ECONSTOR Make Your Publications Visible.

A Service of

ZBW

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Freibauer, Jonas; Grawert, Silja

Article

Testing of a volatility-based trading strategy using behavioral modified asset allocation

Journal of Risk and Financial Management

Provided in Cooperation with: MDPI – Multidisciplinary Digital Publishing Institute, Basel

Suggested Citation: Freibauer, Jonas; Grawert, Silja (2022) : Testing of a volatility-based trading strategy using behavioral modified asset allocation, Journal of Risk and Financial Management, ISSN 1911-8074, MDPI, Basel, Vol. 15, Iss. 10, pp. 1-20, https://doi.org/10.3390/jrfm15100435

This Version is available at: https://hdl.handle.net/10419/274955

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.



WWW.ECONSTOR.EU

https://creativecommons.org/licenses/by/4.0/

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.







Article Testing of a Volatility-Based Trading Strategy Using Behavioral Modified Asset Allocation

Jonas Freibauer 🕩 and Silja Grawert *🕩

Faculty of Computer Science and Mathematics, Munich University of Applied Sciences HM, 80335 Munich, Germany

* Correspondence: grawert@hm.edu

Abstract: The performance of volatility-based trading strategies depends, among other factors, on the asset selection and the associated risk preference. For this study, we conducted a representative survey for Germany to determine the asset preferences of individuals with lower-risk and higher-risk preference. These two types of behavioral modified asset allocations (lower-risk and higher-risk) form the basis for testing our volatility-based trading strategy with different risk and loss levels. The tests are based on historical asset price data over a period of nearly the last eleven years. The goal was to historically outperform the broad market by changing various factors, such as the initial asset allocation, the asset reallocation, and the risk and loss level underlying the trading strategy. We achieve this by using the riskier initial asset allocation and applying our trading strategy with a risk and loss level of 10% each. In this case, a historical return of 326% could have been achieved with our trading strategy over the period under review.

Keywords: volatility-based trading strategy; behavioral portfolio; risk behavior; copula construction; behavioral asset allocation



Achieving a better return than the broad market with one's own portfolio or strategy is probably one of the most-pursued goals of both private and institutional investors. At the same time, it is one of the most difficult tasks, as the financial markets change permanently, and asset prices cannot be predicted. One of the key insights that is important for creating a successful trading strategy is that asset returns do not correlate with each other. The correlation between the returns of the same stock is always close to zero (Fama 1970, p. 383). It can therefore not be used as a substantial basis for profitable trading strategies and systems.

This raises the question of on what basis trading strategies should be based. Already in 1963, Mandelbrot found that market phases with high volatility are usually followed by market phases with high volatility. The sign of the high or low volatility is irrelevant (Mandelbrot 1963). This finding suggests that the timing of the portfolio rebalancing of a trading strategy has a decisive influence on the portfolio return. Therefore, a trading strategy is programmed in this study which rebalances the assets every 20 days. This rebalancing is done using simulated future returns of the assets based on the past volatility of three years. Based on our definition, the volatility of the last three years of the multi-asset portfolio represents the long-term volatility, which is most appropriate for a long-term-oriented investor. Since the low returns of today are partially compensated by an increase in expected returns in the future (Campbell and Shiller 1988; Poterba and Summers 1988), it is obvious that short-term stock market volatility is not a suitable risk measure for a long-term investor (Moreira and Muir 2017).

Previous work has focused on the mathematical foundations of a volatility-based trading strategy, such as the use of Vine Copula models to model the interdependency structures between the different assets (Fink et al. 2017). Furthermore, volatility-based



Citation: Freibauer, Jonas, and Silja Grawert. 2022. Testing of a Volatility-Based Trading Strategy Using Behavioral Modified Asset Allocation. *Journal of Risk and Financial Management* 15: 435. https://doi.org/10.3390/ jrfm15100435

Academic Editor: Thanasis Stengos

Received: 25 August 2022 Accepted: 23 September 2022 Published: 27 September 2022

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). portfolio strategies have already been tested in different variations, even finding that the success of volatility-based trading strategies is not diminished by transaction costs (Moreira and Muir 2017). In addition, it has been investigated how a low-volatility portfolio strategy can be further optimized with regard to taxes incurred, while at the same time maintaining the good performance (high returns) of a volatility-based trading strategy (Zhang 2022). Furthermore, current research shows that volatility indices have a long-term memory (Ghosh et al. 2022). This indicates that using forecast models based on past volatility to predict or simulate future prices of financial products could lead to a profitable trading strategy. In addition, the VIX is used for volatility-based trading strategies and forecasts of the volatility in a few studies (Ballestra et al. 2019; Wang et al. 2022). Researchers have focused on the prediction of the VIX based on implied volatility. So far, a few studies dealt with the profitability of trading strategies based on VIX predictions. There is evidence that the VIX is predictable, but at the same time, it is difficult to use this for a profitable trading strategy, since the VIX can only be traded via derivatives (Ballestra et al. 2019). In this context, Ballestra et al. found, in 2019, that predicting directional changes of VIX-Futures (VIX-Futures open-to-close Returns) using a neural network leads to plausible results with 65.8% of correct predictions of directional changes on trading days. (Wang et al. 2022) focused on the investigation of the correlation between the VIX of the S&P500 and the VIX of five major US companies in 2022 and were able to confirm this within their study.

Our study focuses primarily on the previously unexamined research linkage between behavioral finance and portfolio theory. Furthermore, we examine a different approach for simulating future returns on the basis of volatility forecasting than that of the current research about prediction of volatility and volatility-based trading strategies listed above. For this, we use the findings of previous work, for example, on Vine Copula models, to model the dependency structures of assets (Fink et al. 2017). It is particularly important to find out whether a volatility-based trading strategy applied to behavioral modified initial asset weights, that reflects the asset preferences and risk attitudes of a broad segment of the population, can achieve better long-term returns than the broad market. We tested the strategy under different circumstances, such as different risk and loss levels and different approaches for the asset reallocation.

