF, if the daily 99%-VaR remains below 2% or the current 50-day moving average (SMA) is above the 200-day SMA of the S&P500 index. On the other hand, if the daily 99%-VaR is above 5%, the model does not invest at all. A similar defensive approach is taken when the 50-day average index price is neither above its 200-day SMA nor its daily 99%-VaR below 2% (Figure 2.1), since the model assumes that the stock market is likely to change its trend and decides not to invest. Hence, the signal generating process can be formulated as follows:

Long*:* *if daily 99%-VaR* $< 2\% \vee 50d_t >$ *200-day* MA_t

Neutral: *if daily 99%-VaR* $> 5\% \vee$ *(daily 99%-VaR* $> 2\% \wedge 50d_t <$ *200-day* MA_t*)*

Using two SMA, a longer and shorter SMA, helps to smooth signal process when evaluating trends and avoid distortions through short-term price jumps (Seaton et al., 2012). Transactions costs occur after each signal change and are calculated with 10bps per transaction. The model is able to avoid sharp decline in equity valuations in both, the dotcom burst from 2000 to 2002 and the financial crisis from 2007 to 2009 (Figure 2.2). However, the model had to struggle with the price drop of risky assets during the outbreak of the corona pandemic in 2020. During that time, the strategy recorded its biggest drawdown. Nevertheless, the model achieves to limit its maximum drawdown to -22% (Figure 2.3), while the buy-and-hold strategy suffered a temporarily loss of more than -80% compared to its prior all-time-high (ATH). Hence, the systematic equity index strategy can be considered as a more conservative and risk-controlled approach to investing, without scarifying returns (Table 2). Moreover, the systematic strategy increases the risk-reward from 0.33 to 0.60 and does generate an annual alpha of almost 1%, while significantly reducing its volatility compared to the benchmark from 19.8% to 12.3%. Additionally, the number of positive months can be increased to 75%, contradicting the random walk hypothesis. In 28% of the time, the model has not invested, due to a broken trend and increased market volatility, resulting in an annual Jensen's Alpha of 2.8% (Table 2).

4.3 Systematic Fixed-Income Trading Strategy

Like the equity strategy, the fixed-income model applies a trend-following strategy using moving averages but without a VaR indicator, as bond markets are subject to less price fluctuations. The systematic model shifts between an investment in a US treasury bond ETF and US high yield bond ETF. High yield bonds offer attractive coupons, while an index benefits from its diversification effects, hence the default risk of a single bond is compensated by the substantial number of other bonds within the index. On the other hand, US treasury notes are considered a safe haven in times of rising uncertainty and market volatility. The investment universe of the fixed-income model is limited to these two assets, since they offer less correlation compared to an investment grade or emerging markets bond ETF (Table 3). The high yield bond ETF is even ideally suited, as it has a negative beta close to 0 (β_{HY} = -0.08) and thus correlates at least with the benchmark of US Treasuries. If the price trend of the Bloomberg US Corporate Credit High Yield TR index remains intact, indicated by a current price level above the 200-day moving average (SMA), the model invest in the High Yield index. Otherwise, it will shift to the US Treasury index. High Yield bonds are likely to suffer in recessionary times when growth is slowing, and default expectations are rising. In such periods, there is almost no better asset class than US government bonds, as they have no default risk and serve as a safe haven in financial markets. The dynamic fixed-income model is able to increase its SR to 1.77, compared to 0.74 of its benchmarks, resulting in a risk-reward multiplier of 2.4.

The systematic fixed income strategy is yielding with an annualized return of 8.7% not only the highest return, but also bearing the lowest risk with an annualized volatility of 4.3%, beating all other bond indices in risk-adjusted terms (Table 3). Although the strategy lagged behind the emerging markets bond index in the early 2000s, it started to catch up with the onset of the financial crisis in 2007 (Figure 3.1). Since then, a striking outperformance can be seen, which has just started to decline this year due to rising interest rates. Compared to its benchmark, the systematic strategy achieves constant outperformance, except for the years of the dotcom burst (Figure 3.2 and 3.3).

4.4 Asset Allocation with Risk Parity

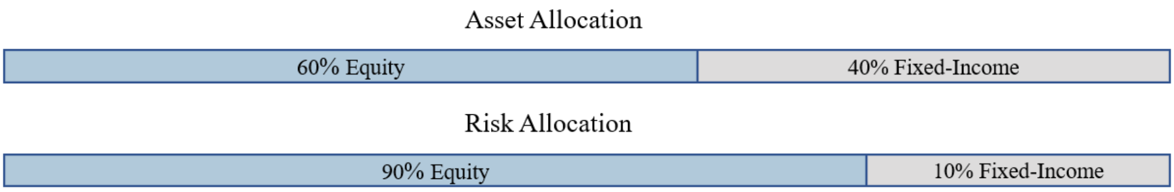
Finally, this chapter puts together both individual strategies in a risk-weighted manner, following the concept of risk parity presented in Chapter 2.7 and 3.8 The trading rules are as follows:

- Benchmark: 60% S&P500 TR Index, 40% Bloomberg US Treasury TR Index
- Target annualized volatility σ_{target} = 8%
- Max. leverage = 2
- Funding costs = 1-month USD ICE Libor
- Current risk-free rate = 3.4% (as of 14th of Oct. 2022, 1-month USD Libor)

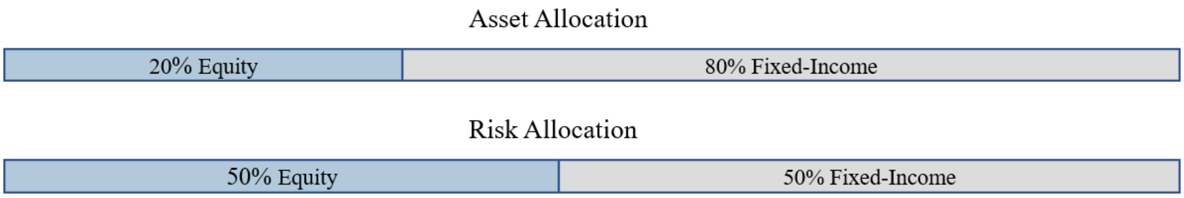
The tactical asset allocation model shifts weights between both strategies according to their *50-day standard deviation*. The target annual volatility is set to 8% and target strategy weights are calculated on a daily basis by dividing the *target portfolio volatility* (σ_{target}) by the annualized standard deviation of the past 50 returns of the respective asset class (σ_i).

$$w_{Ti} = \frac{target\ vol.}{historic\ vol.(i)}\ \frac{\sigma_{target}}{\sigma_i \cdot \sqrt{252}} \tag{10}$$

As mentioned in the prior chapters, risk parity weights the single assets in a way, both contribute equally to the overall portfolio risk. Even if the allocation within a traditional 60/40 portfolio looks well-diversified in value-weighted terms, in risk-weighted terms, the portfolio risk is heavily weighted on the equity side. The following shows the asset- and risk allocation of typical 60/40 Portfolio:



In contrast, equally risk-weighted asset allocation shifts heavily to low-risk assets and only keeps a relatively small portion of the high-risk assets, demonstrated with the asset- and risk allocation of a sample risk parity portfolio:



To not diminishing returns, the model portfolio uses leverage to increase the respective asset weights. The maximum leverage is limited to 2 and the daily funding costs are calculated by dividing the annualized 1-month USD Libor rate by 252. The target weight of the asset classes results from the ratio between target portfolio volatility and realized volatility of the respective asset as seen in equation (10). With σ_E and σ_D = annualized standard deviation of the last 50 returns of the respective strategy, the actual asset weights can be calculated as follows:

$$\text{if } w_{TE} + w_{TFI} > 2 \ (\equiv max\ leverage) \rightarrow W_E = \frac{w_{TE}}{w_{TE}+w_{TFI}} \text{, and } W_{FI} = \frac{w_{TFI}}{w_{TE}+w_{FI}}$$

$$else\ W_E = \frac{w_{TE}}{w_{TE}+w_{TFI}} \bullet 2 \ (\equiv max\ leverage) \tag{11}$$

The daily portfolio return is then calculated by the weighted equity and fixed income return minus the implicit and explicit transaction costs.

$$r_P = W_E \bullet r_E + W_{FI} \bullet r_{FI} - funding\ costs - rebalancing\ costs \tag{12}$$

With *daily funding costs* = $\frac{1-month\ US\ Libor}{252}$ and *rebalancing costs = 10 bps*

4.5 Portfolio Statistics

The model portfolio achieves a Sharpe ratio of 1.40, compared to 0.43 of the 60/40 portfolio over the investigated period from January 2000 until October 2022 (Table 4). With a total return of 275%, it outshines the traditional portfolio by far, which just achieved 114% (Figure 4.1). And even though the current performance year-to-date, like the overall market, is experiencing a significant decline, the current measured portfolio risk of the systematic model remains with a 99%-VaR of 1.5% over the next ten days significantly lower than of the 60/40 portfolio, whose 99%-VaR is with 4.3% almost three times higher. The systematic trading model limits its volatility to a single digit number and decreases the maximum drawdown by more than 27% compared to the benchmark. The strategy is able to deliver consistent outperformance (Figure 4.2) with a remarkable annual alpha of more than 6.9%, while lowering the annualized volatility from 11.2% to 8.4% (Table 4). With a beta of only 0.27, an investor benefits additionally from the low correlation to the benchmark, which indicates a relative low market exposure. With a Jensen's Alpha of 7.9%, the model delivered significantly more return than predicted by the CAPM model. Particularly noteworthy is the robust performance during the financial crisis of 2007 to 2009, when the model managed to avoid the sharp declines in equity and high yield valuations (Figure 4.1), which came under selling pressure during that time, and subsequently benefited from the rapid decreases in interest rates and recovering high yield bond and equity prices. In the first phase of this crisis, US Treasuries were the best asset class, in which the model was also 100% invested at that time (Figure 4.3). US Treasuries are considered to be a safe haven when it comes to turmoil in financial markets. Hence, in uncertain times, this asset class is the best feasible option within our respective investment universe. Such safe havens are particularly beneficial when the market decline is prolonged, as in the case of an economic recession (IMF, 1999). These assets are predicted to retain its value or even increase in value, as they are either uncorrelated or negatively correlated to the overall economy (ECB, 2005).

After interest rates were lowered and asset purchasing programs were implemented by central banks, corporate bonds also recovered quickly, particularly high yield bonds. In 2009, when the crisis was starting to be over, a new upward trend in financial markets began and the systematic multi-asset model started to invest in risky assets again, initially in high-yield bonds and later in the year also in equities (Figure 4.3). The investigated period includes two full bull and bear markets, in which the model managed to be uninvested in equities during both the dotcom burst in 2001/02 and the financial crisis of 2007/08. As of the 20th of November, with an average year-to-date VIX of 26 (Figure 5), compared to 19 historically, there again is an elevated level of uncertainty in financial markets due to further financial tightening, persistently high inflation, and increasing concerns about recession (Figure 6). Since March, the model portfolio is fully invested in US government bonds, with no equity exposure (Figure 4.3), which resembles a cautious and conservative investment style and can be assessed as fully appropriate in the current market environment.

5. Results and Discussion

Motivated by existing evidence against the EMH, this thesis investigated whether outperforming can be done by incorporating trend-following and market risk assessments. Evidence shows that an investor can benefit from the non-normal distribution of stock returns by adding risk management tools such as a VaR-model. For momentum strategies in particular, this approach helps avoiding large declines, reducing volatility, improving risk-adjusted returns, and delivering more consistent performance (Kent, 2011). Moreover, with a risk-weighted asset allocation, performance can be made much more robust and is less susceptible to market turbulences and recessionary periods (Baltas et al., 2015). Therefore, this thesis shed light on the questions, if outperformance is possible at all and how an investor can identify an attractive risk-reward ratio based on the current market environment. Finally, this paper evaluates the portfolio performance across a variety of figures and metrices in absolute and relative terms. As seen in this work, the systematic multi-asset strategy delivers a significant better risk-reward than the traditional 60/40 portfolio, which investors had relied on for decades. This thesis showed that risk-controls, adaptive asset allocation and trend-following can work very well for an investor, who seeks to achieve better results than passive buy-and-hold strategies with index ETFs. More, this work provides strong evidence that even the most liquid financial markets cannot support the hypothesis of being fully efficient. Instead, for both equities and bonds, trends can be identified from past data that allow to outperform the market. The model presented in this paper can consistently outperform its benchmark, while reducing portfolio volatility and limiting drawdowns, thereby increasing the risk-reward for an investor significantly. Compared to the benchmark, the distribution function of the returns was significantly improved in all three strategies (Table 5 to 7).