The approach of applying a trading strategy to a behavioral modified asset allocation differs from the standard models of portfolio theory. The Modern Portfolio Theory (MPT) (Markowitz 1952) states that an investor should maximize his expected return while diversifying his portfolio. Accordingly, the investor should distribute his available capital among those assets that lead to a maximum return. Unlike the MPT, this study uses the preferences and risk attitude of the broad population to allocate the initial asset weights. The difference is that the initial asset allocation is behaviorally based and reflects the preferences and opinions of the broad population. Therefore, the maximum expected return of the respective asset is of minor importance when determining the initial asset allocation can be found in chapter 2. While MPT is often associated with a buy-and-hold strategy, our strategy reallocates the assets every 20 trading days. Nevertheless, the trading strategy programmed in this study is also about maximizing the portfolio return. This is not done during the selection of the initial asset weights, but while selecting the new asset allocation during the rebalancing.

The goal of this approach is to achieve a better return in the long-term by using our volatility-based trading strategy in combination with behavioral modified asset allocations and thus to perform better than the broad market, which is symbolized by the S&P500 in this paper.

2. Determination of the Behavioral Modified Asset Allocation

To identify the asset and risk preferences of a representative part of the German population, it was necessary to conduct a survey in which the risk tolerance of the participants and their preferred assets is recorded. Additionally, the survey was used to prove several heuristics of behavioral finance regarding the influence of private investors in capital investments, but this is not part of this work.

2.1. Survey Design

We conducted an online survey in two stages with a total of 263 participants. In both cases, the questionnaire was programmed and made available to the survey participants via the online survey tool LimeSurvey. The structure and content of the two surveys is identical. In addition, the questionnaire was designed in such a way that abstention was not possible for any of the questions.

The survey was conducted with two test groups. The number of participants who completed the respective survey is as follows:

- 74 participants complete the questionnaire fully in the first survey. (N = 74)
- 189 participants completed the questionnaire fully in the second survey. (N = 189)

The first survey was conducted in the period from 3 January 2022, to 12 January 2022. The participants in the first survey were selected based on their age and education so that the survey would reflect the general population. The second survey started on 11 January 2022 and ended on 19 January 2022. The temporal offset in the implementation of the two surveys is explained by organizational time problems in sending the survey to the sample of 3601 students and employees of the Munich University of Applied Sciences.¹

2.2. Data Evaluation

In both cases, repeated participation was excluded by applying cookies to the LimeSurvey system. In addition, the study has been conducted without a measurement repetition. The results of the first survey can be considered representative, since, according to the results, the age structure and educational level of the survey participants are heterogeneous and reflect the broad mass of the population. The exact age and educational structure of the participants in the first survey can be found in Appendix A.

The results of the second survey consist almost exclusively of responses from students at Munich University of Applied Sciences. Although a higher number of participants was achieved than in the first survey, the study is less representative of the behavior of the population and is therefore used as a control group.

2.3. Analysis of Risk Preferences and Preferred Assets

Please note that all results below are based on the data collected in the first survey. The sought-after risk preferences of the survey participants, based on their own statements according to their risk preference, are shown in Table 1.

Risk Assessment	Male (%)	Female (%)
Low-risk	62.5	88.2
High-risk	37.5	11.8

Table 1. The risk profile of the survey's participants divided into male and female in %.

Consistent with Bogan et al. (2013), Table 1 shows that female individuals in the sample describe themselves as being more risk averse than male individuals. A correlation of -0.2936 between the variables gender and risk attitude indicates that male participants in the survey consider themselves as more risk-tolerant than female participants.

In the survey, participants were asked about their preferred assets with multiple choices possible. The following assets were available for selection: shares, bonds, funds, ETFs, commodities, and real estate. In evaluating the preferred assets, a distinction was made between the lower-risk (risk-averse) and higher-risk survey participants, in order to create the initial assets weights for testing the trading strategy. The answers to the asset preferences of the risk-averse participants were summed up and the proportion of the respective asset in the overall initial asset weights are determined based on this sum. The

result of the risk-averse participants can be seen in Table 2. A total of 107 responses were given.

Asset	Shares	Bonds	Funds	ETFs	Commodities	Real Estate
Answers	23	1	22	29	9	23

Using this empirically collected data, the respective initial share of an asset in the low-risk overall portfolio was calculated. The result is shown in Figure 1.



Figure 1. The initial asset composition for the lower-risk portfolio.

The procedure for establishing the initial weights of the higher-risk portfolio is identical to the procedure described above for the lower-risk portfolio. The number of votes for each asset by the low-risk participants can be found in Table 3. A total of 36 responses were given.

Table 3. The number of votes for each asset by the higher-risk participants.

Asset	Shares	Bonds	Funds	ETFs	Commodities	Real Estate
Answers	12	2	5	11	2	4

Using this empirically collected data, as with the lower-risk portfolio, the initial weights of the assets in the higher-risk portfolio were determined. The results can be found in Figure 2.

Afterwards, we select the products of the respective assets to test the strategy using real historical price data of the assets. The portfolios consist of the six assets listed above and have been supplemented by a seventh asset, "cash". As in reality, it is possible for the strategy to hold part of the assets in cash. This is especially important for rebalancing the assets. The selected products for the six assets defined for the long-term testing of the trading strategy with historical price data, can be seen in Table 4.

When selecting the assets, it was made sure that the historical time series could all be sourced in the same currency (EUR). In addition, it was ensured that the investment products have already existed for at least ten years and at the same time have a volume of at least 500 million EUR. Since there was almost no cash return in the test period of our strategy (24 August 2011–1 February 2022), the cash return in our trading strategy was assumed to be 0%.