6. Concluding Remarks

Systematic strategies allow investment decisions to be done in a methodological manner. Investment objectives, trading rules and model methodology are transparent and automated, allowing fast, cost-efficient, and rule-based trade execution. Systematic strategies benefit from the absence of psychological biases and the presence of adaptive dynamic and data-driven models. Even if quantitative investment strategies look very opaque from the outside and resemble a black box, in reality these models can be very transparent and investment decisions can be methodologically understood – in contrast to many discretionary approaches. In practice, many fund managers cannot beat their benchmark after costs. Instead, they underperform, delivering no real value for their investors. This thesis showed how relatively simple market-timing strategies already beat passive buy-and-hold strategies and the traditional 60/40 portfolio by both, limiting risk and generating steady excess return. When it comes to backtesting, a systematic investor needs to be aware of the fact that historical data cannot predict future results. However, to quote Mark Twain: “History never repeats itself, but it often rhymes”. The systematic model presented in this thesis applies a similar attitude to the validity of historical prices. Even though the weak form of the EMH already states that no outperformance can be achieved through historical data, the systematic portfolio shows something else, as it performs consistently better. Limitations of this work relate firstly to the level of transaction costs, which with 10 basis points are probably difficult for many private investors to achieve and are of course only an estimate of the true costs. These transaction costs refer to the bid/ask spread that occur for each transaction. On top of that, there might be additional brokerage costs, exchange fees, fund expenses or the like, if applicable. Furthermore, the implementation of an asset allocation strategy is difficult for many retail investors within their brokerage environment. However, in the meantime, many online brokers already offer direct API interfaces with Excel, Python or R, so it is only up to the investor's affinity for technology to implement such rule-based strategies. On the other hand, the use of leverage is not easily possible for many investors. Nevertheless, these are things that an investor can still fine-tune as they go along with their investment experiences and creditworthiness. As for further research, there are certainly many more trend-following and risk indicators for quantitative trading strategies, than only simple moving averages and a VaR figure based on historical data. This could for example involve the n-day price slope of an asset, a relative strength index (RSI), Bollinger bands or moving average convergence/divergence (MACD) ratios. Furthermore, the risk assessment could be improved by using a different VaR methodology with implicit volatility measured by option prices to achieve a forward-looking analysis, including a decay-factor, to exponentially weight past return, instead of equally. This would correspond to a parametric VaR (pVaR) instead of the historical VaR (hVaR) used in this work. Another extension of such systematic trading strategies could be to extent the investment universe beyond stocks and bonds, and add commodities, foreign currencies, cryptocurrencies, REITs, hedge funds, and other liquid alternative assets, to achieve further diversification benefits, higher risk-adjusted returns, and less drawdowns.

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8. Appendix

Tables

Table 1. Descriptive Statistics: S&P500 index returns

S&P500 daily log returns	
Mean	0.0181%
Standard Error	0.0161%
Median	0.06%
Mode	0
Standard Deviation	1.24%
Sample Variance	0.02%
Kurtosis	10.110
Skewness	-0.385
Range	23.72%
Minimum	-12.77%
Maximum	10.96%
Sum	107.89%
Count	5960
Confidence Level(95.0%)	0.032%

To better understand our dataset, daily logarithm returns of the S&P500 index are analysed for their characteristics, such as variability measures, distribution properties, and outlier detection. With mean and median, both positive, an investor can expect more positive, than negative days in the stock market. The returns show a leptokurtic distribution (Kurtosis = 10.1) with a negative skewness (Skewness = -0.385). In contrast to a Gaussian bell distribution, a leptokurtic distribution has tails that approach zero asymptotically more slowly, which results in more outliers than the normal distribution (Finner et al., 2009). A negatively skewed distribution of returns suggests that an investor may expect frequent modest profits and seldom large losses. Some investors favour negative skewness because they prefer stable profits above frequent losses. The possibility of enormous losses should not be disregarded, though, as it may cancel out any smaller gains. The range of daily fluctuations is wide with nearly 24%. The sample returns are from 1999:10 to 2022:11.

Table 2. Systematic Equity Model vs. Passive S&P500 Index Strategy

	Systematic Equity Model	S&P500 Buy-and-Hold
Annualized Return	7.4%	6.6%
Annualized SD	12.3%	19.8%
Total Return	170.14%	152.61%
Sharpe Ratio	0.60	0.33
Risk Reward Multiplier	1.81	1
Annual Alpha	0.8%	
Information Ratio	0.02	
Treynor Ratio	0.19	0.07
Jensen's Alpha	2.82%	0.00%
Beta	0.39	1.00
Tracking Error	0.10%	
Transaction Costs	10 bps	
Positive Months	75%	66%
Days not invested	28%	0%
VaR(0.99), 10d	-4.2%	-7.9%
Max. drawdown	-22.1%	-80.4%

In order to better relate the performance of a trading strategy and thus make it easier to interpret, we compare our systematic equity model with the performance of a S&P500 buy-and-hold strategy, and evaluate the results based on figures and ratios, which are explained in chapter 3.8 and 3.9. The rule-based approach to investing in the S&P500 achieves a SR of 0.56 compared to 0.33 of the buy-and-hold strategy, hence resulting in a better risk-reward. With a maximum drawdown of only -32.27%, the model is able to limit its downside risk far better than its benchmark, which lost temporarily -80.41% from its prior high. An investor can benefit from smart market-timing by avoiding high-volatile times and following upward trends, resulting in a post-fee alpha of 0.5% annually and a Jensen`s Alpha of 2.43%. An investor would not only have earned 10% more total return with this strategy, but also limit the risk significantly with an annual volatility to only 12.2%, instead of 19.8% with a passive strategy. With a beta of only 0.40, the model carries significantly lower systematic risk, resulting in a less volatile behaviour than the market. The sample returns are from 2000:1 to 2022:11.

Table 3. Systematic FI Strategy vs. Different Bond Index Strategies

	Systematic FI Model	US Treasuries	IG	HY	EM
Annualized Return	7.5%	3.4%	4.4%	5.7%	6.2%
Annualized SD	4.3%	4.6%	5.3%	5.1%	5.4%
Total Return	178%	81%	105%	134%	145%
Sharpe Ratio	1.77	0.74	0.83	1.12	1.14
Risk Reward Multiplier	2.39	1.00	1.12	1.50	1.54
Annual Alpha	4.1%	0.0%	1.0%	2.3%	2.8%
Information Ratio	0.11	0.00	0.01	-0.29	0.11
Treynor Ratio	0.21	0.03	0.05	-0.73	0.26
Jensen's Alpha	6.29%	0.00%	1.28%	5.96%	5.35%
Beta to Benchmark	0.37	1.00	0.92	-0.08	0.24
Tracking Error	0.18%	0.00%	0.05%	0.12%	0.15%
Transaction Costs	10 bps				
Positive Days	61%	52%	53%	61%	56%
VaR(0.99), 10d	-0.5%	-1.5%	-1.6%	-1.2%	-1.3%
Max. drawdown	-15%	-19%	-23%	-44%	-37%

To evaluate the systematic fixed income trading strategy, we compare its performance with different bond classes, including US treasuries, US investment grade, US high yield and US-denominated emerging markets debt. Benchmark for the systematic fixed income model is the Bloomberg US Treasury total return index (Ticker: LUATTRUU, ISIN: IE00B44CND37). The systematic strategy achieves the best performance in terms of risk-reward with the highest SR of 1.77. With an annual alpha of 4.1% and a total return of 178%, the strategy outperforms its benchmark significantly, while bearing the less risk. The sample returns are from 2000:1 to 2022:11.

Table 4. Systematic Multi-Asset Strategy vs. Traditional 60/40 Portfolio

	Systematic Multi-Asset Portfolio	60/40 Portfolio
Annualized Return	11.7%	4.8%
Annualized Volatility	8.4%	11.2%
Total Return	275%	114%
Sharpe Ratio	1.40	0.43
Risk Reward Multiplier	3.28	1.00
Annual Alpha	6.91%	
Information Ratio	0.26	
Treynor Ratio	0.43	0.05
Jensen's Alpha	7.92%	0.00%
Beta	0.27	1.00
Tracking Error	0.58%	0.00%
Positive Months	68%	65%
VaR(0.99), 10d	-1.5%	-4.3%
Max. drawdown	-30.9%	-42.5%

The combined systematic multi-asset portfolio achieves the best performance improvement with a Sharpe Ratio of 1.40, which is 3.28 times higher than the benchmarks Sharpe Ratio of 0.43. The strategy achieves an annual outperformance of 6.9% and a total return more than twice as much as the benchmark, while volatility is reduced from 11.2% to 8.4%. At the same time, with a beta of only 0.26, the systematic strategy is associated with much lower systematic risk and relatively low dependence on the market behaviour. The systematic multi-asset portfolio delivers a Jensen’s alpha of almost 8% annually, while carrying significantly lower risk with 10-day VaR of only 1.6% versus 4.3% and a maximum drawdown which is almost 12% compared to the benchmark.

Table 5. Descriptive Statistics: S&P500 vs the Systematic Equity Strategy

S&P500 Index: daily log returns		**Systematic Equity Strategy**	
Mean	0.0256%	Mean	0.0285%
Standard Error	0.0161%	Standard Error	0.0099%
Median	0.07%	Median	0.00%
Mode	0	Mode	0
Standard Deviation	1.245%	Standard Deviation	0.767%
Sample Variance	0.01550%	Sample Variance	0.00588%
Kurtosis	10.104	Kurtosis	8.658
Skewness	-0.383	Skewness	-0.705
Range	23.72%	Range	12.66%
Minimum	-12.76%	Minimum	-7.99%
Maximum	10.96%	Maximum	4.67%
Sum	152%	Sum	170%
Count	5960	Count	5960
Confidence Level(99.	0.042%	Confidence Level(99.	0.026%

The daily logarithm returns of the systematic equity strategy are compared to the S&P500 returns, to better understand the improvement through the market timing strategy. A higher mean, together with a lower standard deviation already present a significant improvement in the performance. With a less leptokurtic distribution (Kurtosis = 8.658) than the buy-and-hold strategy and with an even more negatively skewed distribution (Skewness = -0.705), the systematic model has not only less fat-fails, but also more stable returns. The variance can be significantly reduced, making the dispersion of returns around their average much smaller and thus returns more stable and reliable, with a narrower possible range. This range can be almost halved with reducing the range from the minimum to the maximum return from 23.72% to only 12.66%. The sample returns are from 1999:10 to 2022:11.

Table 6. Descriptive Statistics: US Treasury vs. Systematic Fixed Income Strategy

Bloomberg US Treasury TR Index		Systematic Fixed Income Strategy	
Mean	0.010%	Mean	0.030%
Standard Error	0.004%	Standard Error	0.003%
Median	0.008%	Median	0.039%
Mode	0	Mode	0
Standard Deviation	0.2817%	Standard Deviation	0.2684%
Sample Variance	0.0008%	Sample Variance	0.0007%
Kurtosis	2.47	Kurtosis	42.89
Skewness	-0.43	Skewness	-2.36
Range	2.94%	Range	7.53%
Minimum	-1.92%	Minimum	-5.44%
Maximum	1.02%	Maximum	2.09%
Sum	61.04%	Sum	177.66%
Count	5945	Count	5945
Confidence Level(95.0%)	0.0072%	Confidence Level(95.0%)	0.0068%

The systematic fixed income strategy delivers a three times higher average daily return, while decreasing the standard deviation compared to the Bloomberg US treasury index. The return range widens as the systematic strategy also invests corporate bonds, which carry higher risk. Due to the higher kurtosis, an investor will probably experience more extreme returns, fat-tails, compared to the treasury index. The skewness can be further reduced to -2.36, giving investors more frequent small gains with few large losses. The variance could not be reduced much. However, as kurtosis increases strongly from only 2.47 to 42.89, partly caused by the wider range of historical returns, this indicates a potentially higher risk. Therefore, this risk compensation could be one of the explanations for the tripling of the daily average return.

The sample returns are from 1999:10 to 2022:10.

Table 7. Descriptive Statistics: 60/40 Portfolio vs. Systematic Multi-Asset Portfolio

60/40 Portfolio		Systematic Multi-Asset Portfolio	
Mean	0.019%	Mean	0.046%
Standard Error	0.009%	Standard Error	0.007%
Median	0.027%	Median	0.065%
Mode	0	Mode	0
Standard Deviation	0.7084%	Standard Deviation	0.5255%
Sample Variance	0.0050%	Sample Variance	0.0028%
Kurtosis	10.83	Kurtosis	46.27
Skewness	-0.36	Skewness	-2.90
Range	13.56%	Range	14.02%
Minimum	-6.99%	Minimum	-10.90%
Maximum	6.57%	Maximum	3.13%
Sum	114.01%	Sum	275.21%
Count	5945	Count	5945
Confidence Level(99.0%)	0.0237%	Confidence Level(99.0%)	0.0176%

The systematic risk parity model delivers more than twice the daily returns (net of fees) while the standard deviation is notably reduced compared to the traditional 60/40 portfolio (60% S&P 500 ETF & 40% US Treasury ETF). The kurtosis can be increased, leading to a more leptokurtic distribution, hence lower overall variance. The distribution gets more negatively skewed, leading to more frequent positive returns and less outliners. The sample returns are from 1999:10 to 2022:11.

Table 8.1. Systematic Equity Index Strategy Monthly Performance

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	-5.15%	0.00%	0.00%	0.00%	1.82%	-2.47%	2.61%	1.50%	0.00%	0.00%	-3.66%	2.34%	-0.36%	5.05%	-3.52%	-3.05%	-8.36%	1.88%	5.57%	0.00%	-0.04%	-1.01%	-5.31%
2	-1.91%	0.00%	0.00%	0.00%	1.38%	2.08%	0.27%	-1.98%	0.00%	0.00%	3.05%	3.37%	4.23%	1.35%	4.47%	5.59%	0.00%	3.89%	-3.76%	0.00%	-8.59%	2.72%	-3.04%
3	9.33%	0.00%	0.00%	0.00%	-1.52%	-1.79%	1.24%	1.11%	0.00%	0.00%	5.86%	0.04%	3.24%	3.68%	0.84%	-1.59%	0.00%	0.12%	-2.57%	0.00%	-7.34%	4.29%	-2.70%
4	-3.05%	0.00%	-4.47%	0.00%	-1.58%	-1.91%	1.33%	4.33%	0.00%	0.00%	1.57%	2.92%	-0.63%	1.91%	0.74%	0.95%	-1.78%	1.02%	0.38%	3.97%	0.00%	5.20%	0.00%
5	-2.07%	0.00%	1.42%	1.94%	1.36%	3.13%	-2.92%	3.43%	0.00%	0.00%	-8.32%	-1.14%	-6.20%	2.31%	2.32%	1.28%	1.78%	1.40%	2.38%	-6.57%	0.00%	0.70%	0.00%
6	2.44%	0.00%	0.00%	1.27%	1.93%	0.14%	0.14%	-1.68%	0.00%	0.06%	-5.38%	-1.68%	4.04%	-1.35%	2.04%	-1.95%	0.26%	0.62%	0.61%	6.81%	0.00%	2.31%	0.00%
7	-1.58%	0.00%	0.00%	1.75%	-3.37%	3.65%	-0.16%	-3.15%	0.00%	7.29%	2.78%	-2.05%	1.38%	4.96%	-1.39%	2.07%	3.62%	2.04%	3.65%	1.43%	2.83%	2.35%	0.00%
8	6.03%	0.00%	0.00%	1.93%	0.40%	-0.92%	2.91%	1.49%	0.00%	3.55%	0.00%	-7.85%	2.23%	-2.94%	3.92%	-6.22%	0.14%	0.31%	3.21%	-1.60%	6.94%	3.00%	0.00%
9	-5.42%	0.00%	0.00%	-1.07%	1.08%	0.81%	2.54%	3.67%	0.00%	3.66%	0.00%	0.00%	2.55%	3.09%	-1.41%	-1.15%	0.02%	2.04%	0.57%	1.85%	-3.87%	-4.76%	0.00%
10	-0.42%	0.00%	0.00%	5.50%	1.52%	-1.68%	3.21%	1.58%	0.00%	-1.88%	0.38%	0.00%	-1.86%	4.49%	2.41%	0.00%	-1.84%	2.31%	-7.08%	2.14%	-2.70%	6.77%	0.00%
11	-0.27%	0.00%	0.00%	0.88%	3.97%	3.71%	1.88%	-4.27%	0.00%	5.83%	0.01%	0.00%	0.58%	3.00%	2.65%	0.00%	3.64%	3.02%	2.02%	3.57%	10.39%	-0.70%	0.00%
12	0.00%	0.00%	0.00%	5.11%	3.35%	0.03%	1.39%	-0.11%	0.00%	1.91%	6.47%	0.00%	0.91%	2.50%	-0.25%	-0.16%	1.96%	1.11%	-4.07%	2.97%	3.77%	4.38%	0.00%
annual return	-2%	0%	-3%	17%	10%	5%	14%	6%	0%	20%	3%	-4%	10%	28%	13%	-4%	-1%	20%	1%	15%	1%	25%	-11%
standard deviation	15%	0%	5%	7%	7%	8%	6%	10%	0%	10%	15%	10%	10%	8%	8%	10%	11%	4%	13%	12%	19%	11%	6%
Sharpe ratio	-0.14	0.00	-0.63	2.46	1.42	0.61	2.44	0.62	0.00	2.11	0.18	-0.40	1.00	3.35	1.56	-0.42	-0.05	5.11	0.07	1.27	0.07	2.31	-1.80
Positive Months	25%	0%	8%	58%	75%	58%	83%	58%	0%	50%	58%	33%	67%	83%	67%	33%	58%	100%	67%	67%	33%	75%	0%

Table 8.2. S&P500 Total Return Index: Monthly Performance

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	-5.15%	3.49%	-1.47%	-2.65%	1.82%	-2.47%	2.61%	1.50%	-6.19%	-8.81%	-3.66%	2.34%	4.38%	5.05%	-3.52%	-3.05%	-5.09%	1.88%	5.57%	7.71%	-0.04%	-1.01%	-5.31%
2	-1.91%	-9.56%	-1.95%	-1.51%	1.38%	2.08%	0.27%	-1.98%	-3.30%	-11.26%	3.05%	3.37%	4.23%	1.35%	4.47%	5.59%	-0.14%	3.89%	-3.76%	3.16%	-8.59%	2.72%	-3.04%
3	9.33%	-6.54%	3.69%	0.97%	-1.52%	-1.79%	1.24%	1.11%	-0.43%	8.40%	5.86%	0.04%	3.24%	3.68%	0.84%	-1.59%	6.56%	0.12%	-2.57%	1.92%	-13.18%	4.29%	3.65%
4	-3.05%	7.48%	-6.25%	7.92%	-1.58%	-1.91%	1.33%	4.33%	4.76%	9.14%	1.57%	2.92%	-0.63%	1.91%	0.74%	0.95%	0.39%	1.02%	0.38%	3.97%	12.06%	5.20%	-9.12%
5	-2.07%	0.67%	-0.74%	5.13%	1.36%	3.13%	-2.92%	3.43%	1.29%	5.44%	-8.32%	-1.14%	-6.20%	2.31%	2.32%	1.28%	1.78%	1.40%	2.38%	-6.57%	4.65%	0.70%	0.18%
6	2.44%	-2.46%	-7.39%	1.27%	1.93%	0.14%	0.14%	-1.68%	-8.81%	0.20%	-5.38%	-1.68%	4.04%	-1.35%	2.04%	-1.95%	0.26%	0.62%	0.61%	6.81%	1.97%	2.31%	-8.62%
7	-1.58%	-0.99%	-8.12%	1.75%	-3.37%	3.65%	0.62%	-3.15%	-0.84%	7.29%	6.77%	-2.05%	1.38%	4.96%	-1.39%	2.07%	3.62%	2.04%	3.65%	1.43%	5.49%	2.35%	8.82%
8	6.03%	-6.47%	0.66%	1.93%	0.40%	-0.92%	2.35%	1.49%	1.44%	3.55%	-4.62%	-5.59%	2.23%	-2.94%	3.92%	-6.22%	0.14%	0.31%	3.21%	-1.60%	6.94%	3.00%	-4.16%
9	-5.42%	-8.42%	-11.51%	-1.07%	1.08%	0.81%	2.54%	3.67%	-9.33%	3.66%	8.55%	-7.29%	2.55%	3.09%	-1.41%	-2.51%	0.02%	2.04%	0.57%	1.85%	-3.87%	-4.76%	-9.66%
10	-0.42%	1.89%	8.44%	5.50%	1.52%	-1.68%	3.21%	1.58%	-18.39%	-1.88%	3.73%	10.37%	-1.86%	4.49%	2.41%	8.10%	-1.84%	2.31%	-7.08%	2.14%	-2.70%	6.77%	7.79%
11	-8.21%	7.39%	5.72%	0.88%	3.97%	3.71%	1.88%	-4.27%	-7.45%	5.83%	0.01%	-0.22%	0.58%	3.00%	2.65%	0.30%	3.64%	3.02%	2.02%	3.57%	10.39%	-0.70%	5.44%
12	0.49%	0.87%	-6.05%	5.11%	3.35%	0.03%	1.39%	-0.70%	1.06%	1.91%	6.47%	1.02%	0.91%	2.50%	-0.25%	-1.59%	1.96%	1.11%	-9.46%	2.97%	3.77%	4.38%	0.00%
annual return	-10%	-13%	-25%	25%	10%	5%	15%	5%	-46%	23%	14%	2%	15%	28%	13%	1%	11%	20%	-4%	27%	17%	25%	-14%
standard deviation	17%	20%	21%	11%	7%	8%	6%	10%	22%	22%	19%	16%	11%	8%	8%	13%	10%	4%	16%	13%	26%	11%	23%
Sharpe ratio	-0.56	-0.63	-1.19	2.27	1.42	0.61	2.61	0.55	-2.07	1.05	0.73	0.13	1.40	3.35	1.56	0.10	1.11	5.11	-0.29	2.14	0.65	2.31	-0.62
Positive Months	33%	50%	33%	75%	75%	58%	92%	58%	33%	75%	67%	50%	75%	83%	67%	50%	75%	100%	67%	83%	58%	75%	42%

Table 9.1. Systematic Fixed-Income Strategy: Monthly Performance:

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	-0.16%	3.67%	0.69%	3.28%	1.89%	-0.13%	1.58%	1.11%	2.51%	-2.96%	1.26%	2.18%	2.99%	1.33%	0.70%	2.55%	2.11%	1.44%	0.60%	1.23%	0.03%	0.33%	-2.01%
2	0.19%	1.32%	-1.62%	1.23%	-0.25%	1.46%	0.67%	1.39%	1.13%	-0.53%	0.17%	1.30%	2.35%	0.51%	2.00%	-0.08%	0.89%	1.44%	-2.36%	1.65%	-1.42%	0.37%	-0.66%
3	1.04%	-2.38%	1.42%	2.84%	0.68%	-2.95%	0.60%	0.11%	0.69%	2.16%	3.09%	0.32%	-0.14%	1.01%	0.24%	-0.55%	-1.79%	-0.22%	-0.46%	0.94%	-4.96%	0.15%	-3.16%
4	-0.32%	-2.51%	1.55%	5.76%	-0.68%	-0.51%	0.61%	1.29%	0.37%	5.98%	2.32%	1.54%	1.04%	1.79%	0.63%	1.20%	3.84%	1.15%	-0.18%	1.41%	0.63%	1.08%	-3.15%
5	0.15%	1.78%	-0.52%	1.03%	-2.14%	1.58%	-0.01%	0.74%	0.36%	6.51%	-3.66%	0.49%	-1.31%	-0.58%	0.92%	0.30%	0.62%	0.87%	-0.75%	-1.20%	-0.25%	0.30%	0.18%
6	1.67%	-3.50%	-6.56%	2.84%	1.42%	1.94%	-0.35%	-1.81%	-1.14%	2.82%	1.24%	-0.98%	2.09%	-3.31%	0.83%	-1.50%	0.92%	0.14%	0.40%	2.25%	-0.42%	1.33%	-0.88%
7	0.66%	2.71%	2.34%	-1.11%	1.35%	1.73%	0.97%	-0.58%	0.42%	5.91%	3.49%	1.15%	1.88%	1.88%	-1.34%	-0.31%	2.67%	1.10%	1.09%	0.56%	4.58%	0.38%	1.58%
8	0.68%	1.17%	2.14%	1.14%	1.94%	0.19%	1.61%	1.56%	1.24%	1.85%	0.04%	-3.07%	1.16%	-0.61%	1.57%	0.04%	2.07%	-0.04%	0.74%	0.40%	0.95%	0.51%	-2.51%
9	-0.88%	-4.45%	2.66%	2.70%	1.44%	-1.00%	1.41%	1.11%	0.61%	5.54%	2.97%	1.73%	1.38%	0.99%	-2.26%	0.87%	0.66%	0.89%	0.56%	0.36%	-1.03%	-0.01%	-3.51%
10	0.21%	2.73%	-1.11%	2.00%	1.79%	-1.12%	1.35%	0.60%	-0.11%	1.78%	2.55%	-2.01%	0.87%	2.47%	1.00%	-0.37%	0.39%	0.42%	-1.61%	0.28%	0.51%	-0.17%	-0.93%
11	2.03%	-2.96%	-1.14%	1.50%	1.20%	0.52%	1.67%	0.13%	5.17%	1.00%	-1.17%	-0.95%	0.80%	0.51%	-0.23%	-0.41%	-0.48%	-0.26%	-0.03%	0.33%	3.88%	-0.98%	0.00%
12	1.89%	-0.41%	1.39%	2.24%	1.48%	0.86%	1.09%	0.08%	3.33%	3.23%	1.80%	1.07%	1.56%	0.54%	0.14%	-0.16%	1.83%	0.30%	2.13%	1.98%	1.86%	1.86%	0.00%
annual return	7%	-3%	1%	25%	10%	3%	11%	6%	15%	33%	14%	3%	15%	7%	4%	2%	14%	7%	0%	10%	4%	5%	-15%
standard deviation	3%	10%	9%	6%	4%	5%	2%	3%	6%	10%	7%	6%	4%	5%	4%	4%	5%	2%	4%	3%	9%	3%	6%
Sharpe ratio	2.27	-0.29	0.14	4.47	2.34	0.51	4.96	1.70	2.48	3.34	1.97	0.49	3.71	1.24	1.02	0.45	2.67	3.35	0.03	3.14	0.51	2.02	-2.71
Positive Months	75%	50%	58%	92%	75%	58%	83%	83%	83%	83%	83%	67%	83%	75%	75%	42%	83%	75%	50%	92%	58%	75%	17%