Figure 2. The initial asset composition for the higher-risk portfolio.

Asset	Shares	Symbol
Shares	Apple Inc share	APC.F
Bonds	Xtrackers II Germany Government Bonds UCITS ETF 1C	X03G.DE
Funds	Deka-MegaTrends CF (equity fund worldwide)	-
ETFs	iShares MSCI World UCITS ETF	IQQW.DE
Commodities	WisdomTree Physical Gold ETC	PHAU.MI
Real Estate	iShares Developed Markets Property Yield UCITS ETF	IQQ6.DE

Table 4. The selection of the six investment products for the testing of the trading strategy.

2.4. Procedure and the Programming of the Trading Strategy

R programming language was used to construct the initial asset weights and the trading strategy. The historical time series of all assets were obtained from the public available website https://de.finance.yahoo.com/ (accessed on 22 February 2022). The historical data of the Deka fund was obtained from Deka's publicly available website (DekaBank 2022). For the historical asset price data, only the close price was extracted. The close price reflects the respective closing price at the end of a trading day. To ensure comparability of the asset time series, the "NA-values" were removed from all time series. As a result, the respective time series of all assets are of equal length.

The trading strategy is based on the rebalancing of the asset weights on the basis of a volatility forecast. Transaction costs and taxes are not taken into account. The period in which the strategy is reviewed using the historical asset time series, ranges from 24 August 2011 to 1 February 2022.

The procedure described below provides a basic understanding of the trading strategy, the models, and the methods we used for this purpose. The exact procedure of the strategy on a rebalancing day is detailed in Section 2.5.

The first step was to set up the portfolios consisting of the assets shown in Table 4 with the respective behavioral modified asset weights. Subsequently, it was necessary to define a forecast time window on the basis of which the reallocation days could be determined. In this case, the reallocation of the assets took place every 20 days. This time window was chosen because working with a longer time span of, for example 50 or 100 days, would be unlikely to deliver reliable results. The reason is that R cannot reliably simulate the volatility of the assets and consequently cannot simulate the future returns for 50 or 100 days into the future. Next, the strategy was set to the respective behavioral modified asset allocation for the first 750 days. This also determined the initial weights of the six assets. Consequently, the first rebalancing day was trading day 751. The time window of 750 trading days was

chosen because the returns of the next 20 days were estimated on the basis of the volatility of the past 750 trading days.

The optimization of the asset weights could thus start on the 751st trading day. In addition to the six assets listed in Table 4, the strategy could also reallocate and hold the portfolio assets, or part thereof, in the additional asset "cash". A loss level and a risk level were built into the code of the strategy. These two metrics were used to prescribe whether the strategy should act in a low-risk or high-risk manner. In the case of the lower-risk initial asset weights, both values were set to 0.05. This means that the strategy was prepared to incur a loss of 5% in 95% of the best cases (possible future returns) in one year. For the initially riskier asset weights, the two values were increased to 0.10 each.

The strategy rebalanced assets on a rebalancing day based on the projected returns of the six assets over the next 20 trading days. These were estimated based on the historical volatility of the respective asset over the last 750 trading days for 1000 paths (possibilities). After the simulation, there were 1000 possibilities for each of the six assets as to what price the respective asset could have in 20 trading days. The selection from each of the 1000 simulated possibilities per asset was done with the help of a global optimizer, which maximizes the possible return of the next 20 trading days of each asset. For this purpose, the optimizer Deoptim was used, which normally minimizes the function to be optimized (Ardia et al. 2021). Since in this case the maximum was sought, we needed to switch the sign of the optimizer. The global optimizer must maximize the return under two manually programmed constraints (Fink 2021). On the one hand, a value-at-risk condition, which depends on the risk level and the loss level, must be fulfilled. This condition pursues the goal, that the loss level will not be undercut. On the other hand, the weights of the assets must not exceed the value of 1. This condition ensures that the strategy works without leveraged positions.

When programming a trading strategy applied to a multi-asset portfolio, the dependency structures of the individual assets are of decisive importance. These are modeled by using Vine Copula models when simulating future returns. The detailed explanation of the use of these Vine Copula models, as well as the step-by-step description of how the strategy proceeds on a rebalancing day, is presented in the next subchapter.

2.5. The Procedure of the Trading Strategy on a Rebalancing Day

The trading strategy rebalances the assets every 20 trading days. The reallocation is based on the return forecast by the strategy for the next 20 trading days, which are estimated, based on the volatility of the past 750 trading days. The short-term volatility of securities is not a suitable risk measure for a long-term investor to determine the asset weights for a maximum return below the desired risk level and loss level (Moreira and Muir 2017). Since the strategy aims to be successful over the long-term, future returns are simulated here, based on the volatility of the last 750 trading days (3 years). The assets were assumed to be stochastic and have interdependency structures. These dependency structures need to persist when simulating the future possible returns of the next 20 trading days and are therefore modeled using Vine Copula models. The following description of the procedure refers to a rebalancing day. Accordingly, these steps were repeated every 20 trading days. On one of the other trading days, no rebalancing took place and only the wealth process was calculated on this day.

Step 1—Calculation of log-returns:

On a rebalancing day, the log-returns of the last 750 trading days are calculated manually with a loop for each asset. This is a total of 749 log-returns per asset.

Step 2—Creation of a GARCH model:

Next, a GARCH(1,1) model is created, whose distribution model is the Student's t distribution. This GARCH model is used to simulate the future volatility clusters of the assets (Fink 2021). (Andersen et al. 2003) have shown in 2003, that the quasi-maximum likelihood parameter estimated by a GARCH(1,1) model of Engle (1982) and Bollerslev (1986) indicate a strong volatility persistence.

Step 3—Adjustment of log-returns with the GARCH-model:

The log-returns can be represented with the GARCH-model as follows:

$$r_t = sigma_t * epsilon_t \tag{1}$$

 $r_t = \log$ -returns

 $sigma_t$ = log-returns adjusted, using the GARCH-model $epsilon_t$ = residuals of $sigma_t$

The 749 log-returns per asset are fitted using the GARCH-model, which creates the $sigma_t$ from equation 1. Afterwards, the *residuals* command in R is used to calculate the *epsilon*_t from the adjusted log-returns ($sigma_t$) (Fink 2021).

Step 4—Preparation of the data for modeling dependency structures with a Vine Copula model:

In order to model the asset dependency structures with a Vine Copula model, the data must be uniformly distributed on the interval [0,1] (Fink et al. 2017). Any distribution can be made uniform on [0,1] by fitting the values with the associated distribution function. In building the GARCH-model, we specify that the data come from a Student's t distribution. For applying the distribution function, a skew and a shape parameter is needed. Both parameters are estimated by the GARCH-model and are therefore already available.

After applying the distribution function of the Student's t distribution to the data, the data are now uniformly distributed on [0,1] (Fink 2021). The data is now called *udata*, which is the classical notation of the basic data when using Vine Copula models. In these *udata*, the dependence structures of the asset time series are still present.

Step 5—Creating the Vine Copula structure:

To model the dependency structures of the assets in the next step, a Vine Copula model must be created. To do this, the strategy estimates the appropriate Vine Copula structure based on the udata. From all possible trees (1000 simulations per asset), the bivariate copulas are selected one after the other, which then combine to form the entire multivariate Vine Copula structure. Additionally, it has to be clarified which bivariate Copulas are allowed in the estimation of the Copula structure (Nagler et al. 2022). In this case, we use the Student's t Copulas and the Gumbel Copulas in all four variations (Fink et al. 2017).

Step 6—Simulation of the data with the Vine Copula structure:

With the Vine Copula structure, the udata can then be simulated. This simulated udata is univariate distributed.

Step 7—Back transformation of the simulated udata:

The udata simulated with the Vine Copula, is now transformed back to the residuals (*epsilon*_t from Equation (1)). The quantile function *qdist* is used for this purpose. This transforms the simulated udata back into the univariate student-t distribution. The advantage of this procedure is that the simulated residuals (simulated *epsilon*_t) still show the dependence structures, but now already come from the Student's t distribution (Fink 2021).

Step 8—Simulation of future log-returns:

The next step is the conversion of the simulated residuals with the GARCH-model to simulated log-returns. For this, the data for $sigma_t$ and $epsilon_t$ can be given to the GARCH-model (Fink 2021).

The simulated log-returns are not predicted returns. The object consists of six columns of 1000 rows each, because 1000 paths are simulated in this strategy. Each of the 1000 paths represents a possibility of how that asset might perform over the next 20 trading days.

The simulated returns of each asset are also dependent. If the strategy had worked without modeling the dependency structures between the assets with the Vine Copula model, the correlation between the simulated log-returns of the individual assets would be zero. This implies the lack of dependency structure between the assets. Since in this case, the simulated log-returns of the assets are related via the Vine Copula in the background, the price time series calculated from them for the next 20 trading days are simulated time

series that have the dependency structures of the initial time series. This is desirable in our multi-asset portfolio strategy.

Step 9—Calculate the simulated future price of the assets:

From the simulated log-returns, the potential prices of the assets in 20 trading days are calculated for all 1000 paths per asset. Consequently, there are 1000 simulated future prices per asset at this point of time.

Step 10—Optimization of asset weights for a maximum return:

To select from the 1000 possibilities per asset, the *Deoptim* optimizer is used. It selects the best of the 1000 simulated future scenarios per asset under two manually programmed conditions, so that the return is maximized (Fink 2021). As described, the first condition is a value-at-risk constraint. At a risk level and loss level of 0.05 each, the investor is willing to bear an annual loss of 5% in 95% of the best cases.

The second condition ensures that the strategy cannot take leveraged positions and therefore the sum of the weights of all assets must equal one.

Step 11—Calculation of the wealth process:

After the best scenario per asset is selected, the wealth process of the strategy is then calculated based on the best reallocation.

These eleven steps are now repeated on each rebalancing day. For example, the second rebalancing day is trading day 771. For the simulation of the future price time series of the assets, the data of trading days 21 to 770 are used as a basis. After this detailed description of the procedure on a rebalancing day, the results of our strategy backtests now follow in the next chapter.

3. Results of the Portfolio and Trading Strategy Analysis

3.1. Portfolio Analysis in Comparison with the S&P500

Since our strategy was expected to outperform the broad market, we first compared the annualized return of the composite portfolio (Table 4), assuming a steady equal weighting throughout the observation period (24 August 2011–1 February 2022), to the annualized return of the S&P500 Index. The S&P500 symbolizes the broad market in this paper. The result of this comparison is displayed in Table 5 below.

Table 5. Comparison of the annualized portfolio return with the annualized return of the S&P500.

Asset	Annualized Return (24 August 2011–1 February 2022)
Portfolio	+10.31%
S&P500	+12.95%

The comparison clearly shows that the annualized return of the chosen multi-asset portfolio (+10.31%), was historically lower than that of the S&P500 (+12.95%).

This shows that with this portfolio (steadily equal weights of the assets), no better return could have been achieved compared to the return of the broad market. This starting point is ideal for testing our programmed trading strategy, as it allows us to test whether our strategy would have performed better than the broad market under certain circumstances and with empirically determined initial asset weights, when applying to the portfolio. As shown, this would not have been possible in the case of an investment in a constant equally weighted portfolio consisting of the assets listed in Table 4.

The following subsection provides information and results about the four different scenarios on which we tested our trading strategy.