Table 9.2. US Treasury TR index: Quarterly Performance

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	0.26%	0.81%	0.67%	-0.30%	0.85%	0.73%	-0.30%	-0.16%	2.51%	-2.96%	1.57%	-0.02%	0.42%	-0.81%	1.35%	2.55%	2.11%	0.23%	-1.37%	0.47%	2.41%	-0.96%	-1.91%
2	1.49%	1.20%	0.90%	1.71%	1.23%	-0.82%	0.15%	1.64%	1.13%	-0.53%	0.39%	-0.07%	-0.71%	0.53%	0.27%	-1.56%	0.89%	0.49%	-0.76%	-0.27%	2.62%	-1.83%	-0.66%
3	1.97%	0.32%	-2.44%	-0.42%	0.93%	-0.33%	-1.08%	-0.05%	0.69%	2.16%	-0.85%	-0.06%	-1.01%	0.10%	-0.29%	0.63%	0.16%	-0.05%	0.94%	1.89%	2.85%	-1.55%	-3.16%
4	-0.32%	-1.25%	2.46%	0.46%	-3.27%	1.74%	-0.41%	0.51%	-1.73%	-1.84%	1.04%	1.15%	1.44%	0.89%	0.55%	-0.53%	-0.11%	0.69%	-0.81%	-0.28%	0.63%	0.75%	-3.15%
5	0.15%	0.31%	0.56%	2.84%	-0.34%	1.21%	0.03%	-0.90%	-1.17%	-1.01%	1.70%	1.55%	1.70%	-1.72%	0.94%	-0.18%	0.00%	0.65%	0.89%	2.32%	-0.25%	0.34%	0.18%
6	1.67%	0.54%	1.40%	-0.61%	0.40%	0.61%	0.32%	-0.04%	0.78%	-0.21%	1.84%	-0.34%	-0.35%	-1.11%	-0.14%	-0.89%	2.18%	-0.16%	0.02%	0.92%	0.09%	0.64%	-0.88%
7	1.02%	2.46%	2.34%	-4.49%	0.95%	-1.37%	1.23%	1.64%	0.42%	0.42%	0.68%	1.81%	1.00%	-0.11%	-0.16%	0.83%	0.40%	0.17%	-0.42%	-0.12%	1.14%	1.35%	1.58%
8	1.46%	1.32%	2.14%	0.59%	2.05%	1.58%	1.46%	1.56%	1.24%	0.89%	1.99%	2.74%	-0.13%	-0.49%	1.05%	0.04%	-0.55%	1.08%	0.76%	3.34%	-1.10%	-0.18%	-2.51%
9	0.08%	1.57%	2.66%	2.97%	0.26%	-1.34%	0.92%	0.54%	0.61%	0.78%	0.02%	1.73%	-0.31%	0.70%	-0.55%	0.87%	-0.13%	-0.86%	-0.94%	-0.85%	0.14%	-1.09%	-3.51%
10	0.97%	2.73%	-1.11%	-1.54%	0.79%	-0.79%	0.51%	0.78%	-0.11%	-0.05%	-0.16%	-0.82%	-0.17%	0.48%	0.97%	-0.37%	-1.11%	-0.12%	-0.48%	0.07%	-0.95%	-0.07%	-0.93%
11	2.03%	-2.51%	-1.00%	0.12%	-1.35%	0.48%	1.04%	3.02%	5.17%	1.38%	-0.70%	0.74%	0.52%	-0.33%	0.80%	-0.41%	-2.70%	-0.14%	0.88%	-0.30%	0.35%	0.76%	0.00%
12	1.89%	-0.98%	2.57%	0.88%	0.99%	1.03%	-0.83%	0.08%	3.33%	-2.65%	-1.82%	0.96%	-0.44%	-0.91%	0.14%	-0.16%	-0.11%	0.31%	2.13%	-0.56%	-0.23%	-0.51%	0.00%
annual return	13%	7%	11%	2%	3%	3%	3%	9%	13%	-4%	6%	9%	2%	-3%	5%	1%	1%	2%	1%	7%	8%	-2%	-15%
standard deviation	3%	5%	6%	7%	5%	4%	3%	4%	7%	5%	4%	4%	3%	3%	2%	4%	5%	2%	4%	5%	5%	3%	6%
Sharpe ratio	4.43	1.24	1.91	0.32	0.72	0.71	1.07	2.31	1.97	-0.66	1.36	2.54	0.66	-1.00	2.31	0.23	0.23	1.30	0.24	1.46	1.65	-0.67	-2.70
Positive Months	92%	75%	75%	58%	75%	58%	67%	67%	75%	42%	67%	58%	42%	42%	67%	42%	42%	58%	50%	50%	67%	42%	17%

Table 10.1. Traditional 60/40 Portfolio: Monthly Performance:

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	-2.21%	2.42%	-0.61%	-1.71%	1.43%	-1.19%	1.45%	0.84%	-2.71%	-6.47%	-1.57%	1.40%	2.80%	2.71%	-1.57%	-0.81%	-2.21%	1.22%	2.79%	4.81%	0.94%	-0.99%	-3.95%
2	-0.55%	-5.26%	-0.81%	-0.22%	1.32%	0.92%	0.22%	-0.53%	-1.53%	-6.97%	1.99%	1.99%	2.25%	1.02%	2.79%	2.73%	0.27%	2.53%	-2.56%	1.79%	-4.11%	0.90%	-2.09%
3	6.39%	-3.80%	1.24%	0.41%	-0.54%	-1.20%	0.31%	0.65%	0.02%	5.90%	3.18%	0.00%	1.54%	2.25%	0.39%	-0.70%	4.00%	0.05%	-1.17%	1.91%	-6.77%	1.95%	0.92%
4	-1.96%	3.99%	-2.77%	4.93%	-2.26%	-0.45%	0.63%	2.81%	2.16%	4.75%	1.36%	2.21%	0.20%	1.50%	0.66%	0.36%	0.19%	0.89%	-0.10%	2.27%	7.49%	3.42%	-6.73%
5	-1.18%	0.53%	-0.22%	4.22%	0.68%	2.37%	-1.74%	1.70%	0.30%	2.86%	-4.31%	-0.06%	-3.04%	0.70%	1.77%	0.69%	1.07%	1.10%	1.79%	-3.01%	2.69%	0.56%	0.18%
6	2.13%	-1.26%	-3.87%	0.52%	1.32%	0.33%	0.21%	-1.02%	-4.97%	0.03%	-2.49%	-1.14%	2.28%	-1.25%	1.17%	-1.53%	1.03%	0.31%	0.38%	4.45%	1.22%	1.64%	-5.52%
7	-0.54%	0.39%	-3.93%	-0.75%	-1.64%	1.64%	0.86%	-1.23%	-0.34%	4.54%	4.33%	-0.51%	1.23%	2.93%	-0.90%	1.58%	2.33%	1.29%	2.02%	0.81%	3.75%	1.95%	5.92%
8	4.20%	-3.35%	1.25%	1.40%	1.06%	0.08%	1.99%	1.51%	1.36%	2.48%	-1.98%	-2.26%	1.28%	-1.96%	2.77%	-3.72%	-0.14%	0.61%	2.23%	0.38%	3.72%	1.73%	-3.50%
9	-3.22%	-4.42%	-5.84%	0.55%	0.75%	-0.05%	1.90%	2.42%	-5.36%	2.51%	5.14%	-3.68%	1.41%	2.13%	-1.07%	-1.15%	-0.04%	0.88%	-0.03%	0.77%	-2.27%	-3.29%	-7.20%
10	0.13%	2.23%	4.62%	2.69%	1.23%	-1.32%	2.13%	1.26%	-11.08%	-1.14%	2.18%	5.90%	-1.19%	2.89%	1.84%	4.71%	-1.55%	1.34%	-4.44%	1.31%	-2.00%	4.03%	1.00%
11	-4.12%	3.43%	3.03%	0.58%	1.84%	2.42%	1.55%	-1.35%	-2.40%	4.05%	-0.27%	0.16%	0.55%	1.67%	1.91%	0.01%	1.10%	1.76%	1.56%	2.02%	6.37%	-0.11%	0.00%
12	1.05%	0.13%	-2.61%	3.42%	2.40%	0.43%	0.51%	-0.39%	1.97%	0.09%	3.16%	1.00%	0.37%	1.14%	-0.09%	-1.02%	1.13%	0.79%	-4.83%	1.56%	2.17%	2.42%	0.00%
annual ret	0.1%	-5.0%	-10.5%	16.0%	7.6%	4.0%	10.0%	6.7%	-22.6%	12.6%	10.7%	5.0%	9.7%	15.7%	9.7%	1.2%	7.2%	12.8%	-2.3%	19.1%	13.2%	14.2%	-21.0%
std dev	10.6%	11.0%	10.7%	7.1%	4.9%	4.5%	3.7%	5.0%	13.2%	14.5%	10.3%	8.4%	5.6%	5.4%	5.1%	7.6%	5.6%	2.3%	8.9%	6.9%	14.6%	6.9%	13.2%
IS	0.0%	-45.2%	-98.6%	225.5%	156.3%	87.8%	267.5%	133.8%	-171.0%	87.0%	103.8%	59.5%	172.6%	292.1%	188.1%	15.4%	127.3%	562.0%	-26.3%	277.4%	90.3%	206.7%	-158.6%
Positive Months	41.7%	58.3%	33.3%	75.0%	75.0%	58.3%	91.7%	58.3%	41.7%	75.0%	58.3%	50.0%	83.3%	83.3%	66.7%	50.0%	66.7%	100.0%	50.0%	91.7%	66.7%	75.0%	33.3%

Table 10.2. Traditional 60/40 Portfolio: Quarterly Performance

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Q1	3.63%	-6.64%	-0.18%	-1.53%	2.21%	-1.47%	1.98%	0.96%	-4.22%	-7.53%	3.59%	3.39%	6.59%	5.97%	1.61%	1.22%	2.06%	3.80%	-0.93%	8.51%	-9.94%	1.86%	-5.12%
Q2	-1.01%	3.25%	-6.86%	9.67%	-0.26%	2.24%	-0.90%	3.48%	-2.51%	7.64%	-5.45%	1.00%	-0.56%	0.94%	3.60%	-0.47%	2.29%	2.30%	2.07%	3.71%	11.40%	5.61%	-12.07%
Q3	0.44%	-7.38%	-8.52%	1.20%	0.17%	1.67%	4.75%	2.70%	-4.34%	9.53%	7.50%	-6.45%	3.92%	3.11%	0.81%	-3.29%	2.16%	2.78%	4.22%	1.96%	5.20%	0.38%	-4.78%
Q4	-2.93%	5.79%	5.04%	6.68%	5.47%	1.53%	4.18%	-0.48%	-11.51%	2.99%	5.06%	7.06%	-0.26%	5.69%	3.65%	3.71%	0.69%	3.88%	-7.70%	4.89%	6.55%	6.35%	1.00%
Positive Quarters		50%	25%	75%	75%	75%	75%	75%	0%	75%	75%	75%	50%	100%	100%	50%	100%	100%	50%	100%	75%	100%	25%

Table 11.1. Systematic Multi-Asset Portfolio: Monthly Performance

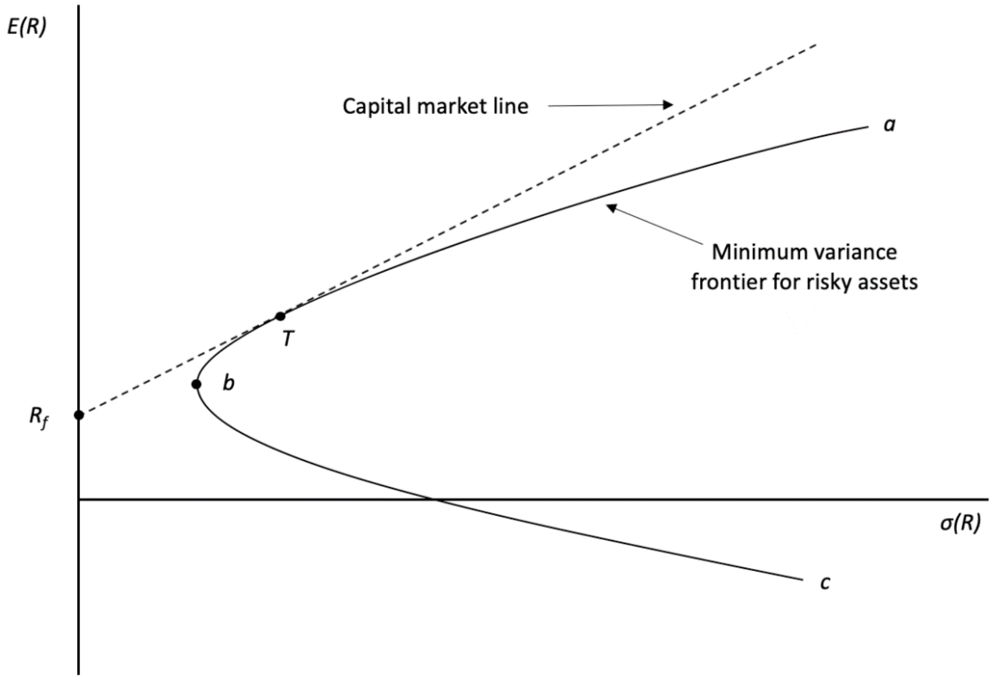
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
1	0.63%	6.58%	0.46%	5.42%	3.65%	-0.96%	3.17%	2.34%	3.49%	-3.46%	0.46%	3.70%	3.92%	3.66%	0.26%	2.65%	-1.34%	2.43%	3.21%	1.88%	-0.15%	0.01%	-5.13%
2	1.09%	1.88%	-3.24%	2.45%	0.18%	3.11%	1.21%	1.66%	0.53%	-0.57%	1.00%	2.66%	6.21%	1.16%	4.42%	1.89%	0.98%	3.46%	-5.50%	2.26%	-4.96%	1.18%	-2.52%
3	4.57%	-4.38%	2.85%	5.67%	0.01%	-5.48%	1.39%	0.57%	0.46%	2.42%	6.74%	-0.17%	1.25%	2.72%	0.50%	-1.76%	-3.43%	-1.22%	-1.78%	0.83%	-9.81%	1.11%	-5.27%
4	-1.46%	-5.02%	-1.86%	11.50%	-1.56%	-1.86%	1.44%	3.53%	0.33%	5.48%	3.62%	2.92%	1.26%	3.33%	1.19%	1.98%	3.06%	1.81%	-0.59%	3.84%	0.38%	3.13%	-3.52%
5	-0.38%	3.57%	-0.90%	1.89%	-2.95%	3.79%	-0.90%	1.88%	0.17%	5.70%	-9.58%	0.12%	-4.34%	-0.78%	1.87%	0.64%	1.85%	1.26%	-1.20%	-4.03%	-0.18%	0.56%	-0.26%
6	3.44%	-6.90%	-10.90%	5.22%	3.10%	2.84%	-0.44%	-3.44%	-2.32%	2.74%	-0.33%	-2.47%	4.81%	-5.79%	1.55%	-3.42%	0.34%	-0.19%	0.36%	5.77%	-0.21%	2.84%	-1.58%
7	0.65%	4.82%	2.17%	-0.93%	-0.18%	4.43%	1.61%	-2.64%	0.64%	11.57%	4.92%	1.04%	3.29%	5.51%	-3.02%	-0.32%	5.38%	1.97%	2.58%	1.45%	7.33%	1.35%	1.65%
8	2.97%	1.99%	1.74%	2.34%	3.42%	-0.11%	3.61%	2.85%	1.95%	3.91%	-0.57%	-8.08%	2.56%	-2.71%	3.90%	-3.32%	2.69%	-0.44%	2.05%	-0.09%	6.25%	1.75%	-2.65%
9	-3.13%	-10.13%	2.79%	3.51%	2.77%	-1.46%	2.91%	3.17%	1.43%	9.96%	4.40%	2.04%	2.68%	2.96%	-4.25%	0.68%	0.04%	1.70%	0.61%	1.15%	-3.62%	-1.47%	-4.41%
10	-0.12%	1.64%	-1.51%	5.51%	3.63%	-2.22%	3.17%	1.30%	0.12%	1.92%	3.84%	-2.74%	0.51%	5.36%	2.10%	-0.93%	-0.66%	0.92%	-5.69%	1.05%	0.03%	1.45%	-1.05%
11	3.32%	-1.80%	-1.63%	2.39%	2.93%	2.32%	3.27%	-1.36%	4.20%	3.86%	-2.22%	-1.37%	1.14%	1.67%	0.52%	-0.91%	0.13%	0.45%	-0.05%	1.47%	9.70%	-0.93%	0.00%
12	3.06%	-0.60%	1.92%	5.02%	3.32%	1.40%	2.27%	-0.38%	3.12%	6.06%	4.89%	1.74%	2.82%	1.57%	-0.09%	-1.49%	3.28%	0.64%	2.21%	4.27%	4.47%	4.45%	0.00%
Annual Return	15%	-8%	-8%	50%	18%	6%	23%	9%	14%	50%	17%	-1%	26%	19%	9%	-4%	12%	13%	-4%	20%	9%	15%	-25%
Annual Stdev.	8%	18%	13%	11%	8%	10%	5%	8%	6%	14%	15%	11%	9%	11%	9%	7%	8%	5%	10%	8%	19%	6%	8%
Sharpe Ratio	0.00	-0.48	-0.61	4.74	2.30	0.56	4.48	1.19	2.28	3.47	1.12	-0.05	2.86	1.64	1.04	-0.62	1.50	2.80	-0.38	2.34	0.48	2.66	-3.20
Positive Months	67%	50%	50%	92%	75%	50%	83%	67%	92%	83%	67%	58%	92%	75%	75%	42%	75%	75%	50%	83%	50%	83%	8%

Table 11.2. Systematic Multi-Asset Portfolio: Quarterly Performance

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Q1	6.3%	4.1%	0.1%	13.5%	3.8%	-3.3%	5.8%	4.6%	4.5%	-1.6%	8.2%	6.2%	11.4%	7.5%	5.2%	2.8%	-3.8%	4.7%	-4.1%	5.0%	-14.9%	2.3%	-12.9%
Q2	1.6%	-8.3%	-13.7%	18.6%	-1.4%	4.8%	0.1%	2.0%	-1.8%	13.9%	-6.3%	0.6%	1.7%	-3.2%	4.6%	-0.8%	5.2%	2.9%	-1.4%	5.6%	0.0%	6.5%	-5.4%
Q3	0.5%	-3.3%	6.7%	4.9%	6.0%	2.8%	8.1%	3.4%	4.0%	25.4%	8.7%	-5.0%	8.5%	5.8%	-3.4%	-3.0%	8.1%	3.2%	5.2%	2.5%	10.0%	1.6%	-5.4%
Q4	6.3%	-0.8%	-1.2%	12.9%	9.9%	1.5%	8.7%	-0.4%	7.4%	11.8%	6.5%	-2.4%	4.5%	8.6%	2.5%	-3.3%	2.8%	2.0%	-3.5%	6.8%	14.2%	5.0%	-1.0%
Positive Quarters		25.0%	50.0%	100.0%	75.0%	75.0%	100.0%	75.0%	75.0%	75.0%	75.0%	50.0%	100.0%	75.0%	75.0%	25.0%	75.0%	100.0%	25.0%	100.0%	50.0%	100.0%	0.0%

Figures

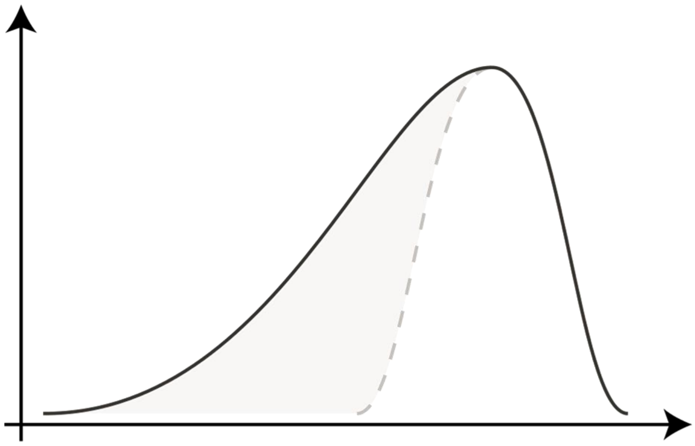
Figure 1. Capital Asset Allocation Model



The graph illustrates the Capital Asset Pricing Model (CAPM). There are a set of different allocation strategies an investor can choose. The vertical axis represents expected portfolio returns, *E(R)*, while the horizontal axis represents the standard deviation of portfolio returns, *σ(R)*. The minimum variance frontier is represented by the horizontal parabola *abc*, which tracks all possible portfolio configurations of risky securities with the lowest risk for a given amount of expected return. With the existence of risk-free borrowing and lending, rational investors are only interested in portfolio combinations between the risk-free asset *Rf* and the risky tangent portfolio *T*, which is somewhere on the dotted *capital market line* and represents the mean-variance efficient options when there is risk-free borrowing and lending.

Source: Fama, E. F. and French, K. R. (2004), „The Capital Asset Pricing Model: Theory and Evidence", *Journal of Economic Perspectives* 18(3), Page 27

Figure 2. Negative Skewness: Left-tailed Distribution

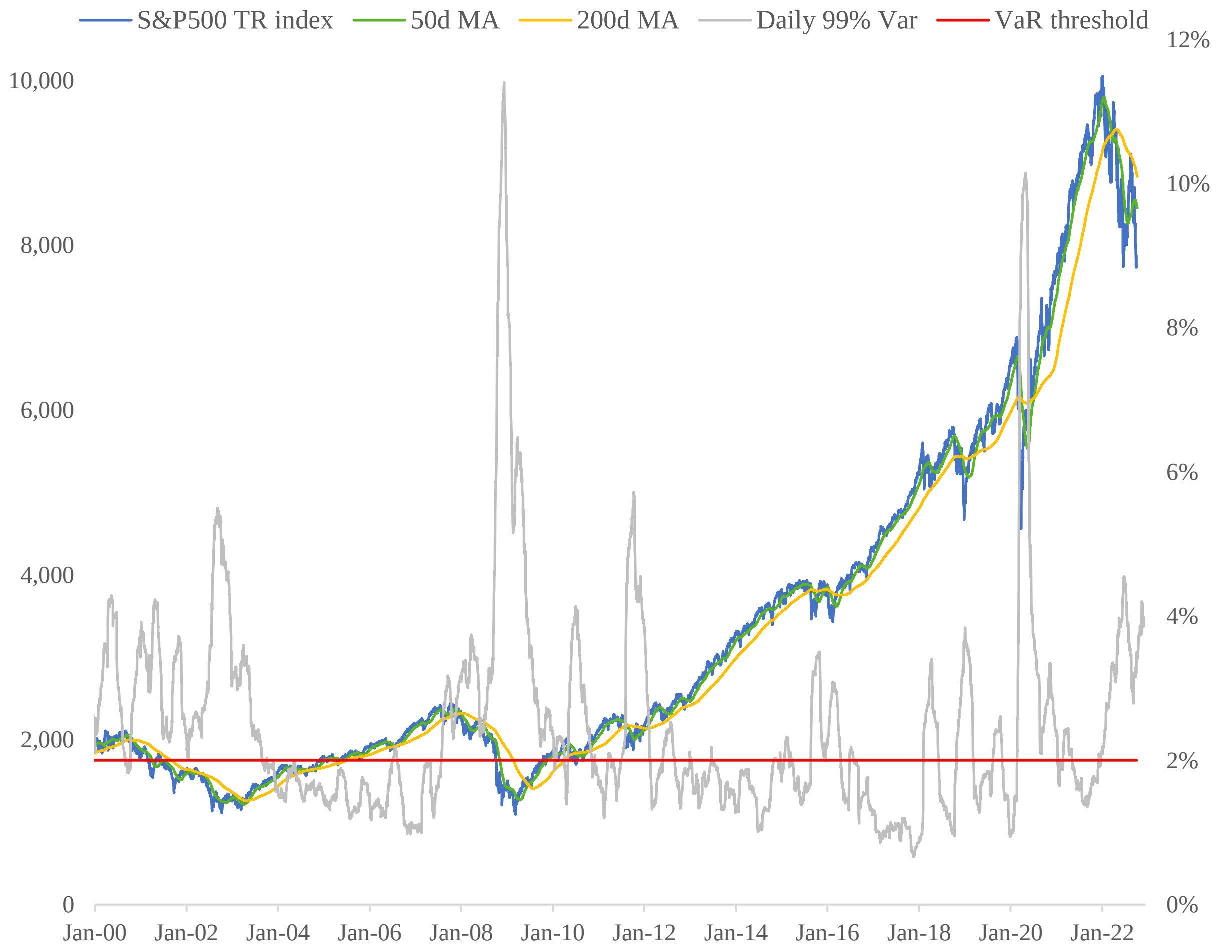


Skewness measures the asymmetry in the distribution of a dataset around its mean. Skewness can be either positive or negative, or zero for symmetric distributions such as the normal (Gaussian) distribution. Figure 2 shows a negatively skewed distribution, with most of the distribution concentrated on the right side of the distribution, where the values are above the mean. In addition, while less data is found on the rather long left tail, which has values below the mean, these can be very large deviations in some circumstances, so-called "fat-tails". Simply put, when the random variable has negative skewness, the results are typically numbers slightly above the mean and, less often, numbers below the mean, which can be extremely large. This negative skewness in the distribution of asset returns was found in the descriptive statistical analysis of the assets which we considered for our strategies (Table 1 and 5-7).