3.2. The Scenarios for Testing the Trading Strategy and the Respective Results

As mentioned, the strategy is tested in four different scenarios using historical asset price data. Each of the four scenarios is described below and the associated historical strategy backtest result is shown. 1. Strategy 1 (first scenario)—lower-risk strategy applied to an initial equally weighted portfolio:

In this case, the strategy is applied to the initial equally weighted portfolio. The strategy is structured in such a way that it initially tracks the performance of the S&P500 for the first 750 trading days, as the first rebalancing day is trading day 751.

The potential asset prices in 20 trading days are simulated using the last 750 trading days. Setting the strategy on the S&P500 has the advantage of being able to compare the performance. A risk level and a loss level of 0.05 (5%) each are used. Therefore, according to our definition, this is a lower-risk strategy. It should be noted that the meaning of the value 0.05 as risk level and loss level is different for each investor. In addition to applying the strategy to this portfolio, the performance of the strategy is compared to the performance of the S&P500 index and the performance of a continuously equally weighted portfolio consisting of the same assets.

Figure 3 clearly shows that a profit could have been generated by applying Strategy 1 during the period under consideration. The starting value of all three asset processes is 1177.60. However, the S&P500 performs better, both compared to the equally weighted strategy and compared to the Strategy 1. The performance of the S&P500 and the equally weighted portfolio is nearly identical with final asset values of 4546.54 (S&P500) and 4498.78 (constant equally weighted portfolio). Strategy 1, on the other hand, performs much worse with a final value of 3067.75.



Figure 3. The development of the wealth process of the S&P500 (black), Strategy 1 (orange) and a constant equally weighted portfolio (green).

Nevertheless, the development of the portfolio wealth when applying Strategy 1 shows that the volatility of the portfolio is lower overall. The stock market crash in December 2018, as well as the stock market crash at the beginning of the Covid-19 pandemic 2020,

have only a minor impact on the wealth of Strategy 1 compared to the S&P500. This is the positive effect of a lower-risk volatility-based trading strategy. As a result, using Strategy 1 with a lower risk and loss level of 0.05 each is ideal for low-risk investors, who are not willing to tolerate high losses during the investment period. In addition, it is important to understand that the portfolio of Strategy 1 is applied to a multi-asset portfolio and this may be the reason for the loss of return. As long as the correlation between the different assets is not 1, a multi-asset portfolio is not penalized.

Figure 4 shows the development of the asset weights of the portfolio using Strategy 1 during the entire period under review. The portfolio was rebalanced every 20 trading days. As expected, the assets cash and bonds are partly high weighted, compared to the remaining assets in this lower-risk strategy. The real estate ETF (Real Estate) and the MSCI World ETF (ETFs) are almost constantly weighted low.



Asset weighting plot - Strategy 1

Figure 4. The asset weights plot of Strategy 1.

2. Strategy 2 (scenario 2)—higher-risk strategy applied to an initial equally weighted portfolio:

The structure of Strategy 2 is completely the same as Strategy 1, with the only difference being that the risk level and the loss level are set to 0.10 (10%) each. Thus, this strategy is riskier than Strategy 1. This is an attempt to see if a higher risk and loss level can improve the performance of the portfolio when starting with an initial equal weighting of the six assets. The goal here is to compare the strategy with the S&P500 performance and the performance of the constant equally weighted portfolio.

The higher-risk Strategy 2 performs best compared to the other two developments shown in Figure 5. Using a starting value of 1177.60 and a final value of 6002.41, this corresponds to a total return of 411.41% over the entire period under consideration (excluding taxes and transaction costs). The S&P500 return over the same period totals 286.09%. The

riskier Strategy 2 significantly outperforms the S&P500 and the equally weighted strategy in terms of return. Nevertheless, it must be mentioned that the volatility of the portfolio's asset process using Strategy 2 is significantly more volatile than the asset process using Strategy 1. This is largely due to the different risk and loss levels. It can be seen particularly clearly in Figure 5 that Strategy 2 follows the performance of the S&P500 for the first 750 trading days, as specified. Therefore, in contrast to the green line (wealth process of the constant equally weighted portfolio), the orange line (wealth process with Strategy 2 applied to the initial equally weighted portfolio) is not visible at the beginning because it is below the black line (S&P500 performance).



Figure 5. The development of the wealth process of the S&P500 (black), Strategy 2 (orange), and a constant equally weighted portfolio (green).

Figure 6 shows that the weight of *Shares* (Apples shares) is consistently high. Furthermore, it is noticeable that the cash weight is significantly lower than in the asset weights plot of Strategy 1 shown in Figure 4 (lower-risk portfolio). The weights of the real estate ETF (*Real Estate*) and the gold ETF (*Commodities*) are consistently low.

The result of Strategy 2 shows that applying the strategy to the multi-asset portfolio set-up, with a risk and loss level of 0.10 (10%) each and initial equal weights of the assets, historically, a better return could have been achieved than with the broad market. The next step is to test whether this effect can also be achieved when working with the initial asset weights determined in the course of the survey, conducted for this study.



Figure 6. The asset weights plot of Strategy 2.

3. Strategy 3 (third scenario)—lower-risk strategy applied to the established portfolio with the empirically determined initial asset weights of the low-risk survey participants:

The structure of Strategy 3 is similar to Strategy 1 and 2. Strategy 3 starts on the first day (24 August 2011) of the period under review with the asset weights of the low-risk participants determined in the survey. The initial capital calculated on this basis is therefore 2985.74 EUR. Strategy 3 is determined by the development of the empirically determined portfolio with the initial asset weights shown in Table 3 on the first 750 trading days. The asset *Cash* has a weight of 0% at the beginning. Since Strategy 1 has already performed worse than the associated equally weighted strategy, a similar result has to be expected here as well, as the risk level and the loss level are again set to 0.05 (5%) each. The performance of Strategy 3 is compared with the performance of the same portfolio with the same initial asset weights and which is not rebalanced over the entire period and starts with the same amount of capital.