Source: Karehnke, P. (2020), "Systematic Skewness and Stock Returns", ESCP Business School

Figure 3.1. Behind the Systematic Equity Strategy

S&P500 Index and its 50d-SMA, 200d-SMA, and daily 99% VaR

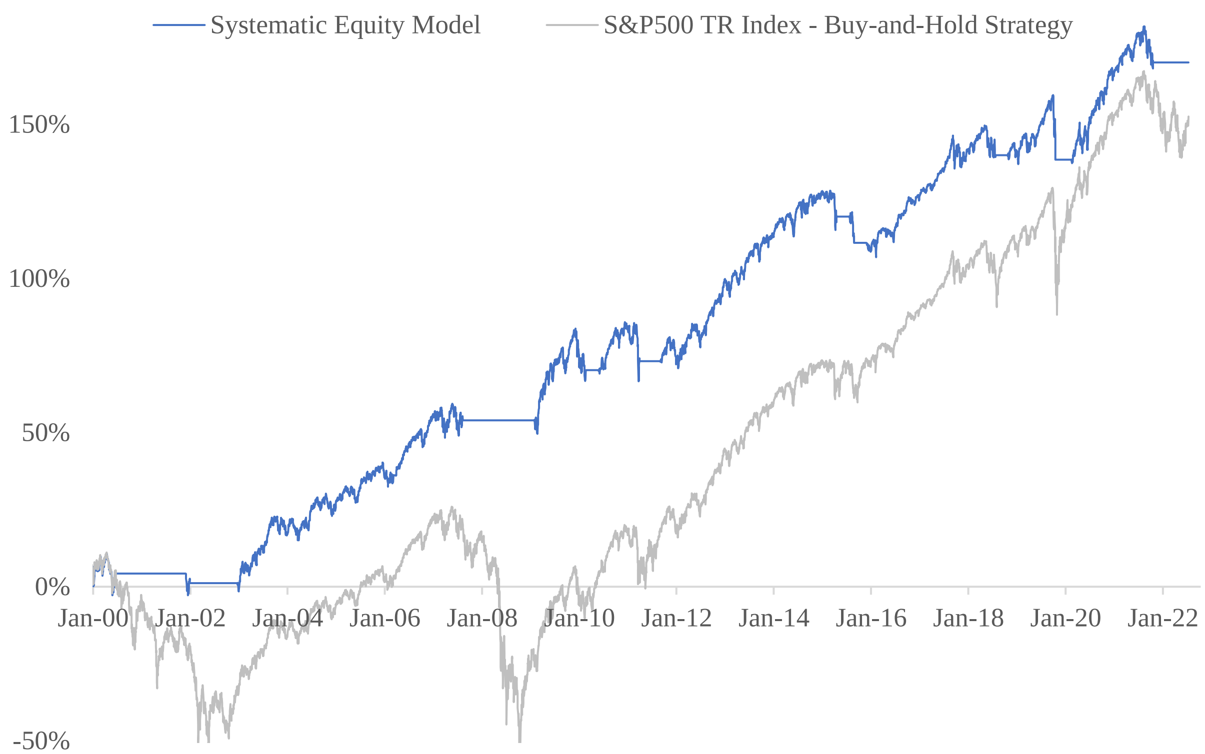


Long: *if daily 99%-VaR < 2%* $\vee$ *50d*$_t$ *> 200-day MA*$_t$

Neutral: *if daily 99%-VaR > 5%* $\vee$ *(daily 99%-VaR > 2%* $\wedge$ *50d*$_t$ *< 200-day MA*$_t$*)*

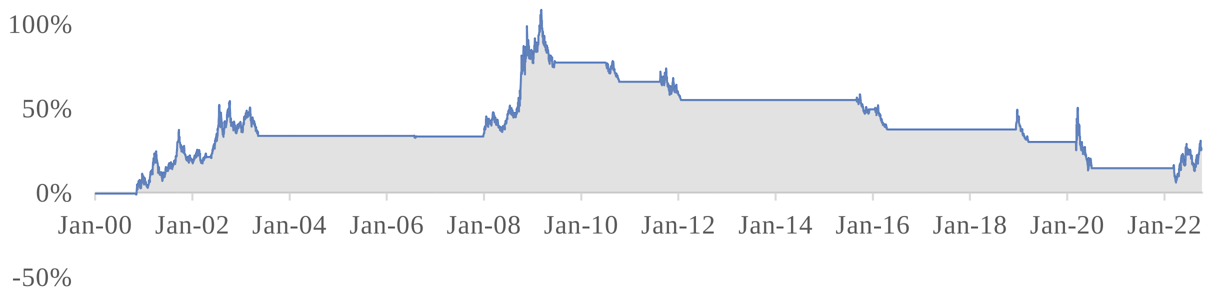
This graph shows the key indicators for the signal process of the systematic equity model. The model invests, if the 50-day SMA is greater than the 200-day SMA (Trend-Following), or as long as the daily 99%-VaR of the S&P500 index remains below 2%, while periods with a daily 99%-VaR greater than 5% are generally avoided. In both major downturns during the dotcom burst 2000 – 2002 and the financial crisis 2007 – 2009, both indicators signalled not to invest, as the VaR remained above 2% during that period and the 50day MA below the 200d MA, indicating a downward trend. Since beginning of this year, the VaR rose and remains above 2%, while the 50d MA remains still below the 200d MA, signalling a defensive investment strategy within the current market environment.

Figure 3.2. Systematic Equity Model vs. S&P500 Buy-and-Hold Strategy
Indexed performance, %-growth since 2000



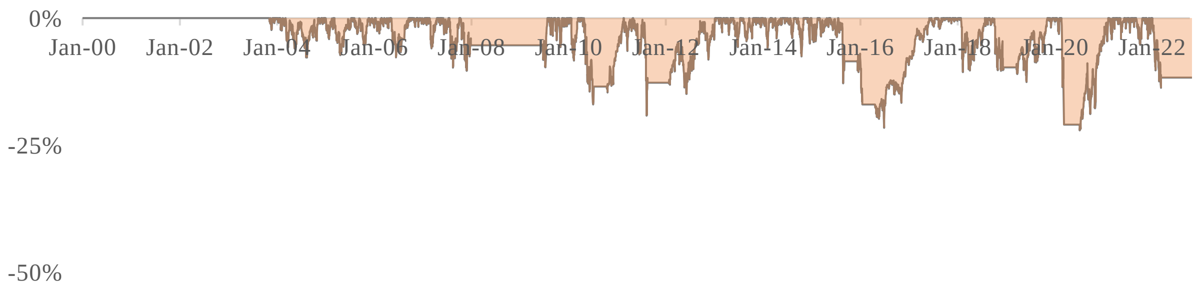
The systematic equity model is able to generate good market-timing results with avoiding both large crisis within the last two decades, the dotcom-burst in 2000-2002 and the financial crisis in 2007-2009. However, during the outbreak of the Corona pandemic, the strategy suffered at lot. Since the Corona crisis was an exogenous shock, the VaR model was not able to anticipate these sudden and sharp decline in asset valuations. Both, market volatility and the trend-following indicator, predicted an ongoing upwards trend. Currently, as interest rates rise and equity valuations adjust, the model seems to have expected this higher volatility back in February of this year, as stopped being exposed to the S&P500 index. More volatile markets bear more risk and deliver lower risk-adjusted returns; hence a risk-off behaviour is very appropriate in the current equity markets.

Figure 3.3. Systematic Equity Model: Alpha



An investor who preferred the systematic strategy over the passive strategy in 2000 benefited from a consistent alpha without ever lagging behind the benchmark. Due to the risk-limiting signals, the outperformance can be realized mainly in periods of sustain equity market turmoil such as 2000 to 2002 and 2008 to 2009.

Figure 3.4. Systematic Equity Model: Maximum Drawdown

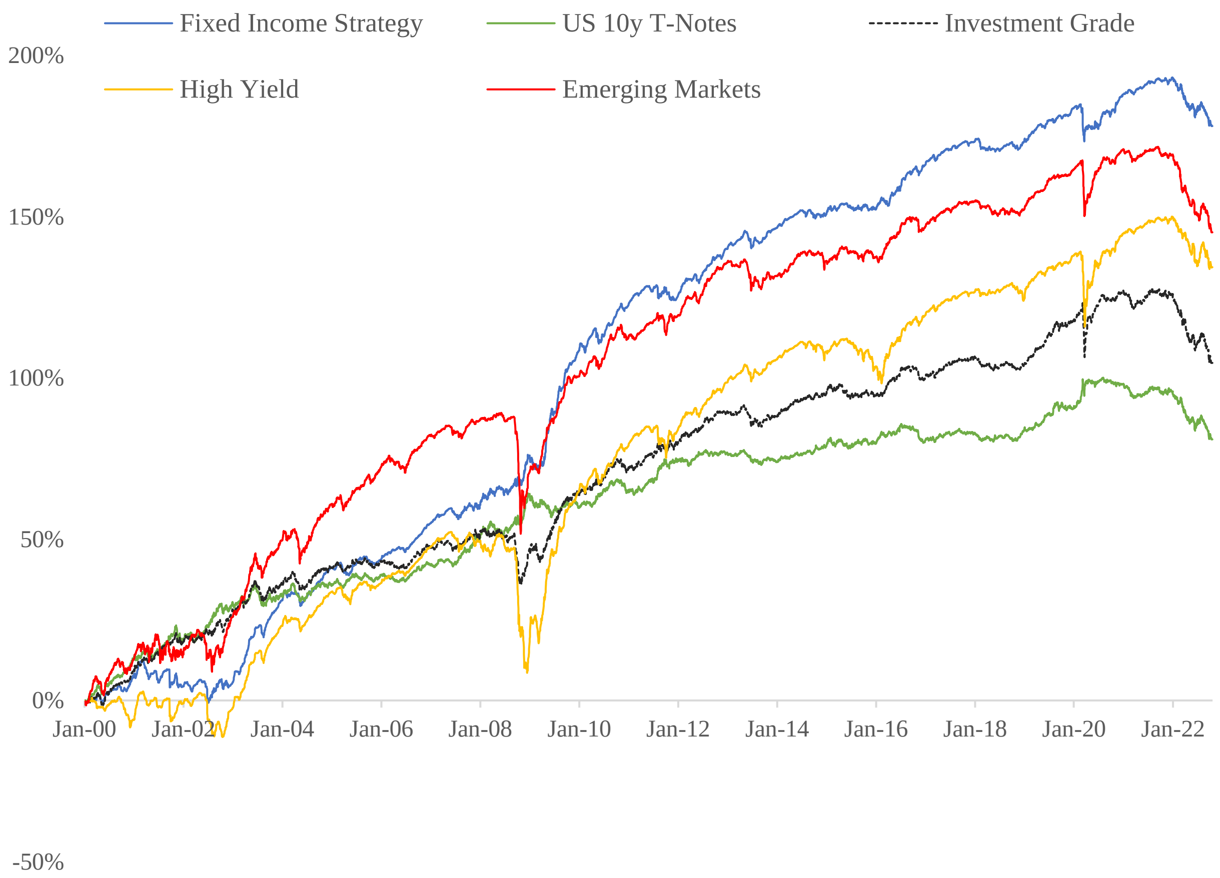


While the S&P500 index temporarily lost over -82% (Table 2), the systematic equity index strategy had its largest decline during the Covid crash in March 2020, limiting its maximum drawdown to only -22%, indicating a more cautious approach to investing than the buy-and-hold strategy. Hence, the model is able to capture good performing times, while avoiding bad performing times, without sacrificing returns.

Figure 4.1. Systematic Fixed-Income Strategy vs. different bond classes:

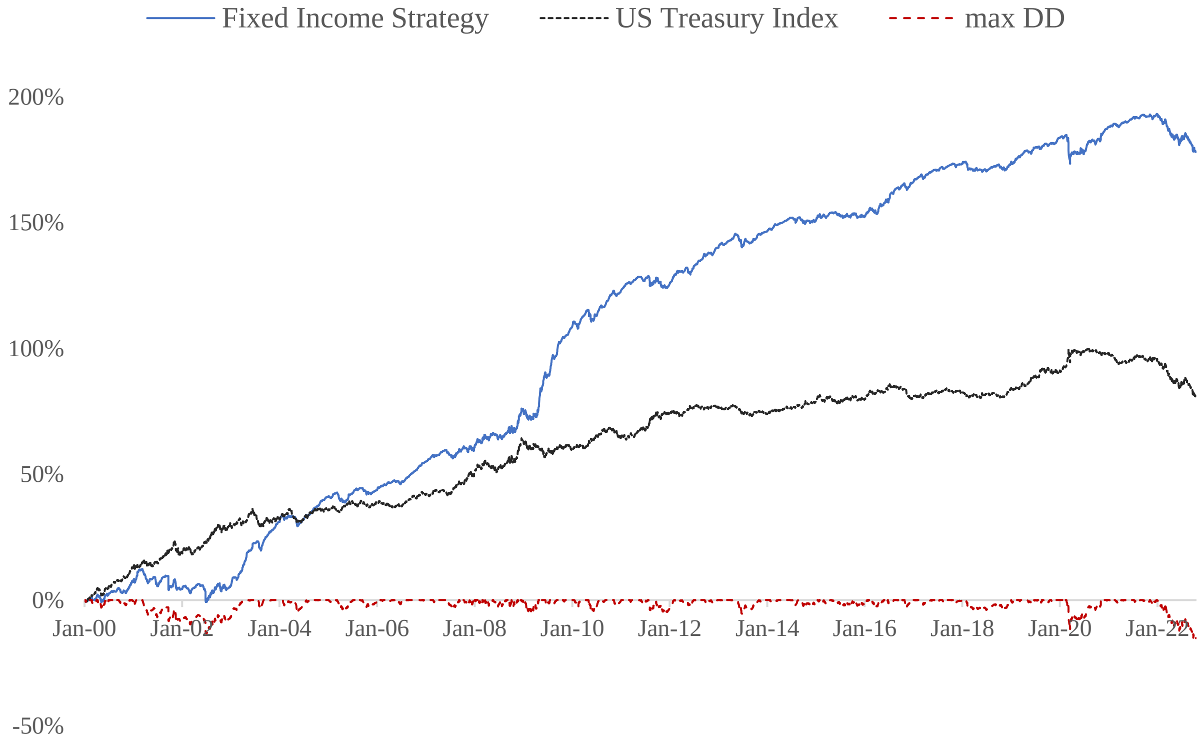
Comparison with US Treasuries, Investment Grade, High Yield and Emerging Markets

Indexed performance, %-growth since 2000



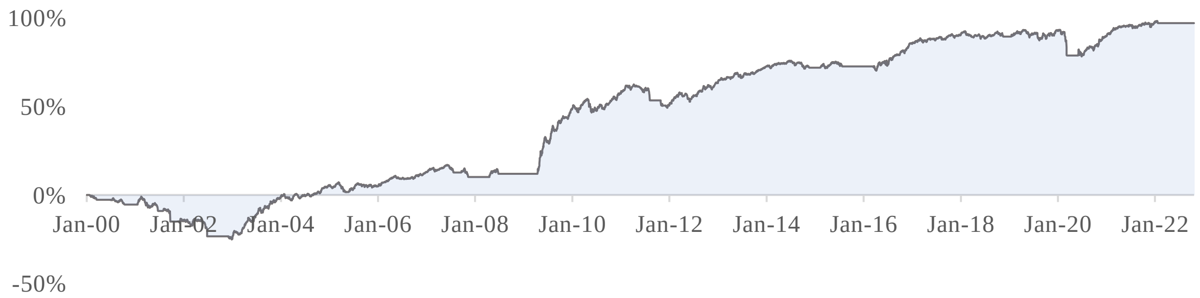
Over the sample period from 2000:01 to 2022:10, the systematic fixed income strategy achieved the highest total return, with no large downturn period. Recently, the strategy is, like all other bond classes, suffering from restrictive monetary policy that is rising rates at a historic pace. The systematic strategy was able to mitigate the financial crisis in 2008 very effectively by exposed to US treasuries, which served as safe haven at that time.

Figure 4.2. Systematic Fixed-Income Strategy vs. Bloomberg US Treasury Total Return Index



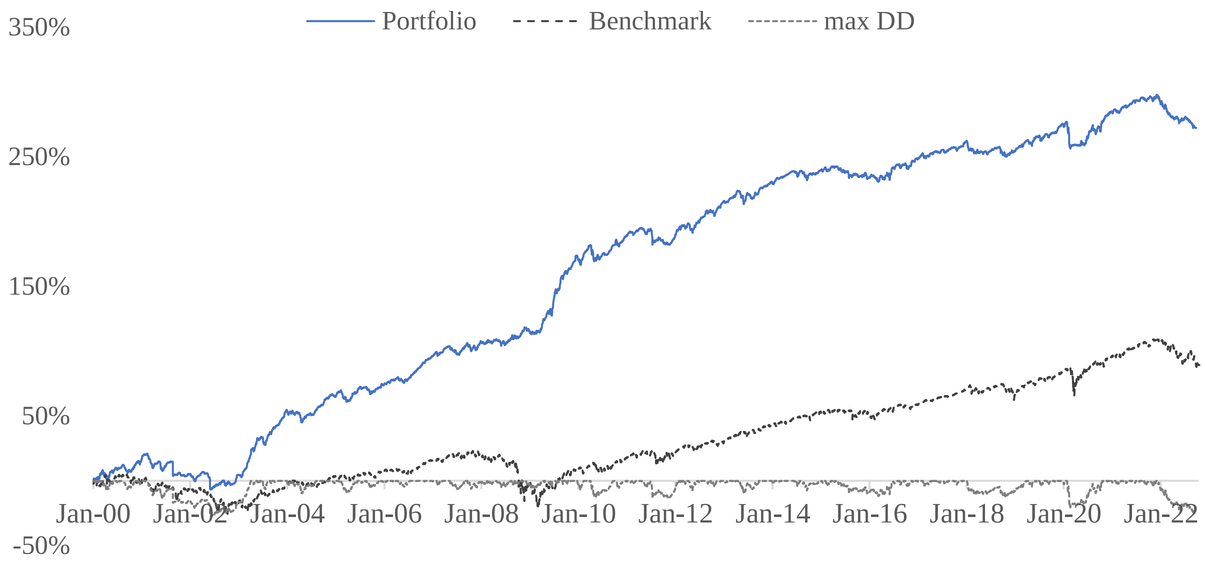
Apart from the beginning of the 2000s and this year, the systematic bond model delivered a constant positive performance, being after the fade of dotcom burst consistently ahead of the benchmark, with a particularly good performance after 2008, when rates were falling, and quantitative easing was introduced. The systematic strategy achieved a total return of 178% (Table 3), more than twice as much as the benchmark with 81%.

Figure 4.3. Outperformance of the Systematic Fixed-Income Strategy compared to US 10-year T-Notes



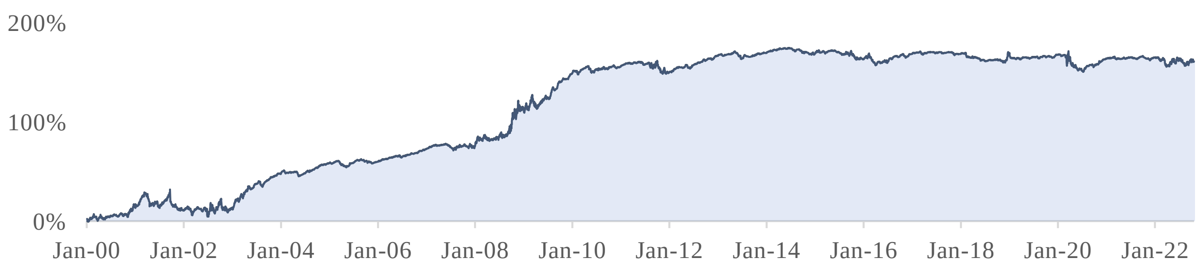
The systematic strategy achieves an annual alpha of 4.1%, while carrying less volatility, hence delivering significantly better performance than US government bonds.

Figure 5.1. Systematic Multi-Asset Strategy vs. 60/40 Portfolio Buy-and-Hold Strategy



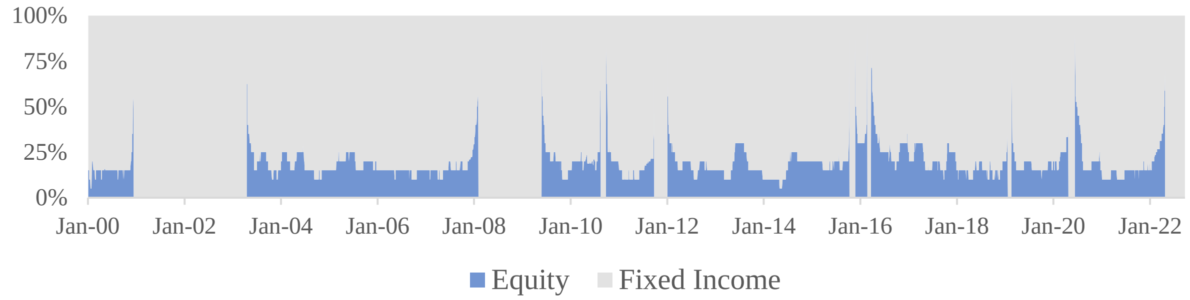
The strategy achieves an annual outperformance of 7.83% and a total return three times higher than the benchmark, while volatility is reduced from 11.2% to 8.3%. The systematic multi-asset strategy is able to perform consistently above the benchmark and particularly well in relative terms, when the benchmark is experienced a prolonged downturn, such as during the financial crisis in 2007/08. With a beta of only 0.26, the systematic strategy is associated with much lower systematic risk and less market correlation, resulting in significantly lower maximum drawdowns. The sample period from 2000:01 to 2022:10 include two full bull and bear cycles.

Figure 5.2. Systematic Multi-Asset Strategy: Consistent Alpha



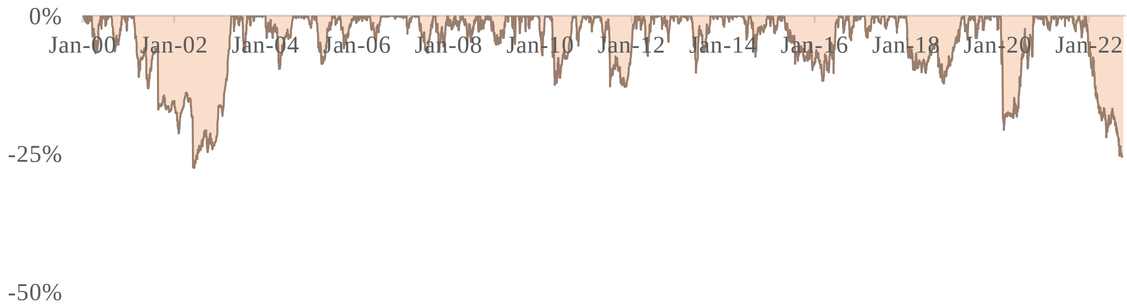
The strategy manages to outperform its benchmark almost consistently with not a single period of significant underperformance. An investor who would have pursued this strategy would have generated more than 160% more in returns.

Figure 5.3. Systematic Multi-Asset Strategy: Equity/Bond ratio over time



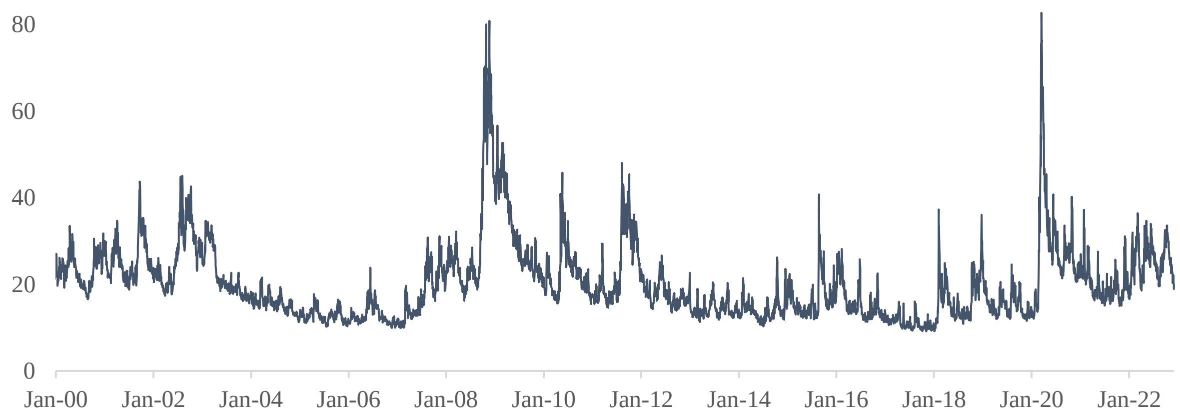
The model is able to precisely avoid the periods in the equity markets that were affected by sharp declines. These periods include dotcom burst from 2000 to 2002, the financial crisis from 2008 to 2009 and the recent correction on equity valuations, triggered by sharp interest rate hikes. Aside from that, the fixed income strategy will always remain overweighted due to its lower volatility and the risk-weighted allocation model (risk parity). It is remarkable how the strategy mitigates both bear cycles within the sample period from 2000 to 2002 and 2007 to 2009.

Figure 5.4. Systematic Multi-Asset Strategy: Maximum Drawdowns over time



Even though the multi-asset portfolio was not invested in equities, it had its largest decline of 30% during the dotcom burst in 2002, when bonds suffered from rising rates, similarly to recently in 2022. As of November 2022, the portfolio suffered almost 25% compared to its ATH back in January 2022.