As shown in Figure 7, the empirical, lower-risk portfolio performs worse under Strategy 3 than the same constant empirical weighted portfolio with the same initial capital. However, as with Strategy 1, the volatility of the wealth process of the portfolio is comparatively low, which is particularly evident during the aforementioned stock market crashes. The respective returns achieved and the starting and end capital of the two compared portfolio wealth processes are shown in Table 6 below.

Asset weighting plot – Strategy 2



Figure 7. The development of the wealth process of Strategy 3 (orange) and the portfolio with the constant empirical low-risk asset weights (green).

Table 6. Performance comparison of the empirical lower-risk strategy and the constant empirical asset weighted portfolio.

Strategy	Strategy 3	Portfolio with Constant Empirical Asset Weights
Starting capital	2985.74 EUR	2985.74 EUR
End capital	6194.78 EUR	8958.94 EUR
Return ¹	107.48%	200.06%

¹ Please note that no transaction costs and taxes have been taken into account when calculating the return.

The difference in the end capital of the two strategies shown in Table 6 is 2764.13 EUR. Using the given initial asset weights and the risk and loss level parameters selected for a low-risk portfolio, Strategy 3 earns 2764.13 EUR less than the portfolio with the constant empirical asset weights. Thus, the low-risk survey respondents would have achieved a better return on an investment in the portfolio in the past if the portfolio had been held with the initial, empirically determined asset weights and no asset rebalancing had occurred. Based on experience, Strategy 3 would need to have the assets Cash and Bonds weighted high and the asset Shares weighted low. Figure 8 provides further information on this.



Figure 8. The asset weights plot of Strategy 3.

As suspected, the asset weights profile is similar to that of Strategy 1, as the asset *Bonds* is almost constantly weighted high, and the asset *Shares* is weighted low. The cash position is also highly weighted compared to the other assets during the period under review.

The approach of Strategy 3 is tested in the following with the initial asset weights which are determined from the answers of the high-risk survey participants.

4. Strategy 4 (fourth scenario)—higher-risk strategy applied to the established portfolio with the empirically determined initial asset weights of the high-risk survey participants:

Strategy 4 starts with a starting capital of 1122.02 EUR. The portfolio is initially composed of the asset weights of the six assets listed in Table 3, which results from the responses of the high-risk participants in the survey. The asset *Cash* has a weight of 0% at the beginning. The strategy creation procedure is similar to Strategy 3. The portfolio is fixed for the first 750 trading days to the development of the empirically determined portfolio, which ensures the determined initial asset weights of Table 3 on day one. The first rebalancing day is therefore the 1 September 2014. Since Table 3 shows the responses of the risky survey participants, the strategy should act accordingly riskier. This is ensured by increasing the risk and loss levels from 0.05 each to 0.10 each. After a better return is achieved with the higher-risk Strategy 2, compared to the low-risk Strategy 1, this is now also expected for Strategy 4 compared to Strategy 3.

The plot in Figure 9 shows that the two wealth processes develop completely identically over the first three years (750 trading days with 250 trading days per year), as specified. Afterwards, a permanently better development of the Strategy 4 is seen. The exact values of the starting and end capital, as well as the achieved return of the Strategy 4, are listed in Table 7 below. In addition, Table 7 shows a comparison between the performance of both



riskier strategies (Strategy 2 and Strategy 4) tested in this study and the performance of the S&P500.

Figure 9. The development of the wealth process of the Strategy 4 (orange) and the portfolio with the constant empirical high-risk asset weights (green).

Table 7. The starting and end capital as well as the achieved return during the observation period of the riskier strategies and the S&P500.

Strategy	Strategy 2	Strategy 4	S&P500
Starting capital	1122.02 EUR	1122.02 EUR	1122.02 EUR
End capital	3310.36 EUR	4781.82 EUR	4331.95 EUR
Return ¹	195.04%	326.18%	286.09%

¹ Please note that no transaction costs or taxes have been taken into account when calculating the return.

Strategy 4 outperforms Strategy 2 (195.04 %) with a total return of 326.18%. The high-risk survey participants who would have invested in the portfolio with the risky initial asset weights on 24 August 2011 would have achieved a return of 326.18% when applying Strategy 4 with risk and loss levels of 0.10 (10 %) each by 1 February 2022. As can be seen in Table 7, Strategy 4 also wins against a classic buy-and-hold strategy with the S&P500 index, for the same initial capital in the period under review. Please note that for the sake of simplicity, it is assumed that it is possible to invest in the S&P500 without detours.

Table 8 shows the respective cumulative return of Strategy 4 and the S&P500, which symbolizes the broad market. In the calculation of the cumulative returns, geometric chaining was used to aggregate the returns. Strategy 4, applied to the riskier behavioral modified asset allocation, would have generated a better cumulative return (293.6%) over the period under consideration than the S&P500 (232.2%). This shows that the goal of

developing a strategy that would have generated a better return than the broad market was achieved.

Table 8. Comparison of the cumulative returns of Strategy 4 and the S&P500 in the period from 24 August 2011 to 1 February 2022.

	Strategy 4	S&P500
Cumulative Return	293.6%	232.2%

In the weights plot of Strategy 4, it is noticeable that each of the seven assets is highly weighted (>0.35) at least once. Furthermore, as expected, the weight of the asset *Shares* increases and the weight of the asset *Cash* and the asset *Bonds* decreases overall, compared to the weights plot of Strategy 3. Moreover, Figure 10 shows that, just as in the three preceding weights plots, the asset *Commodities* (pink) is partially weighted higher only after the sixtieth rebalancing day. Unlike the favoured initial weights of the empirically risky asset weights of Table 3, the asset *Funds*, in contrast to the asset *ETFs*, has a higher importance in the asset weights during the period under consideration.