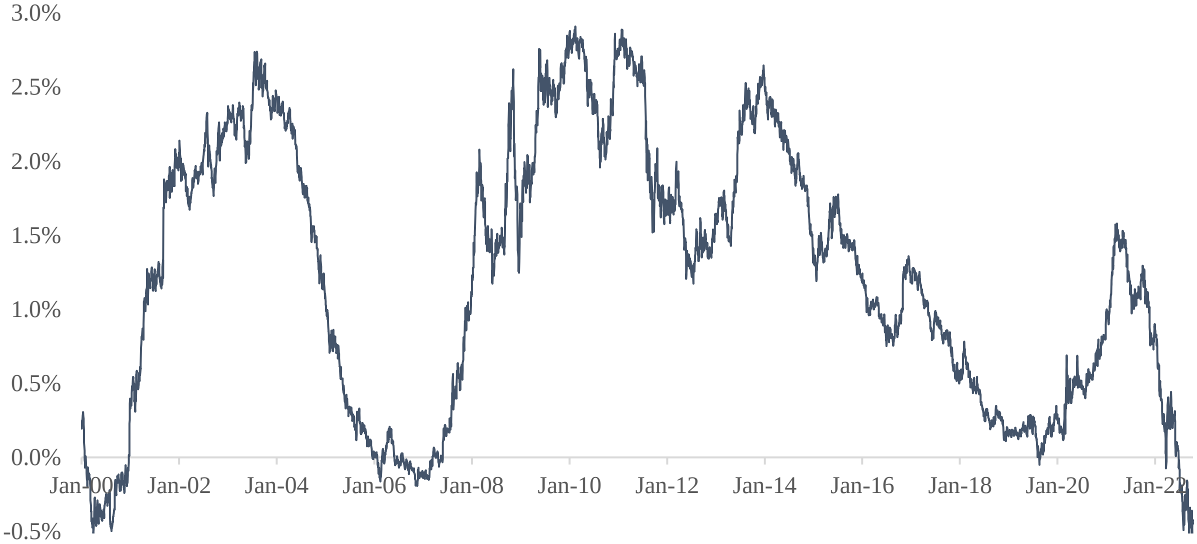
Figure 6. VIX Index: Historical closing values



The volatility index (VIX) measures market expectations of short-term price fluctuations for the S&P 500 index. The index is generated from S&P index options pricing and produce a 30-day forecast of the volatility. VIX values above 30 indicate a high market uncertainty as market participants expect high volatility. We may get a sense of how the market responded by seeing how the VIX changed throughout 2022, given that this year is marked by a high level of uncertainty, double-digit inflation rates, and changes in both the macroeconomic and geopolitical landscape. As of 1st of December, the VIX is signalling increased uncertainty with an average year-to-date value of 26, compared to 19 historically. As the VIX rose since the start of 2022, the S&P500 index dropped by 15%, showing the negative correlation between the VIX and the S&P500 index.

Source: Chicago Board Options Exchange (CBOE)

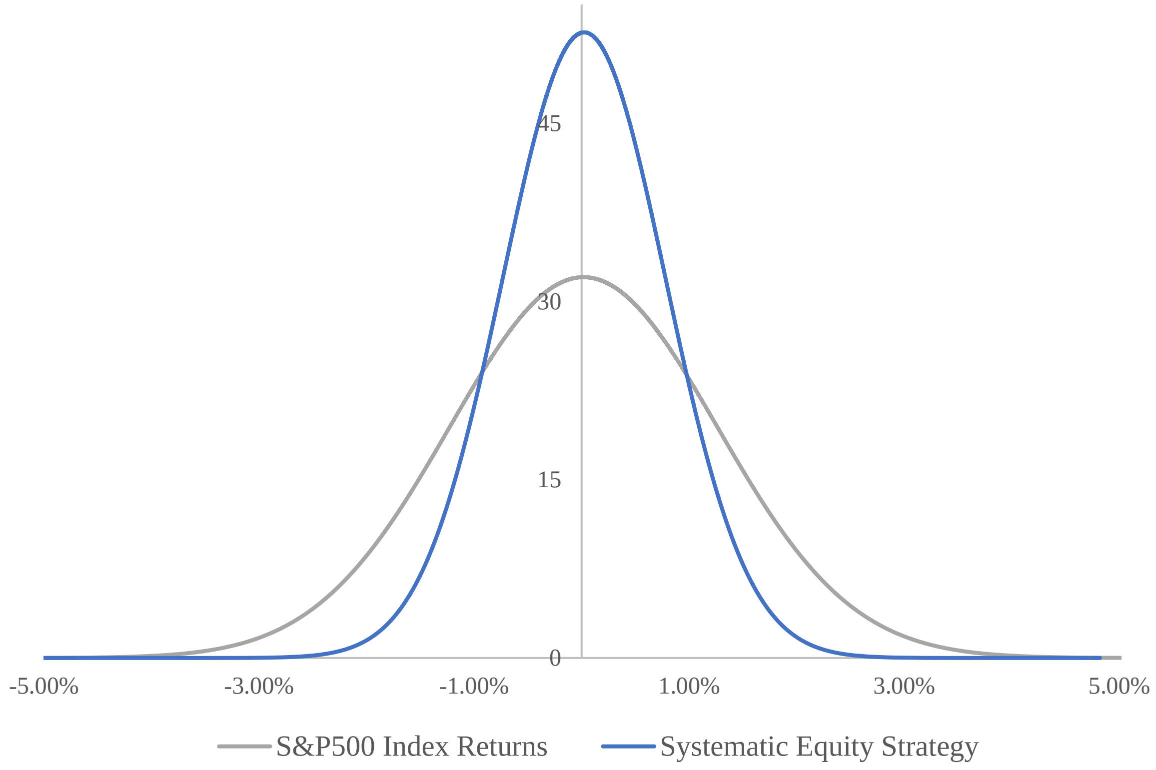
Figure 7. Yield-Curve: Spread between US 2-year Treasury Bills and 10-year Treasury Notes



This yield curve can be illustrated by calculating the difference in yields between short- and long-term treasury bonds over a time-series. In this case, the yield curve is represented by the difference between the yield on 2-year and 10-year U.S. Treasury bonds. Currently, the US treasury yield curve is inverted, meaning that short-term rates are rising and approaching (or higher than) long-term rates. An inversion of the yield curve is an unusual event that has historically been a remarkably accurate indicator of an impending economic recession. It occurs when investors are concerned about the future, expect lower growth and shift their capital to short-duration assets.

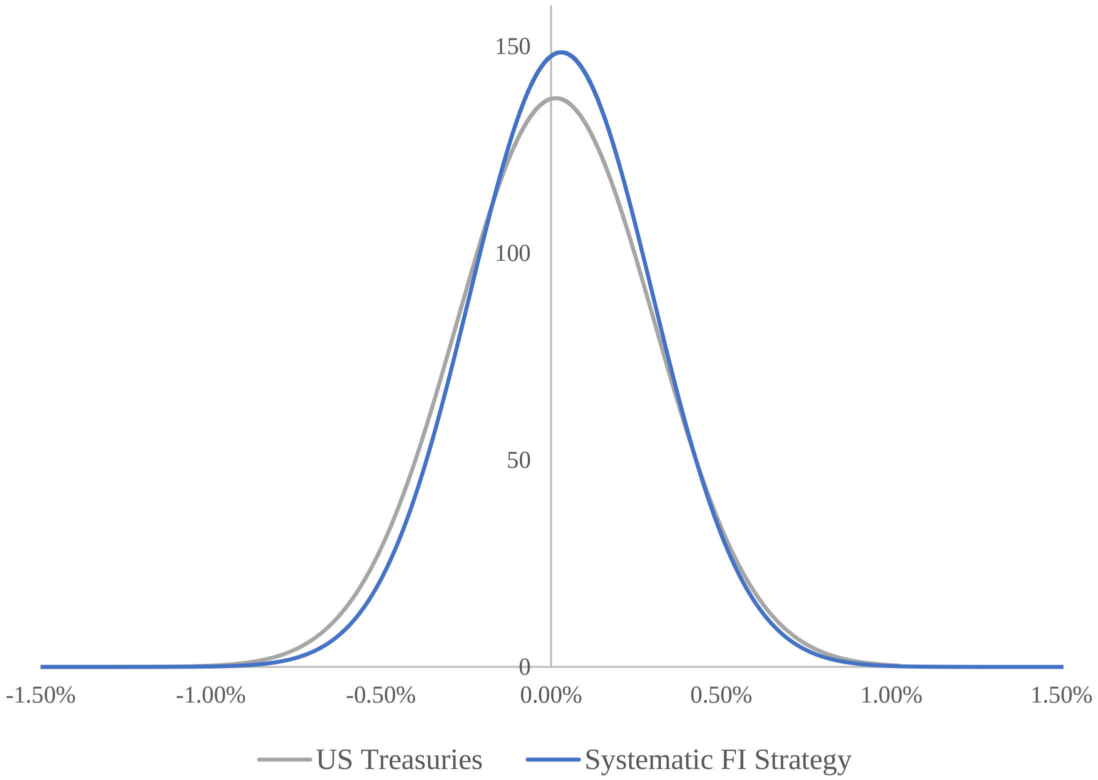
Source: Bloomberg

Figure 8.1. Distribution Function: S&P500 TR index vs. Systematic Equity Strategy



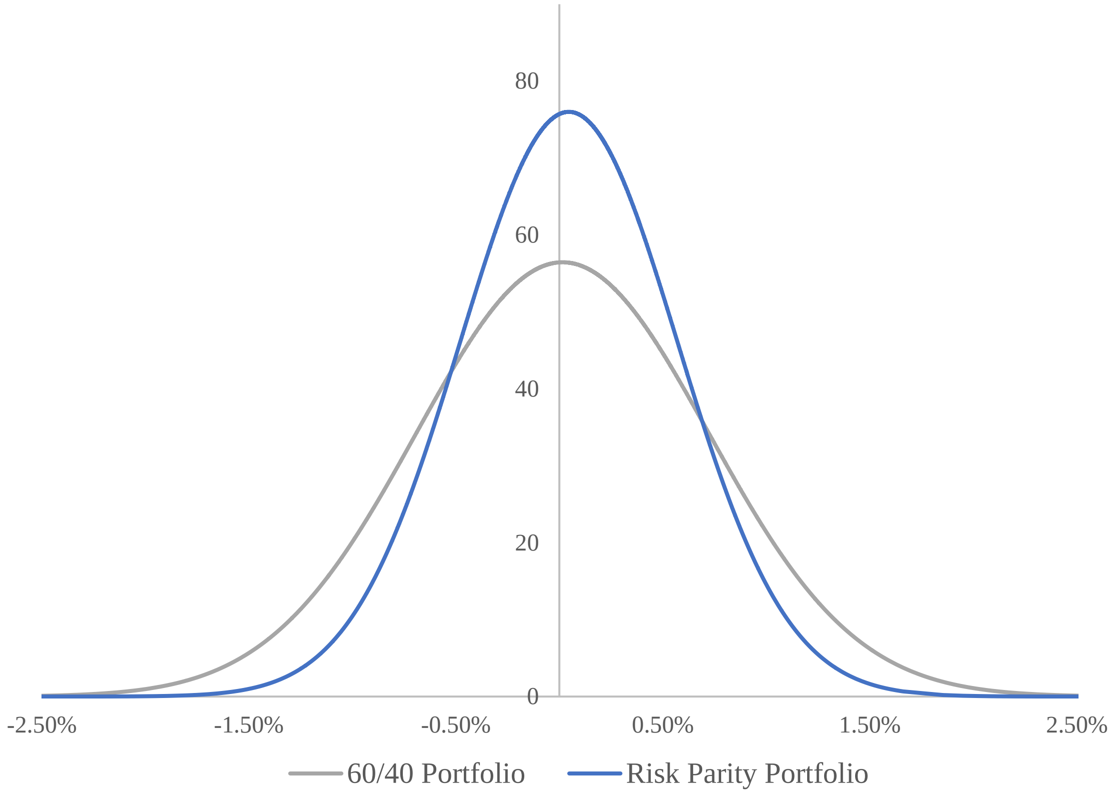
To further understand the success and impact of systematic strategies, it is not enough to just compare their absolute performance with an index (Figures 3.2, 4.1, 4.2, 5.1); one should also carry about the distribution function to better assess the changing probability measure. As Figure 8.1 shows, returns get more centralized and diminish on the further tails which leads to a lower variance and a narrower range of possible outcomes, hence more reliable and steady returns. This is mainly caused by the more frequent occurrence of the 0% return, as the systematic model pursues a market-timing strategy and is not invested in about 28% of the period (Table 2). Moreover, the kurtosis decreases with the systematic strategy and leads to less extreme outliers than before. The negative skewness is difficult to picture in this figure but was already apparent from the analysis of the descriptive statistics in Table 5. The investigated dataset includes 5960 daily returns in the period from 10.1999 to 11.2022.

Figure 8.2. Distribution Function: Bloomberg US Treasury Bond ETF vs Systematic Fixed-Income Strategy



The above figure shows a comparison of the systematic FI strategy and the returns of the US Treasury Bond TR ETF. While the centralization compared to the systematic equity strategy slightly disappears, the shift in skewness is better visible than in the prior analysis (Figure 8.1) showing a lower skewness from -0.43 to -2.36 (Table 6). The systematic strategy generates more positive returns than the bond index, shifting its peak to the right, while also having slightly tighter tails. Moreover, the systematic FI strategy manages to better centralize returns, although still less than as the equity strategy which is always invested and thus the 0% return does not occur as often as in the previous analysis. The peak of the cumulative distribution function shifts to the right, indicating higher expected returns. As kurtosis increases, partly caused by the wider range of historical returns (Table 6), the increase in the average daily return can be seen as a reward for further fat-tails within the data set. The sample returns are from 1999.10 to 2022.11.

Figure 8.3. Distribution Function: Systematic Multi-Asset RP Strategy vs. Traditional 60/40 Portfolio



This comparison can be seen as a mixture of the two previous ones. While again a centralization of returns can be observed, the peak also shifts slightly to the right into positive territory as in the previous figure, giving an investor more positive returns. Although the range between the minimum and maximum range of the both time-series are very different (Table 7), this is not directly evident from this graph, as it only shows the majority of the returns. Instead, the shift in skewness from -0.36 to -3.01 can be seen with the intersection of both graphs being noticeably lower on the right than on the left, given the shift of the distribution function to the right with a steeper tail.

The sample returns are from 1999.10 to 2022.11.