Asset weighting plot – Strategy 4

Figure 10. The asset weights plot of Strategy 4.

4. Discussion

In summary, the two higher-risk strategies (Strategy 2 and Strategy 4) perform better than the corresponding equally weighted strategies and the two lower-risk strategies (Strategy 1 and Strategy 2). In addition, a profit could have been achieved with all strategies. Note that these results are based on the achieved return without calculating the tax and transaction costs.

Strategy 4 achieves the goal of applying our trading strategy to a portfolio with empirically determined initial asset weights to realize a better return than the broad market.

This would not have been possible with constant equal asset weights or with the empirically determined initial asset weights without rebalancing (whether lower-risk or higher-risk initial weights), as shown in this paper. Therefore, the programmed riskier trading Strategy 4, in combination with the empirically determined initial asset weights of the risky survey participants, contributes decisively to the achievement of this goal.

It should be noted that the values for the risk level and the loss level are chosen arbitrarily and that all strategies will act differently if these parameters are changed. Since the willingness to take losses and risks are individually pronounced and therefore differ for each investor, not every combination of the two parameters could be considered and examined in this study.

Although this paper is not about predicting stock returns based on a volatility index, our results support the finding of (Ghosh et al. 2022) regarding the possible use of historical volatility to set up a profitable trading strategy with regular asset rebalancing. We achieved a profitable result on all four scenarios considered in this paper and even outperformed the broad market in the case of Strategy 4. It is confirmed within the assumptions and models in this paper that past volatility of financial products has a long-term memory and can therefore be used for a profitable trading strategy.

Beyond this study, an application of Strategy 4 to a portfolio with other assets would be interesting to verify whether our strategy can actually win permanently against a buyand-hold strategy with single or multiple assets. In the course of this, further studies should examine whether Strategy 4 can achieve better returns than an equally weighted buy-and-hold portfolio or the S&P500, even taking into account transaction costs and taxes. In this context, the results of the strategies, when adjusting the forecast time window to, for example, 5 instead of 20 trading days, while simultaneously increasing or decreasing the parameters, are also interesting. In addition, when creating the GARCH model in the program, it is possible to work with a different model (here the standard GARCH model sGARCH was used). Since the GARCH model may reach its limits in the case of the leverage effect, for example, it might be useful to test the strategy with an alternative model. However, this is not part of this work.

On the subject of structural breaks in the stock market, it would be interesting to investigate whether the return predictions of our trading strategy changed after the structural break in April 2020 (Karavias et al. 2022) in terms of selecting the return-maximizing asset allocation on a rebalancing day. In particular, it would be necessary to examine whether a structural break in the stock market has an impact on the performance of the strategy at the time of the structural break and afterwards. This could occur, for example, if the volatility of the respective asset exhibits long-lasting extreme spikes before, during, or after the structural break. These could potentially affect the accuracy of the simulation of future returns. However, in our opinion, a structural break has little impact in the performance of our strategy, as the future returns of the assets are simulated based on the volatility of the past 750 trading days.

Within this long (compared to a structural break) time period, we think that the prediction is only slightly affected by a structural break. This assumption needs to be confirmed in further studies.

For further investigations, it is necessary to test the different strategies set up here, for example with different asset combinations, stock companies, and commodities and to compare the results with the results given in this work. It would be particularly important to find out whether Strategy 4, which performed best in this study, would also have won against the market in other constellations and thus could have generated a better return. Furthermore, the period under consideration could be adapted, respectively extended.

In this case, it is particularly interesting to determine whether Strategy 4 continues to perform better than the broad market. It is reasonable to assume that Strategy 4 would have performed better than the broad market even if the period under consideration is extended, for example 2001 to 2022. This period involves a strong economic recession and a weak S&P500. Since the strategy simulates future returns based on past volatility, which tended

to be high (negative) for equities during the financial crisis, equities should be weighted lower by the strategy during this period compared to bonds, for example. Therefore, the strategy should invest in those financial products selected for this backtest which are less volatile, so that the predefined risk and loss level can be maintained. In addition, it can be assumed that the strategy would have performed better than the S&P500 over the period of 2001 to 2022 because the largely weak performance of the S&P500 during the financial crisis. The behavioral modified asset allocation involves, unlike the S&P500, non equity-based financial products, such as commodities, cash, real estate, and bonds. Therefore, during recessions and equity market crashes, the Strategy may increase the capital invested in non-equity based products. This would most likely lead to a better performance than the S&P500.

For the long-term success of the trading strategy in conjunction with behavioral modified asset allocation, reallocation of assets based on further surveys at regular intervals could be beneficial. This assumption is obvious, since the products offered on the market, as well as the asset preferences of the broad population, are constantly changing. For example, during our period under review (2011–2022), the market share of cryptocurrencies and ETFs in total invested capital increased. Thus, these two products are currently more important and respectively popular than in 2011. In order to adjust the asset allocation to the changing asset preferences of the broad population in the long-term, reallocations based on new surveys seem to be a useful method. Whether this improves the performance of the strategy and whether adjusting the asset allocation based on further surveys is practicable, needs to be investigated in further studies.

Another fundamental question is whether the trading strategy does also reallocate the assets reliably and correctly for short-term investments. If this is the case, our trading strategy, in addition to the approach of predicting open-to-close returns, using a neural network (Ballestra et al. 2019), would be another possibility for short-term oriented trading strategies, respectively, for trading strategies with daily rebalancing. In addition, it would be interesting to investigate how the parameter and models would have to be changed for a successful short-term application and whether such a strategy can be used profitably. As described earlier, the scope of the open research topics listed does not allow them to be addressed in this paper. The results and approaches of this study provide the basis for further research, in which the questions listed above can be investigated.

In conclusion, the riskier Strategy 4 performed better, compared to all other strategies and the S&P500. This confirms the statement that a higher return requires a higher risk when investing in securities.

Author Contributions: Conceptualization, J.F. and S.G.; methodology, investigation, data curation, writing—original draft preparation, J.F.; writing—review and editing, J.F. and S.G.; visualization, J.F.; supervision, S.G.. All authors have read and agreed to the published version of the manuscript.

Funding: This work was financially supported by the Munich University of Applied Sciences HM and the German Research Foundation (DFG) through the "Open Access Publishing" program.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Patient consent was waived due to the non existing possibility to infer the survey participants from the survey responses.

Data Availability Statement: Restriction apply to the availability of the survey data, as they were not created exclusively for this study. Nevertheless, all survey results necessary to reproduce the results of the backtest of the trading strategies can be found in this paper. The file was created with the program RStudio—Version 1.4.1717.

Conflicts of Interest: The authors declare no conflict of interest.

19 of 20

Appendix A

Variables	Groups	Number of Participants (%)
	Male	40 (54.1)
Sex	Female	34 (45.9)
	Divers	0 (0.0)
	18–20	3 (4.1)
	21–29	22 (29.7)
	30–39	5 (6.8)
Age	40–49	15 (20.3)
	50–59	21 (28.4)
	60–69	1 (1.4)
	>70	7 (9.5)
	Hauptschule diploma	4 (5.4)
	Realschule diploma	16 (21.6)
Education	High school diploma or equivalent	20 (27.0)
	Bachelor degree	13 (17.6)
	Master degree	16 (21.6)
	PhD	5 (6.8)

Table A1. Personal information of the participants of the first survey.

Note

¹ Both surveys were conducted anonymously, so that there is no possibility to draw conclusions about the individual participant with the help of the answers. The anonymity of the participants is therefore guaranteed.

References

- Andersen, Torben G., Tim Bollerslev, Francis X. Diebold, and Paul Labys. 2003. Modeling and Forecasting Realized Volatility. *Econometrica* 71: 579–625. [CrossRef]
- Ardia, David, Katharine Mullen, Brian Peterson, Joshua Ulrich, and Kris Boudt. 2021. Package 'DEoptim'. Global Optimization by Differential Evolution. Available online: https://cran.r-project.org/web/packages/DEoptim/DEoptim.pdf (accessed on 8 August 2022).
- Ballestra, Luca V., Andrea Guizzardi, and Fabio Palladini. 2019. Forecasting and trading on the VIX futures market: A neural network approach based on open to close returns and coincident indicators. *International Journal of Forecasting* 35: 1250–62. [CrossRef]
- Bogan, Vicki L., David R. Just, and Chekitan S. Dev. 2013. Team gender diversity and investment decision-making behavior. *Review of Behavioral Finance* 5: 134–52. [CrossRef]
- Bollerslev, Tim. 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31: 307–27. [CrossRef]
- Campbell, John Y., and Robert J. Shiller. 1988. The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *The Review of Financial Studies* 1: 195–228. Available online: http://www.jstor.org/stable/2961997 (accessed on 10 August 2022). [CrossRef]
- DekaBank. 2022. Deka-MegaTrends CF. Aktienfonds Weltweit. Available online: https://deka.de/privatkunden/fondsprofil?id=DE0 005152706 (accessed on 9 August 2022).
- Engle, Robert F. 1982. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica* 50: 987–1007. [CrossRef]
- Fama, Eugene F. 1970. Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance* 25: 383–417. [CrossRef] Fink, Holger. 2021. *Financial Econometrics*. Munich: Lecture—Script.
- Fink, Holger, Yulia Klimova, Claudia Czado, and Jakob Stöber. 2017. Regime Switching Vine Copula Models for Global Equity and Volatility Indices. *Econometrics* 5: 3. [CrossRef]
- Ghosh, Bikramaditya, Elie Bouri, and Andreas Pape. 2022. Long Memory and Fractality in the Universe of Volatility Indices. *Complexity* 2022: 6728432. [CrossRef]
- Karavias, Yiannis, Paresh Kumar Narayan, and Joakim Westerlund. 2022. Structural Breaks in Interactive Effects Panels and the Stock Market Reaction to COVID-19. *Journal of Business & Economic Statistics*, 1–14. [CrossRef]
- Mandelbrot, Benoit. 1963. The Variation of Certain Speculative Prices. *The Journal of Business* 36: 394–419. Available online: http://www.jstor.org/stable/2350970 (accessed on 8 August 2022). [CrossRef]
- Markowitz, Harry. 1952. Portfolio Selection. The Journal of Finance 7: 77-91. [CrossRef]

Moreira, Alan, and Tyler Muir. 2017. Volatility Managed Portfolios. The Journal of Finance 72: 1611-44. [CrossRef]

- Nagler, Thomas, Ulf Schepsmeier, Jakob Stoeber, Eike Christian Brechmann, Benedikt Graeler, Tobias Erhardt, Carlos Almeida, Aleksey Min, Claudia Czado, Mathias Hofmann, and et al. 2022. Package 'VineCopula', 5/24/2022. Available online: https://cran.r-project.org/web/packages/VineCopula/VineCopula.pdf (accessed on 9 August 2022).
- Poterba, James M., and Lawrence H. Summers. 1988. Mean reversion in stock prices: Evidence and Implications. *Journal of Financial Economics* 22: 27–59. [CrossRef]

Wang, Zhenkun, Elie Bouri, Paulo Ferreira, Syed Jawad Hussain Shahzad, and Román Ferrer. 2022. A grey-based correlation with multi-scale analysis: S&P 500 VIX and individual VIXs of large US company stocks. *Finance Research Letter* 48: 102872. [CrossRef]
 Zhang, Shaojun. 2022. Toward Tax-Efficient Low-Volatility Investing. *Journal of Portfolio Management* 48: 198207. [CrossRef]